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Advanced Signal Processing and Machine Learning Techniques for Muon Orbital Hit Localization in the ATLAS Experiment at CERN

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Abstract

Accurate reconstruction of charged particle trajectories, particularly muons generated in proton-proton collisions, is a crucial aspect of precision measurements conducted during detector operation at ATLAS (A Toroidal Large Hadron Collider Apparatus). This thesis focuses on integrating and applying advanced signal processing and machine learning techniques to enhance the accuracy of muon hit localization in the Micromegas detectors of the New Small Wheel (NSW), a major upgrade of the ATLAS Muon Spectrometer aimed at improving muon tracking in high-luminosity conditions. The NSW, replacing the innermost endcap chambers, is equipped with Micromegas and sTGC (small-strip Thin Gap Chambers) technologies, designed to handle increased radiation backgrounds and provide enhanced resolution for precision muon measurements. Addressing key challenges such as radiation damage, pile-up effects, and radiative energy losses, this research aims to develop signal processing techniques capable of mitigating noise and correcting signal distortions.

This study seeks to improve data interpretation in the Micromegas detectors, of the New Small Wheel (NSW) inside the ATLAS experiment at CERN, by resolving these identified issues and implementing signal processing protocols that effectively suppress noise and compensate for radiation-induced energy losses. Furthermore, it applies state-of-the-art machine learning algorithms to high-fidelity Monte Carlo simulations of muon interactions, enhancing muon hit localization accuracy. The study evaluates various classification and regression models to optimize spatial resolution and assess their performance through extensive experimental validation.
A comparative analysis of multiple simulation datasets, spanning a range of transverse momenta, is conducted to evaluate the robustness of the proposed techniques. Additionally, statistical

classification methods are employed to distinguish between signal and background events, thereby improving data quality and reducing systematic uncertainties. Finally, the research analyzes muon traces affected by radiation-induced energy loss, categorizing them into signal (cluster signal) and background (cluster background) to further refine localization accuracy.

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This research is dedicated

to my husband Vasilis,

who transformed me to what I am today...

Acknowledgements

1 Introduction

1.1 Background

Particle physics, also known as high-energy physics, explains the fundamental elements of the universe and how they interact. It can be traced back to ancient philosophy. Philosophers such as Democritus (c.460–370 BCE) had suggested that matter was made up of indivisible particles called atoms. Yet it was only in the late 19th and early 20th centuries that the field began to evolve into a scientific discipline. One of the first subatomic particles was discovered in 1897. It was J.J. Thomson who found the electron, contrary to the belief of indivisible atoms. Then, in 1911 came experiments by Ernest Rutherford that established the nucleus as a dense core in the atom surrounded by electrons. However, in the year 1932, James Chadwick had discovered the neutron, giving us our three basic atomic bits and establishing the basis for modern nuclear physics. The introduction of quantum mechanics in the early 20th century transformed particle physics. Basic theories developed by scientists like Max Planck, Niels Bohr and Werner Heisenberg provided a framework for understanding what things were happening in the atomic world. Programs of research exploring the quantized nature of energy levels and yielding wave-particle duality became essential elements of the field.

In the last half of the 20th century, particle physics moved forward both with the invention of particle accelerators and detectors. Cyclotrons and synchrotrons allowed researchers to test the structure of matter at levels of energy never achieved before. For example, groundbreaking experiments resulted in the detection of new particles, like the positron (1932), the muon (1936), and the pion (1947). The identification of these particles pointed to a mind-boggling subatomic world that existed alongside protons, neutrons and electrons. In the 1960s and 1970s the Standard Model of particle physics was developed. This model unified our understanding of

electromagnetic. This was the period when Murray Gell-Mann and George Zweig discovered quarks. Both protons and neutrons were no longer regarded as the only elementary particles. Today, particle physics has open the eyes of researchers with respect to fundamental questions about the universe. For example, concerns like what is dark matter and dark energy, how to unify forces, and what is on the way beyond the Standard Model have been answered. It was these events that would color future experimental discoveries, as large-scale experiments like those at CERN's Large Hadron Collider (LHC) continue to push the boundaries of knowledge and prevent particle physics from being sidelined.

Cycles of atomism are a fundamental characteristic of twentieth-century particle physics. The first of these atomic physics was followed by more detailed nuclear physics and basics behind the physics of behavior of sub-atomic particles. Each was a deeper exploration of matter's complex structure. Scientists at the beginning of the century became increasingly certain that matter was made up of atoms that are composed of a small, positively-charged nucleus encircled by a collection of negatively-charged particles called electrons (Hoddeson, 1997). The outermost layer, the electron cloud, became the domain of atomic physics. Nuclear physics is concerned with the nucleus, which was considered to be a composite particle in its own right. Early studies begun from the observation that each atomic nucleus that could be broken down to sub-particles (Rodríguez, 2004). Physicists believed that every matter was made up of the primordial "elementary particles," protons, neutrons, and electrons. However, after World War II, basic particles such as the proton, neutron, and electron began to appear, and a new subfield of physics was created to study them. These particles were originally not thought of as the building blocks of matter. The new field was given the name high-energy physics (HEP), it involved mainly the use of high-energy particle acceleration in experimentation. Even though research has analyzed the

history of atomic physics, nuclear physics, and of the early days of elementary particle physics, the most recent cycle of atomism is still evolving (Mistry, 2011). In the 1960s and 1970s, physicists dealing with high-energy physics discovered a new type of substance: quarks. This brought to surface the essentiality of protons, neutrons, and other like particles play a role in the nature of matter. The protons and neutrons are parts of the nucleus of atoms which represent the gross matter while quarks make up protons and neutrons (as well as several other types of particles). The aim of this section is to provide an overview in particle physics and an analysis of the role of muons.

1.1.1   Historical overview of particle physics.

A groundbreaking step in the development of physics was made by Marie Curie (1867–1934), who was the first person to weave particle physics with radioactivity. Curie's research showed that atoms themselves, and not the way atoms were arranged to form molecules, were the source of radioactivity (Shanbhag, 2024). The new concept of atoms being solid and immobile was contradicted by this fact. Marie Curies and her husband Pierre discovered that radioactive elements polonium and radium in 1898. From the understanding of electrons, Thompson proposed that cathode rays were composed of particles with a negative charge and he proposed a Thomson's "Plum Pudding" Model based on the newly found particle. According to this model, atoms held electrons in a cloud of positive charge (Hentschel, 2009).

One of the main arguments to undermine the "Plum Pudding" theory was Ernest Rutherford, with his student, who conducted a groundbreaking experiment in 1911. In this experiment, they used a thin metal foil to shoot a beam of positively charged alpha particles. In a manner similar to an empty space, most of the alpha particles have passed through it (Hon & Goldstein, 2013). Yet, a small number of alpha particles were scattered over a wide area, and some of them were even deflected backward. After Rutherford presented a new theory whereby atoms

had particles called proton that is positively charged. He devised a new atomic model, the planetary model, in which the electron goes around the proton in a fashion like that of the Earth orbiting the sun. Nevertheless, the Rutherford model is considered incomplete, like the Thompson atomic model. The similar problem of opposite electric charges of the circulating electron and the proton and the resultant attraction persisted. Electrons would theoretically collide with the proton, with centripetal attraction as it approaches, leading to the annihilation effect.

Neils Bohr (1913) was the one who found the solution to Rutherford problem. However, Bohr had already attached Planck's Hypothesis of quantized energy to the model of the atom, suggesting that electrons were in orbit around the sun and that there could only be a certain number of electrons in each orbit (Maina, 2023). Furthermore, Bohr was in favor of the system's angular momentum in a stationary state be an integral multiple of $h/2\pi$ (Maina, 2023). As a consequence, Bohr was able to determine the hydrogen atom's radius, for which he won a Nobel Prize.

A new concept of particle duality developed with the discovery of quantum theory. In his photoelectric effect, Einstein found that light, which has always been assumed a wave, is indeed a particle. De Broglie demonstrated this duality with light when he made this claim in his doctoral work that particles can also have wave-like characteristics, which became known as The De Broglie's Waves (Hill, 2023). Erwin Schrödinger first formally introduced the Schrödinger Wave equation, an equation that allowed the prediction of a particle's position, energy, momentum, and other parameters (Lima & Karam, 2021). Later, the wave function was developed by the British theoretician, Paul A. M. Dirac (1902–1984), to include the Quantum Electrodynamics (QED) theory. Furthermore, Dirac was able to merge relativity and quantum mechanics, thus, providing completely new insights into the nature of atoms.

1.1.2　Overview of the ATLAS experiment.

The ATLAS experiment comprises a multifunctional laboratory for proton-proton collisions studies. The experiment is carried out using three detector systems: the tracker, the calorimeter, and the muon system. These are split into nine sub-detectors with each specialized to perform a different track-like procedure or particle identification (Nagano & Atlas Collaboration, 2014). This chapter begins by giving a brief introduction to ATLAS and its general infrastructure. This section provides an overview of the ATLAS experiment.

1.1.2.1　Overview of the ATLAS Experiment

The experiments conducted at the LHC that cover the largest range of investigations were an impetus to the new detector design. Since the main goal of the experiment is to increase the proton-proton collision rate to the maximum, one such luminosity at 1034 cm-2 s-1 will be achieved (Gullstrand & Maraš, 2020). Here, it is a matter of a detector that can produce the maximum number of signatures - indications that a significant event occurred. This would mean that there would be about 109 collisions occurring every second. The number of different possibilities for the system makes the issue of the number of different signals to be triggered while travelling the LHC. The study of very precise physics that rely on good cross-checking judgment but, at the same time, point in as many directions as possible is the experiment's contribution.

The detect needs for a global LHC were completely reshaped by its quest for the Higgs boson. One of the main aims of studying collisions that imitate the boson decay process is to distinguish the event's kinematic and geometrical characteristics as they are in a manner that can be measured. A unique state can be accounted for in data by the creation of a Goliath which appears to be the decay of quantified final state particles in a specific manner to either stable particles or decaying particles. Their signals confirm the existence of particles such as photons, electrons,

muons, W and Z bosons, quarks, and gluons. They are mostly noticeable through the particle sprays known as hadronic jets. They are comprised of the particles produced during the decay process of hadronic jets into mesons and baryons. Neutrinos, these neutral weakly interacting leptons are formed, but they sensitive detectors cannot detect them due to their lack of tracks. There is an imbalance in momentum, and consequently, the particle is unable to be formed due to the missing transverse momentum. The experiment will be carried out through the following steps: specify the project task, design the experiment plan, construct the setup, and measure the performance of the system.

The superconducting air-core toroids are constructed out of the segmented coils which are set eightfold symmetrically; besides the calorimeters, there is a thin superconducting solenoid installed in the inner detector cavity. The article discusses the electronic module structure of about 100 million simplified detector layers. The inner tracking detector is a six-sided box with 1 m long, when it's enclosed by a 2 Teslas (T) axial magnetic field around the collision point. The common cylindrical shape of a 7-meter-long and a 1.15-meter radius forms the inner tracking detector (Fox, 2021). The 'continuous' proportional-counting straw-tube detectors, having the transition radiation ability in the outer part of the tracking volume are combined with the discrete high-resolution semiconductor pixel and strip detector layers in the inner part of the tracking volume, which are providing 30–40 signal points along the tracks, as well (Thaprasop, 2021).

The LAr EM sampling calorimetry covers the pseudorapidity region of $|\eta|$<3.2 and has very good calorimetric resolution for both position and the energy. The technology of LAr is used to form the end caps of the cryostats that, in turn, belong to the hadronic calorimeters that are chilled by the cryostats. The LAr forward calorimeters, which are exclusively located in the cryostats, are then responsible for covering the pseudorapidity range to $|\eta|$= 4.9. The distance from the center

axis represents a maximum angle of just 0.85 degrees. The well-functioning scintillator-tile calorimeter, which is the main component of the hadronic calorimetry, is made up of a large main barrel and two other smaller extended barrel components that are situated on either side, thus performing the largest fraction of the hadronic calorimetry. Use of calorimeter technology is a way to provide very good performance of the detector jet and ETmiss. The LAr calorimetry technology is based on the reactor technology that reacts with the time and runner conditions. 1,900 G9 cassettes are arranged in the vertical direction according to the earth's force cut along the 27.5m distant circumference. The thinnest out of the three wheels, though at the same time the lightest out of the three, is made of a silicon wafer. It is 9.0mm in the x-axis and 0.5mm maximum throughout the y-axis. Calorimeter system weights 4000 tones approximately including the solenoid that consists of the steel returns procedure with the tile supporting structure as well.

The muon spectrometer is housed by the calorimeter. A strong magnetic field is created in a lightweight and open space with the help of the air-core toroid system, which consists of a long barrel and two inserted end-cap magnets. Three stations of a device used in high-precision tracking chambers are designed to minimize the multiple scattering effect and also to obtain a better muon momentum resolution. Trigger chambers is the other important part of the muon instrumentation with a quick P+T time. The overall dimensions of the muon spectrometer are determined by the ATLAS detector. The outer chambers of the chamber are 11 meters in length apart. The third layer of the forward muon chambers is the one that is situated on the cavern wall around 23 meters away from the interaction point and has a half-length of 12.5 meters for the barrel coils.

Muon detection and classification serve as a fundamental part of high-energy physics experiments conducted at the Micromegas detector in New Small Wheel (NSW). The NSW was introduced as part of the Phase-1 upgrade of the ATLAS Muon Spectrometer to replace the

previous Small Wheel system, which could no longer sustain the increased hit rates in high-luminosity conditions. The NSW utilizes two complementary gaseous detector technologies—Micromegas and small-strip Thin Gap Chambers (sTGCs)—which provide both precision tracking and fast triggering capabilities. The Micromegas chambers, in particular, play a critical role in achieving high spatial resolution, ensuring robust classification of muon signals in environments with high pile-up and radiation effects. This enhancement is crucial for the High-Luminosity LHC (HL-LHC) era, where higher collision rates necessitate improved tracking efficiency and background suppression techniques.

1.1.2.2   Muon Detection

A muon spectrometer includes accurate tracking chambers and a separate trigger. Measurements of muon tracks in the heavy-duty superconducting air-core toroid magnets and their magnetic deflection are carried out. The toroidal magnet setup prevents the loss of resolution caused by continuous scattering while at the same time creates a field that is mainly perpendicular to the muon routes. The selection and construction of measuring devices of the spectrometer have been largely influenced by the expected quite high particle fluxes, which is resulted in one of the most important key performance metrics such as the radiation hardness, granularity, rate capability, and ageing characteristics. To handle the challenging background conditions that are caused by hadrons entering the calorimeters and radiation backgrounds, mainly neutrons and photons in the 1 MeV range, which are produced by the secondary interactions in the calorimeters, the shielding material, the beam pipe, and the components of the LHC, trigger and reconstruction algorithms are optimized.

1.1.3   Importance of muons in high-energy physics.

The muon has a unique and flexible position in physics ever since it was discovered. Data on muons give detailed knowledge about the spectrum and composition of space radiation, as well as high energy activities in the atmosphere. There is a standout part for muon in subatomic physics. Muon decay research sets higher restrictions on charged-lepton-flavor-violating events and determine the chiral structure and overall strength of weak interactions. The precision of the standard model and the interpretations of some other speculative ideas can be thoroughly scrutinized only if the data of the muon's anomalous magnetic moment are known. Together with the measurements of the proton size, electron mass, and magnetic moment, the sayings muoniums and muonic atoms bring forth measurements that have never been measured before. Besides, novel features in the case of weak interactions between the nucleons and nuclei are examined by the means of muon capture studies.

Muon-based facilities could do the role of the next generation of capabilities and provide phenomenal experimental help for scientists in the physics realms at the Intensity and Energy Frontiers [1]. From the 1960s, a high-brightness muon beams as an essential part of a neutrino factory (NF) or a muon collider (MC) [2] has been proposed. The NF addresses the precision frontier by exploring CP-violation in the neutrino sector, whereas the MC mainly deals with the high-energy frontier through the investigation of precise Higgs physics and beyond. Only that up to the time when the cooling region starts, the current front-end designs of an NF and an MC are comparable.

1.2 Motivation

1.2.1 Challenges in muon detection.

In the late 17th century, Sir Isaac Newton founded analytical physics with his Philosophiae Naturalis Principia Mathematica, and Galileo Galilei studied free fall in the 16th century while measuring his pulse. Quantum mechanics and Einstein's general relativity were developed in the early 20th century. Special relativity was soon added to quantum mechanics. Our knowledge of particle physics is condensed into the Standard Model of Particle Physics by quantum field theory. The Standard Model is a local gauge theory that describes discrete interactions of spin 1/2 fermions through spin 1-gauge bosons. All Standard Model particles except one have been found. The Higgs boson, which gives elementary particles their mass, is the only missing piece. The Large Hadron Collider (LHC) near Geneva on the Franco-Swiss border searches for the Higgs boson. By design, the LHC particle accelerator collides two beams of protons or lead nuclei at 14 TeV or 1148 TeV. The ATLAS detector at the LHC can detect and identify many particles from nuclei collisions. For example, the muon is heavy enough to reach the detector's outer layers without being completely absorbed, but light enough to not decay before reaching the edge. This detector's unique signature and different origins make it a good probe for new physics studies like Supersymmetry or the Higgs boson, as well as jet-associated W and Z boson production.

This thesis measures muon reconstruction efficiencies using the well-known kinematic properties of boson decay into a muon pair. For this task, a pure subsample from ATLAS' data with a defined center of mass energy is selected and tagged and probed. These results are compared to Monte Carlo event simulation efficiencies for comparison. The muon reconstruction efficiency depends on phase space regions and jet variables. The thesis uses natural units, setting the speed of light and Planck's reduced constant to unity ($c = \sim = 1$). This converts mass, momentum, inverse

length, and inverse time to energy units. The electron volt (eV) is the energy a particle with an elementary charge of e = 1:602176487(40) 10^{-19} C gains when crossing a one-volt electrical potential difference.

1.2.2 Role of advanced signal processing in mitigating distortions.

Analyzing the information content of low-contrast μ-radiography and making the best use of the now-available data have two sets of strategies. An essential initial step in distinguishing between the various scenarios of cosmic ray acceleration in astrophysics fields, like the identification of the mass composition of cosmic rays in the galactic to extragalactic cosmic ray transition area. Investigations can be carried out by the muon charge distribution in big air showers, which is the most fundamental parameter in reporting various categories of cosmic rays in space (Mikuni & Canelli, 2021). The time delay can cause one of the things parse is parsing degrading muon detecting performance. Signal distortion, which is principally generated by the frequency combining pieces, is the main reason for the reduction of the precision of measurements.

Consequently, it is necessary to estimate and cancel the instantaneous phase distortion in a timely manner for a more effective system performance. We have developed a program in this research to evaluate and to remove phase mistakes. The sum of random phase fluctuations and systematic phase errors serves as the phase distortions of the beat signal. Through quadrature demodulation and a frequency estimation technique based on the Chirp Z transform (CZT) that is used, the phase inaccuracy is extracted from the intermediate frequency signal along the reference line. The proper cancellation filter is a solution to this problem, and the simulation results display clearly how efficient the method is.

1.2.3   Emerging role of machine learning in particle physics.

The rise of machine learning has already cast a shadow over the traditional collider physics within the span of what seems like a short time. The researcher runs simulations in the beginning and allows the neural network to learn and produce outcomes. In particle physics, machine learning is a data-driven approach. Machine learning for instance is everywhere in particle physics: from string theory, to neutrinos. Among other potential applications in lines of the non-perturbative calculations of the strong interactions within the lattice quantum chromodynamics framework is the biggest one (Géron, 2022).

Even though QCD is consistent and provides the theoretical value of the proton's mass, the actual tasks are time-consuming and the perfection of the current state is not as precise as we would like it to be. With the help of machine learning and the use of the configurations pre-learned approximation or by more efficiently sampling configuration space could be done. Matter form factors relevant to dark matter searches and parton distribution functions of nuclear physics experiments are the two examples of the characteristics of matter that can be may be calculated using ML approaches in case the latter will turn out to be scalable and viable.

1.3   Objectives

The main purpose of this thesis aims at the development and application of sophisticated signal processing and machine learning strategies to improve the accuracy of muon hit localization within the Micromegas detectors of the New Small Wheel (NSW) detector. Problems like radiation damage, pile-up effects, and radiative energy losses are the ones that will be faced and solved. The study aims to enhance the quality of the data interpretation in the Micromegas detectors of the New Small Wheel (NSW) inside the ATLAS experiment by focusing on the mentioned issues.

1.3.1   Core objectives.

1. Develop signal processing protocols that can effectively remove noise and correct for radiation energy losses that are responsible for distorted signals.

2. Implement machine learning techniques to the data that is gathered by the ATLAS experiment and the breakthrough of the accuracy of muon detector location.

3. Test their functionality in extensive experiments and rectify them through new methods.

4. Offer clear points on how new techniques can be applied and make them applicable to other areas of high-energy physics research.

1.4   Thesis Outline

This thesis is designed to focus on all the research procedures and results which relate to the improvement of muon hit localization in the Micromegas detectors of the New Small Wheel (NSW) inside the ATLAS experiment through enhanced signal processing and machine learning methods.

Chapter 2 contains the requisite knowledge that would make the reader understand the backdrop of the research. It encompasses the theoretical basics of particle physics, especially in the case of muons, and gives details about the design and role of the Micromegas detectors of the New Small Wheel (NSW). Furthermore, the part it is dedicated to delves into the signal processing problems in high-energy physics and explains the role of machine learning in dealing with such problems.

Chapter 3 explains the research process through recounting the procedures of data acquisition, preprocessing, and feature selection. It discusses the reason to choose the specific

machine learning models and describes the procedures of training and evaluation. This section is a guide from one step to another to the experimental design and the implementation of the proposed techniques.

Chapter 4 discusses the technical side of the research in depth. It clarifies the tools and technologies that are being employed, like software frameworks and hardware configurations. Completely explicit descriptions are given of the algorithms and experimental settings, thus ensuring that the research is reproducible.

Chapter 5 introduces the results that were obtained from the experiments. Among them are elaborate data analysis, performance measuring of the machine learning models, and visual aids that help to prove the effectiveness of the suggested strategies. The distinctions between existing methods and current ones are made so as to emphasize the opportunities for development.

Finally, Chapter 6 offers a review and interpretation of the results in the context of the significance of the ATLAS experiment and physics of particles. The interpretations of the results as well as the constraints the present study brings along are dealt with. This chapter also explores the suggested topics for further study and enhancement.

Chapter 7 highlights the major outcomes of the thesis and comments on the objectives that were stipulated at the commencement of the thesis. It talks about the role of progress in particle physics and the perspective of future research that may be launched with the aid of the research.

2 Theoretical Background

The main goal of high-energy physics is to explore the basic principles that govern the interaction between particles or nuclei at high energies. High-energy particle physics deals with the most primary concerns, which are elementary particles, the essential components of the cosmos, as well as their interactions. Particle physics is primarily concerned with the study of the characteristics of nuclear matter that comes out from ultra-relativistic nuclear collisions. The cosmos was filled out in the first microsecond of its life with so-called strongly interacting Quark Gluon Plasma (sQGP)—an entity that was the product of the very collision the nuclei particle. This part of the paper introduces the research on HEP in addition to theoretical and phenomenological findings that are related to such phenomena.

2.1   The Universe

Cosmology is the study of the universe, its source and structure, its development to the present stage and its death finally in the future. The exciting realm of physics is built by ideas, experiments, and observations, and that is what makes cosmology so interesting. Cosmology's history is told from the oldest days when the professionals in the field of astronomy- the stargazers- had tracked the movement of celestial bodies. These data were then again analyzed and integrated into the modern observations which have lasted up to our time. The success or the credit of the creation of these theories should be given to the development of good classical myths, religious and philosophical concepts for the start of cosmological thinking. While the ancient Greeks, for example, postulated the idea that stars must be the products of the celestial body from which they are derived, the entire universe would be the first to be produced.

The 20th-century invention of the general theory of relativity by Albert Einstein, it is indeed a milestone in modern cosmology. This novel idea clarifies that gravity is the curvature of space and time. According to the idea proposed by Einstein, the mass and the energy in the universe can be taken as the factor that could determine whether the universe is being expanded or contracted. The 1929 discovery of Edwin Hubble that galaxies in the distance are moving away from us is one of the solid proofs that the universe is expanding. This is why the Big Bang theory was formulated, according to which the universe emerged from a singularity some 13.8 billion years ago, that is - a point of infinite temperature and density. The stages is depicted in the figure below.
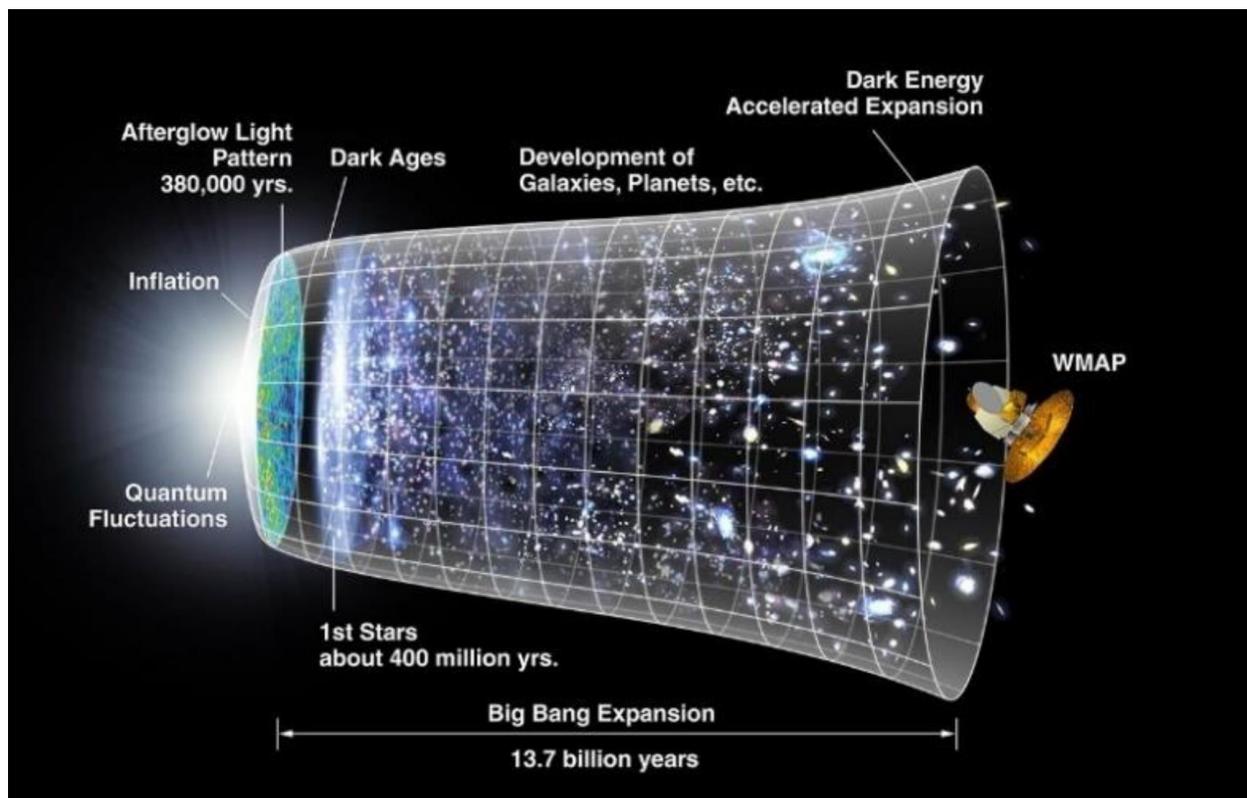
Figure 1: Formation of the universe (Source: https://www.thoughtco.com/what-is-cosmology-2698851)

The Big Bang theory is corroborated by many observations such as the cosmic microwave background radiation, the light element abundance, and the universe's large-scale structure. Moreover, there are still a good number of unsolved problems concerning this most popular and approved hypothesis; the singularity formation, the early circumstances of the universe, and the nature of dark matter and dark energy which includes the mass and energy of the universe are some examples. This is the reason that the cosmologists are not satisfied and still in the quest of a more noncontradictory and thorough theory that will unify the laws of physics and provide comprehensive knowledge of the universe. To comprehend the enigmatic properties of the universe, scientists utilize observations, experimental approaches, and theoretical models without a stop in their search for the truth of its history.

The very early universe: The cosmos was extremely hot, very dense and irregular during the first picosecond (10^{-12} seconds) of cosmic time. The four fundamental forces of nature—gravity, electromagnetism, strong and weak nuclear forces—the Planck epoch, when the laws of physics would not have applied, and the universe's explosive growth as a result of cosmic inflation are all included.

The early universe: From Big Bang to 10^{-12} seconds after, until 20 minutes later, when the universe cooled and radiation and matter separated, the event of the early universe is well known. That is, it sums up the primary creation of the earliest atoms, to be specific, the hydrogen and helium, the nucleosynthesis of atomic nuclei, and the elementary particles' birth as quarks, electrons, and neutrinos.

The middle universe: The first stars' formation and galaxy, fueled by nucleosynthesis, which consequently differentiated to heavier elements black holes and quasars' emission of

radiation, and finally, the re-ionization of the universe, that became visible to the light, are all part of the middle universe, which endured between 20 minutes of Big Bang and 1 billion years.

The late universe: the time starting from around 1 billion years ago to the present, in which the cosmos has continually been cooling and expanding. These are the topics mentioned, the evolution of life and intelligence, the formation of larger structures, clusters and superclusters, planets, moons, and other celestial bodies, and the identification of dark matter and dark energy which together form the majority of the universe's mass and energy.

The far future: the time which lies between now and the final phase, and it has a certain degree of ambiguity depending on the features of dark energy. It, basically, talks about the potential outcomes of the universe's last destiny, including the Big Crunch, the Big Rip, the Big Freeze, and the Big Bounce.
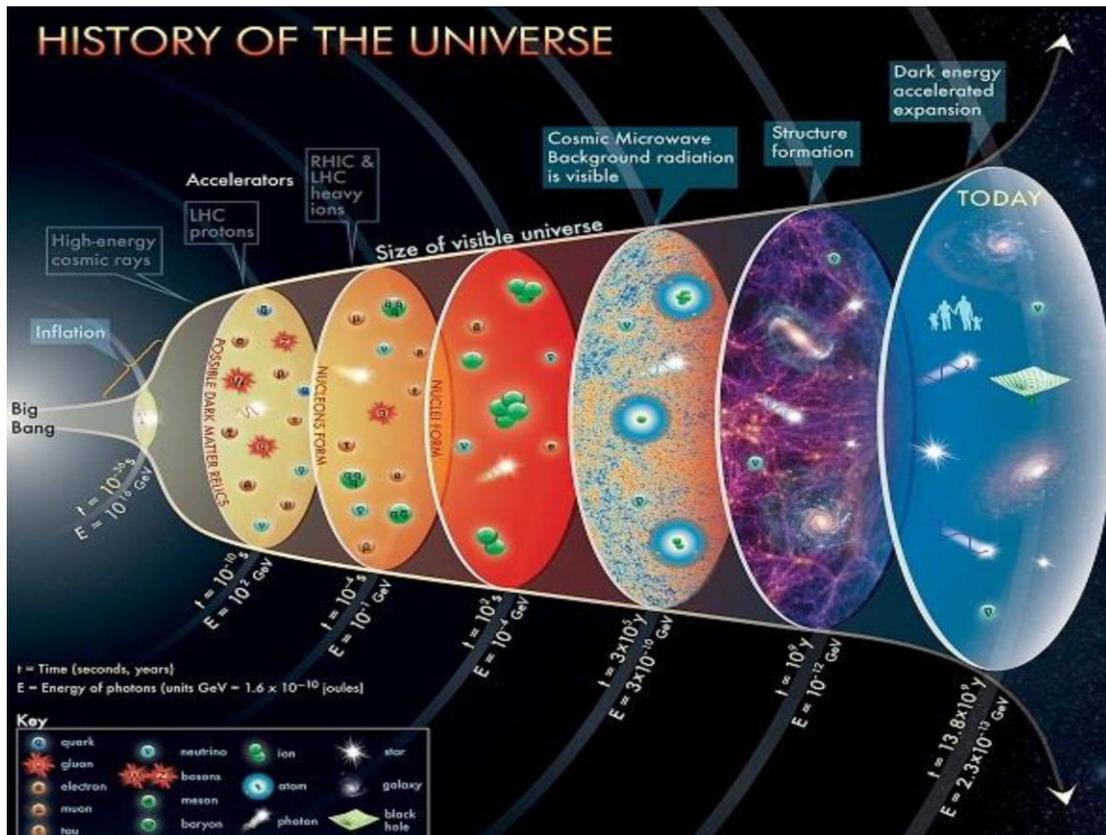
Figure 2: History of the Universe (Source: https://studiousguy.com/the-big-bang-theory)

2.2   Overview of High-Energy Physics

Marie Curie was the first to talk about the weak light that came from uranium salts, she had no idea that she was talking about the interaction of sub-atomic particles. Gunderman (2021), seeing how it seemed that radioactivity contradicted the principle of the conservation of energy, Curie's investigations caused a rethinking of the ideas of classical physics and an entirely new model of matter. Subsequently, radioactivity became a part of a new physics theory that studied how radioactively charged atoms behaved. New discoveries gave rise to the need for further research.

According to Quigg (2021), nature can be broken down into four basic forces; weak, electromagnetic, and strong interactions of leptons and quarks, as outlined by the Standard Model, which projects that the universe is formed from the few basic building blocks, matter. The concept of matter is a part of the broader scientific view of the world in which individual elements interact. As noted by Whitehead, (2021), the concept of interacting particles has received appreciation from the modern scientific community since the discovery of the electron. Despite the fact that some discrepancies remains, this theory has been getting much attention and use. Even so, there is still much to understand about the evolution of mass, oscillating neutrinos, dark matter, dark energy, and CP violation. It is clear that new understanding of physics required, as noted by Vissani (2021), the Standard Model is limited in its explanation of the behavior of particles. Identifying the means of interaction of these elements from the basis of particle physics. At CERN, there are four main experiments that focuses on atomic particles, the ATLAS, the CMS, the LHCb and ALICE, the experiment looks at proton-proton collisions.

2.2.1   Key concepts in particle physics.

Bettini (2024) posits that the concept that all matter is made up of particles and that the properties of matter can be explained by those of these particles is fairly new. Atomic theory was formulated by Dalton in the early 19th century, and it was the first modern scientific theory that postulated the idea of matter being made of atoms (Grossman, 2021). The existence of the electron, discovered by Thomson, is the earliest piece of scientific evidence, particularly relevant to contemporary particle physics. During the transition from the 19th to 20th centuries, Maxwell, Gibbs and Boltzmann were of the opinion that the properties of the atoms out of which are formed all elements of matter can explain the gross behaviors of the said elements (Sarkar & Bhattacharyya, 2022). At the same time, researchers were skeptic of the existence of atomic particles, but they believed the atomistic theory, could produce predictably macroscopic properties.

According to Yock (2021), the increase in the number of known particles over the next fifty years began with the proton, which had been observed by Goldstein much earlier but which Rutherford named as the nuclear particle after his foil experiments in the 1920s and then the neutron, which was identified by Chadwick in 1932, and anti-particles that Dirac predicted. In 1932 Anderson also found the positron and in 1955 Segre and Chamberlain discovered the antiproton (Orrman-Rossiter, 2021). As the necessity of experimental evidence for the particle grew in the 1950s, Gell-Mann formulated the "eightfold way" during the 1960s, which is now a major part of the "standard model of particle physics" (Sanford, 2024). New researchers did not only report on matter, but also the particles that form the mass mechanism (the Higgs particle), that mediate the elementary interactions (the photon and massive gauge bosons).

2.2.2   Historical milestones in Particle Physics.

As noted by Quigg (2021), the four fundamental forces of physics recognized by particle physicists since the 1960s have been strong force, electric force, weak force, and gravitational force. In elementary particle interactions, the strong force largely dominated and was responsible for the binding of protons and neutrons in the short-range nuclei (Sirma, 2021). The force of the strong interaction was by scientific findings estimated at approximately 1000 times stronger than the force of the electromagnetic interaction According to Qin, (2022). The study also claims that the strong interaction was responsible for microscopic electrodynamics, thus it is responsible for the force between atoms and their nuclei and electrons; the weak force was 100000 times weaker than the strong nuclear force and was short-range (Qin, 2022). One of the special circumstances was the radioactive decay of nuclei as well as elementary particles and the energy-producing mechanisms. Similar to the electromagnetic interaction, the gravitational force was a long-range power (Tajmar, 2024). Although it was ten times weaker than the strong force and was responsible for events at a macroscopic level such as apples falling from trees and the earth orbiting the sun, the manifestation of its effects was considered to be completely useless in the world of elementary particles.

A description of the standard particles was associated with this classification. They were the Hayes waiting for the Starke force. Also, among the particles that were the parts of nuclei, protons, and neutrons were indeed the numerous Hadrons. Leptons were very stable particles such as the electron, and a few more mostly motion particles that were never affected by the strong force. With the idea that the parts were put together from parts—hadrons were to think of them as made of simpler components (called quarks). The quark model is an attempt to explain some of

the empirical patterns of the hadron matter spectrum and the hadronic decay processes, but these questions are still not resolved.

In the later years of the 1960s and earlier years of the 1970s, it was commonly thought that the strength scale could be explained by the existence of quarks (Landua, 2024). These building blocks that were unique to a new class of matter were, thus, implied by Quarks. However, there was still no strong evidence of their existence at that time, mainly due to the fact that no other particles with the required characteristics for the proposed fractions (electric charge difference) could be seen in any of the experiments that were being performed (Barrett, 2024). Unlike hadrons, leptons underwent no changes to their status of genuinely elementary particles, so this theoretical model was stable (Yang, 2024).

New ideas about the quarks and leptons interaction were developed in the early 1970s. The primary insight was that, in the scope of a theoretical technique called gauge theory, the weak electromagnetic interactions could be interpreted as the outward forms of a single electroweak force (Horvath, 2024). This consolidation was related to the predictions of charmed particles' existence (confirmed in the 1970s) and the weak neutral current (proven in 1973), which were reminiscent of Maxwell's unification of electricity and magnetism in the 19th century (Horvath, 2022).

The year 1973 brought about the new understanding of a particular gauge theory—dubbed quantum chromodynamics, or QCD—which accounted for the strong interaction among quarks (Aitchison & Hey, 2024). The first observation was developed to illustrate the scaling, then further on it was expressed to reflect the scaling laws. It shed light on a number of other hadronic phenomena as well as the intriguing behaviors of charmed and other particles. As a result, QCD became the most widely accepted theory for the strong force in nature. Quarks in the isolated state

have not yet been sighted (ALICE collaboration, 2024). Nevertheless, the quarks' existence was proven along with the gauge theory description of their interactions, since both QCD and electroweak theory presented the validity of the quark image. It was a commonly accepted truth of the particle physicists of the very end of 1970 that quarks and leptons interacted among the elementary particles of the universe in accordance with the laws of QCD, electroweak theory, and twin gauge theories (Koberinski, 2024). It was found first to explain scaling, and later to explain observed deviations from scaling. It explained certain interesting properties of charmed and other particles, and various other hadronic phenomena. Therefore, QCD became the accepted theory of the strong interactions (Khodjamirian, 2020). Quarks had still not been observed in isolation. But both electroweak theory and QCD assumed the validity of the quark picture, and thus the existence of quarks was established simultaneously with the establishment of the gauge theory description of their interactions (Quigg, 2021). In the late 1970s, particle physicists were agreed that the world of elementary particles was one of quarks and leptons interacting according to the dictates of the twin gauge theories, electroweak theory and QCD.

In conclusion, it was realized that the theory of QCD could be embedded in the unified electroweak theory since both were gauge theories. This last unification also created some more fascinating predictions, because of it, in 1979, experimenters started to be interested. A great many physicists were that these results would be obtained, as they were (Peebles, 2024). Thus, it has been found out that the three forces, namely the strong, electromagnetic, and weak interactions which were initially believed as different forces, they basically were specific manifestations of a single force. Along with this, some experiments also supported it by finding a new building block of matter, quarks.

2.3 The Large Hadron Collider (LHC)

One of the most popular methods used in the study of elementary particles is the collision experiments. These types of experiments enable the replication of conditions which are similar to the early universe relatively early. The idea of destruction and reproduction is common through the universe. However, considering other things, this is a still relatively recent event in the early universe.

2.3.1 Purpose and operational details.

At the LHC, the collision energy of two proton beams is increased to a maximum force of 14 TeV (Fabbietti, 2021). Protons are imparted a 50 MeV acceleration energy with the help of a linear proton accelerator. After they have been sent to the PS Booster, a pre-acceleration complex to 1.4 GeV, the single protons are packed into the Proton Synchrotron (PS) and as soon as they reach 26 GeV, the Super Proton Synchrotron (SPS) (Modak, 2024). The SPS accelerator, is a key component of CERN. Acceleration is achieved by the proton beam at the SPS to an energy level of 450 GeV, before it is bidirectionally injected into the LHC (Barros Marin, 2021). The LHC tube, contains 1232 superconducting dipole magnets that force the particles to go in a 27-kilometer-long circular track (Nunez, 2024).

The calorimetry mechanisms are magnetic lenses that are used at four collision points along the particle paths, this is the primary experiments at the LHC: the LHCb experiment is devoted to the study of the physics related to the B meson (such as the CPB) decay. These two general-purpose experiments, ATLAS and CMS, are placed on the two opposite ends of the LHC tunnel, each serving as a detector to determine the nature of the collision, mainly to study the quark-gluon plasma (Martin Perez, 2022). The fifth experiment, TOTEM, is set up in vacuum chambers

attached to the beam pipe and near the CMS interaction point. It is used for the measurement of highly forward particles.

2.3.2 Physics explored at the LHC.

Even though the Standard Model show high level of precision comparable to practical experiments such as the LEP collider at CERN, there are still many limits to the applications of the SM theory to elementary particles and their interactive behavior, this calls for experiments at LHC (Bruce, 2020). LHC provides a way to conduct experiments on physics such as the mass measurements, the origin of dark matter, baryogenesis, matter–antimatter asymmetry, size of the cosmological constant, the unification of gravity with the other particle forces (Pereira, 2023). Other areas of experimentation at LHC are possible evidence of atmospheric and solar neutrino oscillations, as well as the question of particle masses' origins. Physics at the LHC is also set to answer questions in the experimental proof of the Higgs mechanism, SM implies the Higgs boson's lower limit mass is almost as close to the indirect upper bound value which is obtained from electroweak data (Leung, 2023).
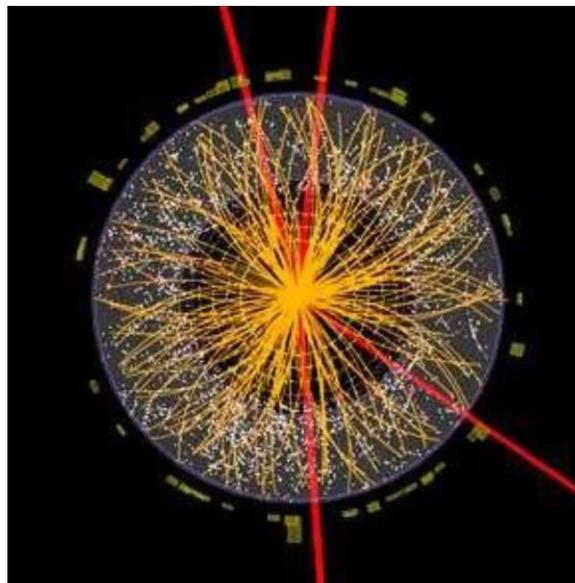
Figure 3: Particle physics at LHC (Source: https://phys.org/news/2012-09-higgs-power-data-mining-astrophysics-biology.html)

According to Leung (2023), the Higgs boson's mass, the only scalar in the theory, increases in the SM due to radioactive corrections, which can be fine-tuned to stabilize it at the electroweak scale. This is the "naturalness" problem, and it is called "fine tuning". As the fermions gather masses, the model's simplicity is shattered, as it contains too many new and unknown specifics.

These concepts are the basis of new understanding of particle physics. Among these concepts are Supersymmetry (SUSY), Technicolor, and theories that introduce new dimensions of physics beyond the Standard Model (Belyaev, 2021). According to Forty (2023), new understanding of physics from LHC experiments goes in the direction of predicting the effect of the mass stabilization of the Higgs boson at the TeV scale. It is evident that the TeV scale is the most intriguing scale in particle physics today, and it is the main factor that very much encourages the development of a device like the LHC that is able to directly examine the high energy range. A new dimension in particle physics is made possible by these functionalities. Supersymmetry (SUSY), Technicolor, and theories with extra dimensions are some candidate scenarios in the understanding of physics beyond the standard model. Bechtle, (2023) adds that the main theme behind physics at LHC is the prediction of new states in the TeV region to stabilize the Higgs boson at its measured mass. The TeV scale is the most exciting domain in particle physics performed at the LHC.

According to Dumancic (2019), experimentation at the LHC shows the possibility of creating new heavy-ion interactions with ultra-relativistic energy of 5.5 TeV per nucleon by colliding the nuclear beams or, in the case of lead beams, at a total center-of-mass energies in the range of 1000 TeV. Müllerv (2016) adds that data extracted from the collisions allow for the scrutiny of matter in a way that is different from that of standard cosmic rays as well as reaching

new frontiers in the understanding of particle physics such as phase transition of regular hadronic matter to a plasma of deconfined quarks and gluons under certain circumstances

2.4   The ATLAS Experiment

The ATLAS is a multifunctional detector that records particles' signals created in proton-proton collisions through more than 60 million electronic channels connected to the Large Hadron Collider at CERN. A key part of the ATLAS experiment is magnetic field outside the toroidal magnets and the inner solenoid; these toroidal magnets and calorimeters are used to create a complete magnetic field. Regardless, the issue of high amount of radiation from the experiment causes problems in particle detection. The image and sections below discuss ATLAS experimental components.
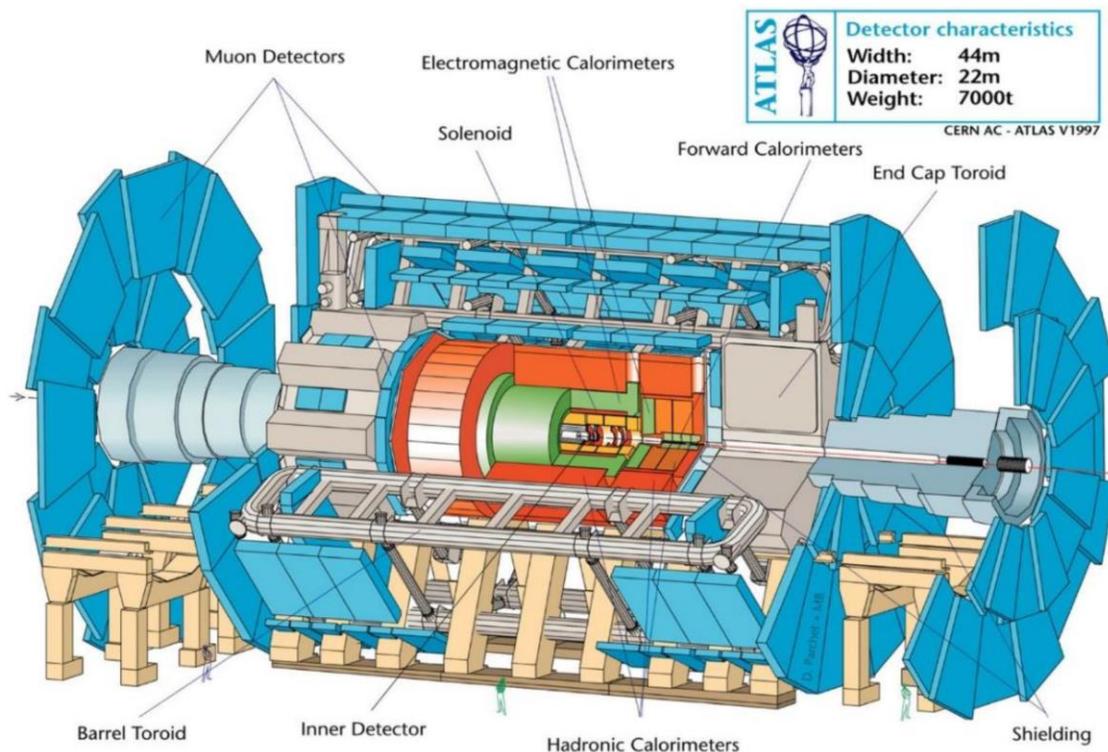
Figure 4: Structure of the ATLAS Experiment Components

(Source: http://www.myconfinedspace.com/2010/04/04/large-hadron-collider/)

2.4.1   Goals and significance of the ATLAS experiment.

Researchers working with ATLAS are looking into quantum-field theory and high energy particles, subjecting the Standard Model to experimental testing as they aim at achieving physics beyond the theoretical concepts within the model. As Chall, (2021) notes, the discovery of the Higgs boson at the LHC in 2012 verified the reliability of the standard model, but its problems have become more visible. For example, the characteristics and formation of dark matter, as well as the mysterious relation between the electroweak and Planck scales, are yet to be explained by the Standard Model. What causes the universe to speed up its expansion, both now and during the inflation, is an unknown on a cosmic scale that require further studies (Guth, 2023). As a result, the ATLAS experiment is an indispensable part of creating new theoretical models that describe physics at particle levels. The LHC has two general-purpose detectors, one of which is ATLAS; it provides physicist with a wide range of studies from the Higgs boson in physics multiplicity, to experimentation on the possible existence of dark matter particles (Linß, 2021).

Researchers depend on direct and indirect experiments in cosmic observatories, accelerators, like the LHC, high-intensity experiments, and dark matter detection experiments to find new physics signatures. Moreover, the investigations of particle theory can further expand the comprehension of the quantum field theory (QFT), which is quite a complex research area, the possibilities behind QFT is one of the key research interest coming from ATLAS experiment-based studies.

2.4.2 Key components and their roles.

2.4.2.1 *Inner Detector.*

The inner detector is made up of a semiconductor tracker (SCT), silicon pixel detector (SPD), and the transition radiation tracker (TRT) (Alici , 2021). These detectors are designed to track and map charged particles across the accelerator; this data is used to extract the trajectory of particles across the detector; The SCT has the ability to accurately record the position of a charged particle across a silicon layer (Eichhorn, 2015). The TRT, which is the external part of the inner detector, consists of 4 mm wide straw tubes; with this detector, incoming charged particles can also be identified (Krasnopevtsev, 2017). The solenoidal field strength of 2 T enables the inner detector to also measure the momentum of the particles (Krasnopevtsev, 2017).

2.4.2.2 *Calorimeters (Electromagnetic and Hadronic).*

Calorimeters measure energy released by the particles. To measure the energy released on the calorimeters, a system is required to produce an output signal in proportion to the input. ATLAS calorimetry is of two types: hadronic (HCAL) and electromagnetic (ECAL) (Moser, 2023). When the electrons and photons rain into the calorimeter material, and create a big number of eAr+ pairs, their energy can be recorded; as the name suggest, the liquid argon calorimeter (LAr) uses liquid argon, also known as the electromagnetic calorimeter (ECAL) (Pezzotti, 2021). Subsequently, the released charges are collected in the electrodes in order to create a current in the readout electronics. According to Bonivento and Terranova (2024), the LAr detector can be used as an electron and photon energy monitor because of its high sensitivity to electromagnetic interactions. Proton-proton collisions generate electro-magnetic showers that can be absorbed by lead (Mc Gowan, 2023). ATLAS's HCAL is also called the Tile Calorimeter. The primary role of the HCAL is the measurement the energy and directions of jets from hadronized quarks and

hadronically decaying particles; as the name suggests, it consists of luminous tiles and steel plates (Nelson, 2019). The diagrams below outlines major parts of the calorimeter.
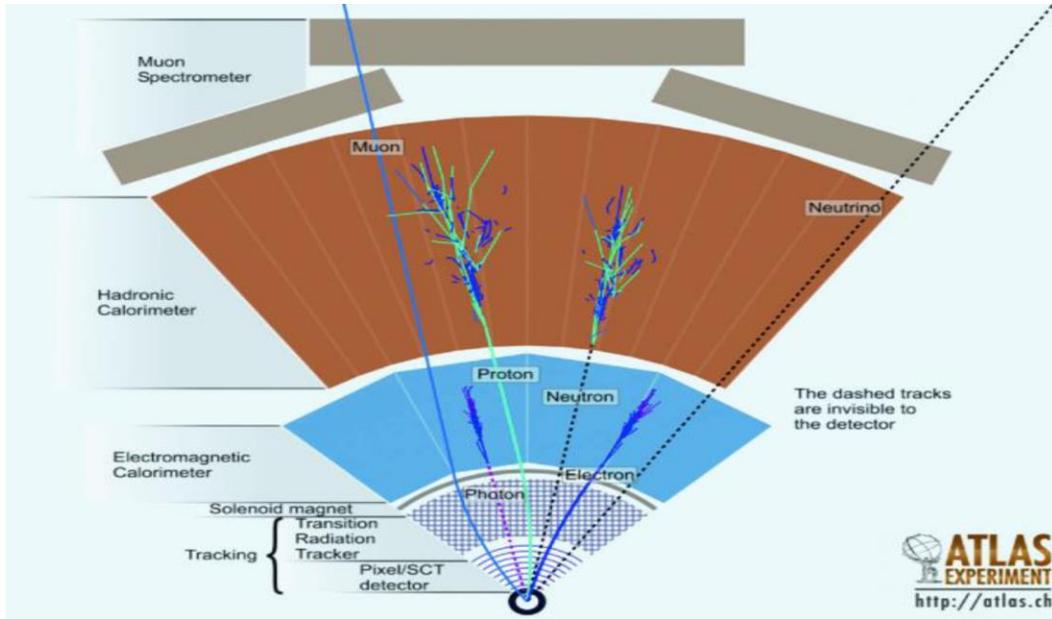
Figure 5: ATLAS calorimeter system (Source: https://media.springernature.com/lw685/springer-static/image/chp%3A10.1007%2F978-3-031-18074-3_1/MediaObjects/)

2.4.2.3   Muon Spectrometer.

The muon spectrometer has two main functions: it rebuilds muon tracks (reconstructs muon tracks) and triggers muon signals (Iodice, 2015). The layer of toroidal magnets is a part of the muon chambers. Magnetic field in the chamber follows the Lorentz force, and operates on charged particles in a highly curved path opposite to the direction of light (Baron, 2024). Knowing the direction of these particles or their energy is complicated by the observation that the particles traveling in the circle also experiences Lorentz' force. According to Gazis (2024), a combined event reconstruction that adopts a combined independent measurement approach from segments of the CMS and the muon track can be propagated from the muon spectrometer through the inner

detector to the muon spectrometers. The reconstruction must consider the detector geometry, the multiplicative scattering, and the energy loss in the calorimeters (Nguyen, 2020).
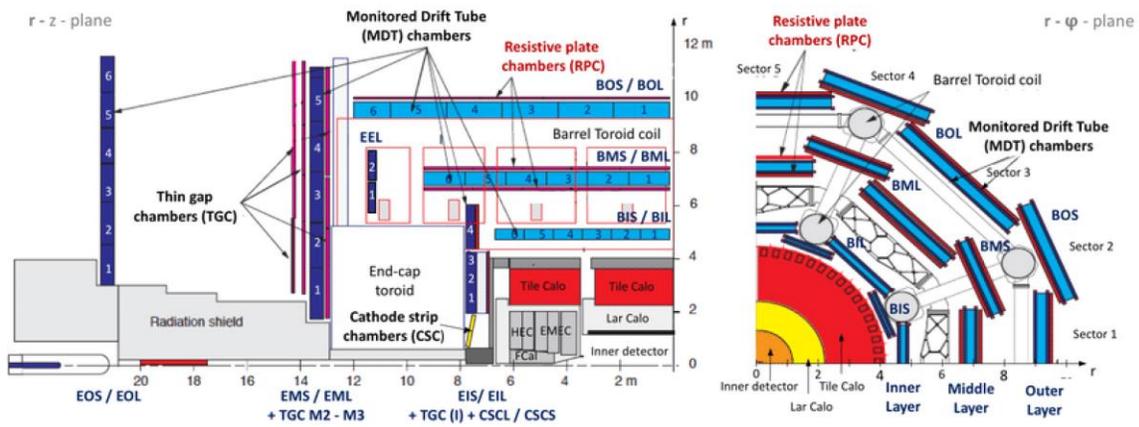
Figure 6: ATLAS muon spectrometer (Source:

2.4.3   The New Small Wheel (NSW) Upgrade and Micromegas Detectors.

The ATLAS Muon Spectrometer underwent a significant Phase-1 upgrade with the introduction of the New Small Wheel (NSW) system, replacing the original Small Wheel chambers that were highly susceptible to background noise, aging effects, and inefficiencies under high-luminosity conditions (ATLAS Collaboration, 2017). This upgrade was necessary to support the increased collision rates of the High-Luminosity Large Hadron Collider (HL-LHC), ensuring improved tracking precision and reduced systematic uncertainties in muon detection (Iakovidis, 2022).

Motivation for the NSW Upgrade

The original Small Wheel was designed during Run 1 and Run 2 of the LHC, but with the advent of HL-LHC conditions, the increasing luminosity posed several challenges (Papaevangelou, 2018):

- o Increased pile-up noise, leading to a higher probability of incorrect muon track reconstruction.

- o High background radiation, significantly affecting gas-based detector efficiency.

- o Aging effects in the previous tracking systems, reducing their long-term reliability.

- o Limited trigger efficiency, affecting real-time data selection.
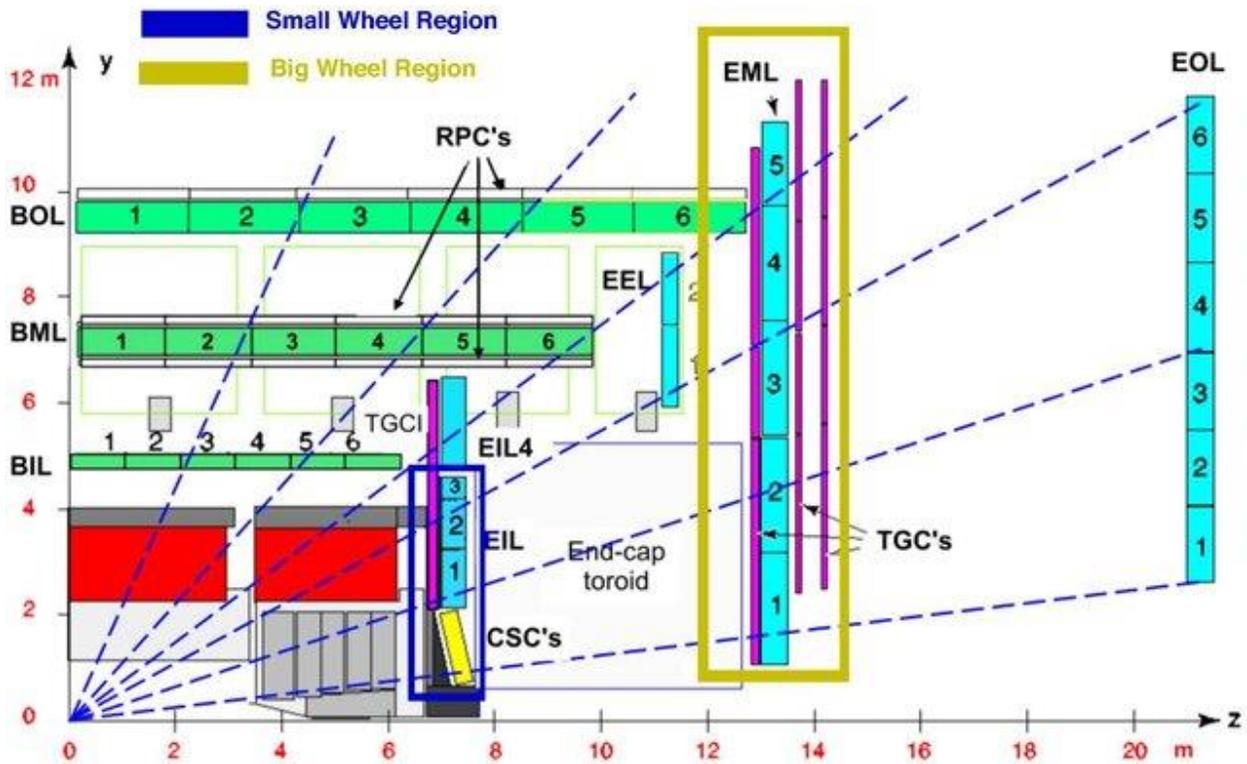
Figure 7: A z-y view of 1/4 of the ATLAS detector. The blue boxes indicate the end-cap Monitored Drift Tube chambers, MDT, and the yellow box in the Small Wheel area the Cathode Strip Chambers, CSC. The green boxes are barrel MDT chambers. The trigger chambers, Resistive Plate chambers, RPC, and Thin Gap Chambers TGC, are indicated by the outlined white and the magenta boxes. This is a cut-out on the muon spectrometer at the large sectors, hence the names 'End-cap Inner Large' (EIL),

To address these challenges, the NSW incorporates two complementary gaseous detector technologies that work together to provide both precision tracking and fast triggering capabilities (Oliveri, 2018):

1. Micromegas Detectors (MMGDs) – High-resolution tracking chambers, optimized for muon hit localization and spatial precision.

2. Small-strip Thin Gap Chambers (sTGCs) – Designed for fast triggering and supplementary tracking, ensuring rapid data filtering.

Structure and Functionality of the NSW Detectors

The Micromegas detectors are Micro-Mesh Gaseous Detectors (MMGDs) that achieve fine spatial resolution using a combination of ionization avalanches and high-precision charge readout (Cerrón Zeballos, 2022). Each Micromegas chamber consists of:

- Drift Region (~5 mm thick) – Where incoming muons ionize the gas, producing electron-ion pairs.

- Micro-mesh Layer (~128 µm gap) – A metallic mesh held at high voltage, separating the drift region from the amplification region.

- Amplification Region (~128 µm thick) – Where an electric field (several kV/cm) accelerates ionized electrons, triggering avalanche multiplication and generating measurable charge signals.

- Readout Strips – Collecting charge signals with spatial resolution of ~100 µm, providing precise muon hit localization.

Advantages of Micromegas in NSW:

- o High spatial resolution (~100 µm) improves track reconstruction.

- o Radiation-resistant design ensures stability under HL-LHC conditions.

- o Faster response times (~100 ns) compared to older tracking chambers.

- o Reduced aging effects, extending detector longevity.

The small-strip Thin Gap Chambers (sTGCs) are specialized detectors optimized for fast muon triggering, ensuring low-latency event filtering (Iakovidis, 2022). Each sTGC consists of:

- o Cathode planes with resistive strips that detect ionization.

- o Multi-wire anode planes for charge collection and signal shaping.

- o Fast gas amplification allowing a response time of ~30 ns, making sTGCs crucial for high-speed trigger selection (ATLAS Collaboration, 2021).

Advantages of sTGCs in NSW:

- o Ultra-fast response (~30 ns), critical for real-time event selection.

- o High-rate capability (~15 kHz/cm²), handling HL-LHC's extreme muon rates.

- o Robust against aging effects, unlike previous resistive plate chambers (Oliveri, 2018).

Impact of the NSW on ATLAS Muon Spectrometry

The New Small Wheel upgrade significantly enhances the ATLAS Muon Spectrometer's performance in multiple areas (Alexopoulos, 2017):

1. Improved Muon Track Resolution:

- o Combination of Micromegas high-precision tracking and sTGC fast triggering reduces reconstruction errors.

- o The spatial resolution of ~100 µm ensures accurate track fitting even in high-background environments.

2. Increased Background Suppression:

- o Micromegas reduces non-muon hit misclassification by distinguishing true muon clusters from pile-up effects.

- o sTGC rapid response time enables real-time filtering of unwanted background hits.

3. Enhanced Trigger Efficiency:

- o The NSW improves ATLAS trigger efficiency for muon selection, reducing false triggers and optimizing data collection.

- o Reduces timing mismatches, ensuring correct event reconstruction in ATLAS.

4. Scalability for HL-LHC Conditions:

- o NSW is designed to handle 5-10× higher event rates compared to its predecessor.

- o Ensures stable performance up to 3,000 fb^{-1} of integrated luminosity, matching HL-LHC's experimental goals.

The Role of NSW in Future ATLAS Operations

The New Small Wheel upgrade is a crucial step toward future-proofing ATLAS for HL-LHC (ATLAS Collaboration, 2021). By integrating Micromegas detectors for high-precision tracking and sTGCs for rapid triggering, NSW:

- Enhances muon classification and reduces background noise.
- Provides high-precision spatial resolution (~100 µm).
- Optimizes trigger efficiency, crucial for real-time event selection.
- Supports scalability for HL-LHC operations, ensuring long-term sustainability.

2.5   Signal Processing in Particle Physics

According to the Atlas Collaboration. (2015), systems factors must be accounted for in the design and operation of particle detectors at the LHC, especially in large scale machines used in particle and nuclear physics. The noise produced in the measurement is of major concern when there is a need for high accuracy measurements. The requirements for different detector and signal processing performance criteria are likely to vary depending on the research field. Most of the recent signal processing breakthroughs have been implemented in circuits that use monolithic CMOS technology (Wang, 2017). Because CMOS transistors are best suited for circuits that require switching of capacitance, this technology has changed the design of signal detection systems.

2.5.1   Nature of signals in detectors.

According to Candy (2016), signal analysis, in the broadest meaning, are the methods used in collecting generated data. Signals can be measured by the nature of an interrelation such as, input data, which can be continuous such as temperature or discrete such as a events count. Predictions and observations often oscillate between continuous and discrete signals depending on the analytical methodologies employed. In the realm of electrical signal analysis, data often takes the continuous time variable. Signals can be digital or analogue; other formats can be stochastic or deterministic, and continuous or discrete (Candy, 2016). By selecting continuous or discrete independent variables in the time or frequency domain respectively and the continuous or discrete dependent variables, the signals produced by LHC detectors can be classified as stochastic.
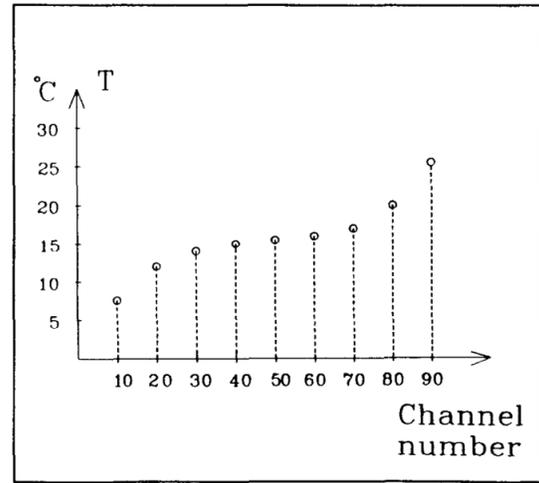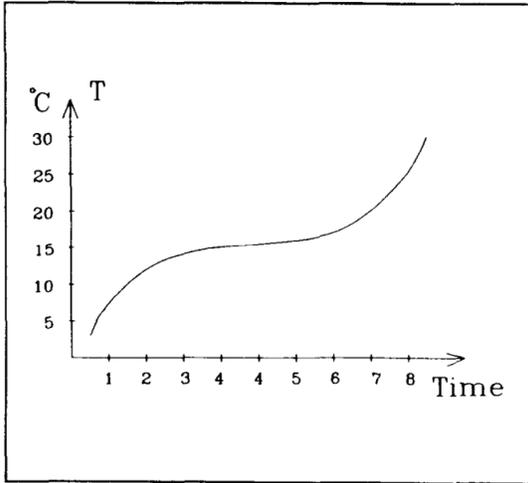
Figure 8: Signal with independent continuous variable (time) Vs Signal with discrete independent variable (channel number)
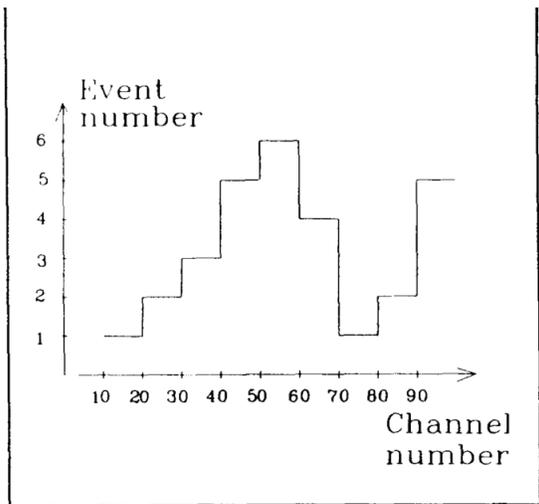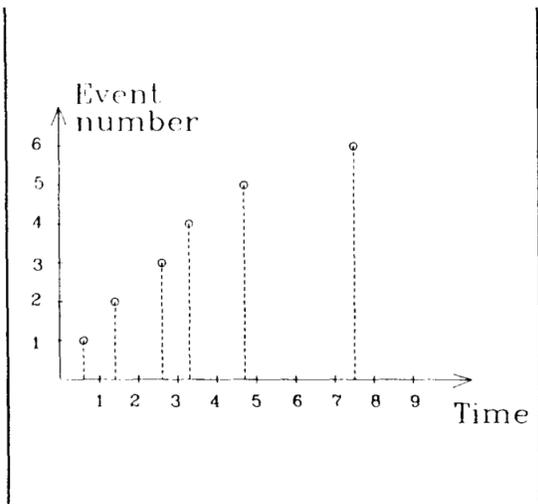
Figure 9: Signal with discrete dependent variable (time) Vs Signal with discrete dependent variable (channel number)

The data shown in figure below can be obtained by passing a continuous time variable signal through a digital signal processing.
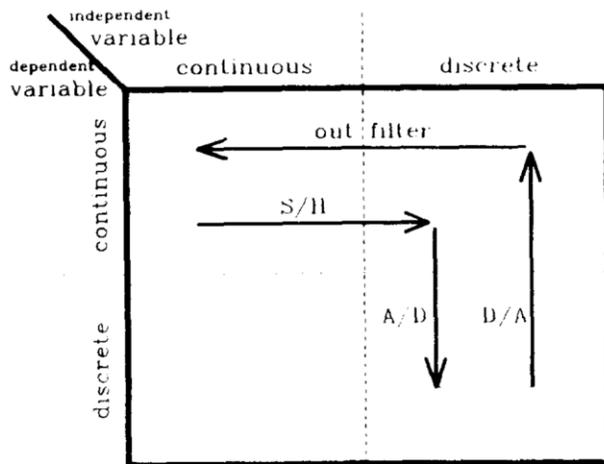
Figure 10: Signal Processing

First, Sampling and Hold (S/H) works by modifying the continuous-time variable input signal with a Pulse Amplitude Modulated (PAM) version. Analog-to-Digital converter (A/D) then transforms it into a Pulse Code Modulated signal (EM) (independent variable = discrete, dependent variable = continuous) (Gustavsson, 2000). Digital Signal Processor (DSP) can then digitally accept the input signal. Prior to the filtering of the analog signal (independent variable continuous, dependent variable continuous) digital information is transformed to analog signals using a digital-to-analog converter (DAC) (independent variable discrete, dependent variable = continuous) (Ortigueira and Machado, 2020). This is illustrated in the figure below.
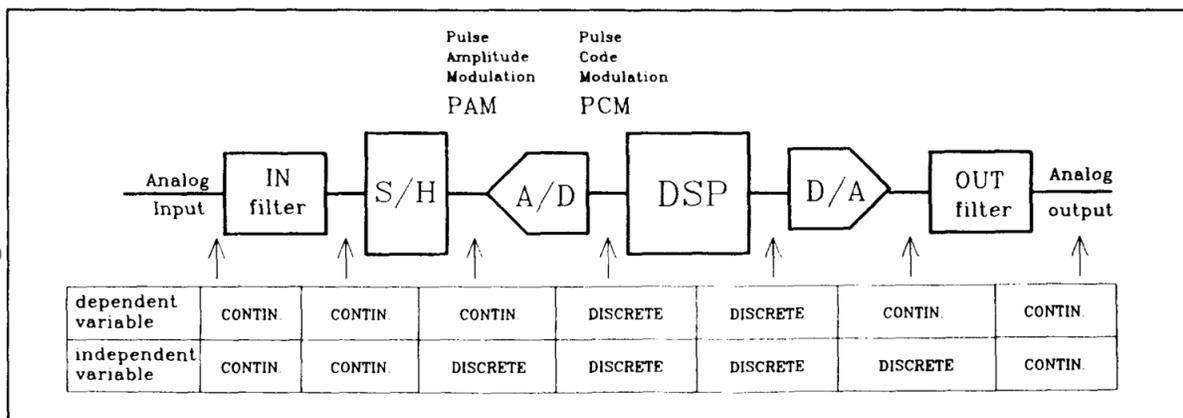
Figure 11: Analogue/Digital signal processing

Being one of the important aspects in signals processing, it is necessary to consider both the frequency domain and the time domain. A wavelength in signals shows signal frequencies and the waveform denotes t (time domain information) plays the role of the frequency domain characteristics such as amplitudes and phases information. The difference between the two types of description is based on their performances, and computational use in signal processing (Stranneby, 2004). Stochastic and deterministic are the two types of signals often processed from detectors. While the latter transfer information, the former is critical in experimental studies. The terms "stochastic" implies the characteristics of the signal that can only be seen through its statistical characteristics within a certain range.

2.5.2 Types of noise and challenges in data extraction.

According to Radeka (2020), noise in signal processing can originate from a sequence of elementary impulses, each being of Poisson-type with rate n (Mali, 2015). The traditional noise waveforms that we observed oscilloscope are the merging of responses to individual impulses when one is working on a physical system with an impulse response much greater than (n)−1 (Radeka, 2020). The Campbell-Schoenburgt theorem can be used to estimate noise variance at the physical system's output (basic RC filter or a full readout system), it states that the variance is a sum of all preceding impulses' mean square contributions (Radeka, 2020). Thus, these are exact variance expressions, if the average is first subtracted. This is illustrated in the figure below.
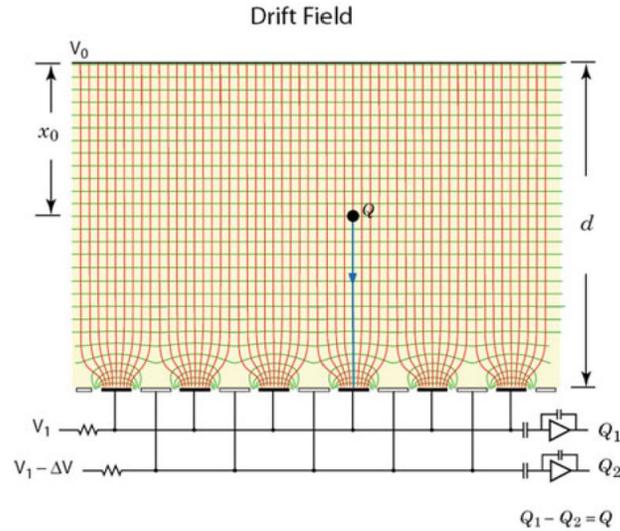
Figure 12: Drift filed for coplanar electrodes
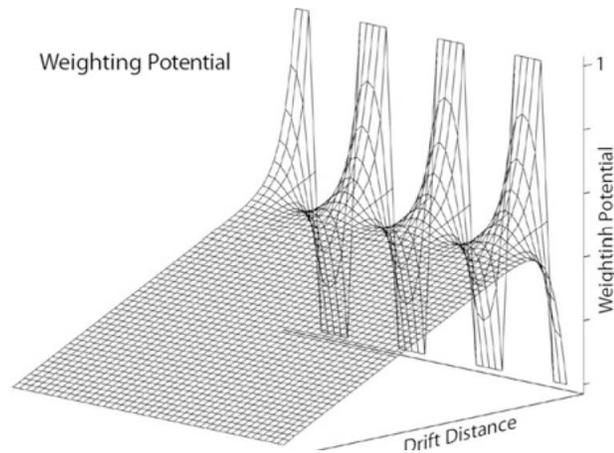
Figure 13: Weighting potential for coplanar electrodes

The impulse response, h(t), or the weighting function, w(t) of the measurement system, the preamplifier, and the readout chain that follow, as well as the rate of impulses (n) and their area q (charge) are the defining elements of the variance (Radeka, 2020).

$$\sigma^2 = (n)q^2 \int_{-\infty}^{\infty} h^2(t) \, \mathrm{d}t = (n)q^2 \int_{-\infty}^{\infty} w^2(t) \, \mathrm{d}t$$

The noise process, the rate of impulses (n), their area q (charge), and the impulse response h(t) all contribute to the noise variance. The variance can be measured non-intrusively from (n) and time (t), but the variables (n) and q cannot be identified. The only way to calculate the rate and charge of impulses from σ2 and I0, when randomly generated carriers move in one direction and the mean current is I0 = (n)q. Radeka (2020) argues that the mathematical convolved current spectral density is the convolve of the initialization level of the system with the different signals in the frequency domain (n)q2, while the real one (physical) is equal to i2 n = 2 (n) q2. This is illustrated below;
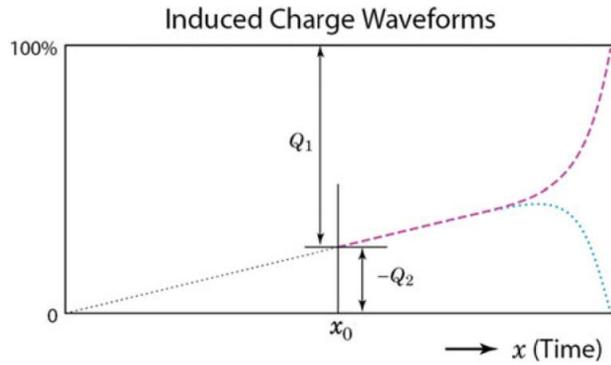
Figure 14: Induced charges in coplanar electrodes
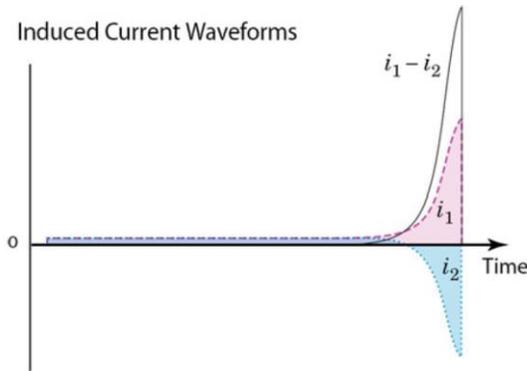
Figure 15: Induced current in coplanar electrodes

2.5.3   Current techniques in signal processing.

Linear and non-linear processing are typically two different approaches in signal analysis theory. The linear component, which can be represented as linear differential (continuous) or difference (discrete) equations with constant coefficients, is the more understood approach (Pospisil, 2017). There are two primary approaches to linear processing.
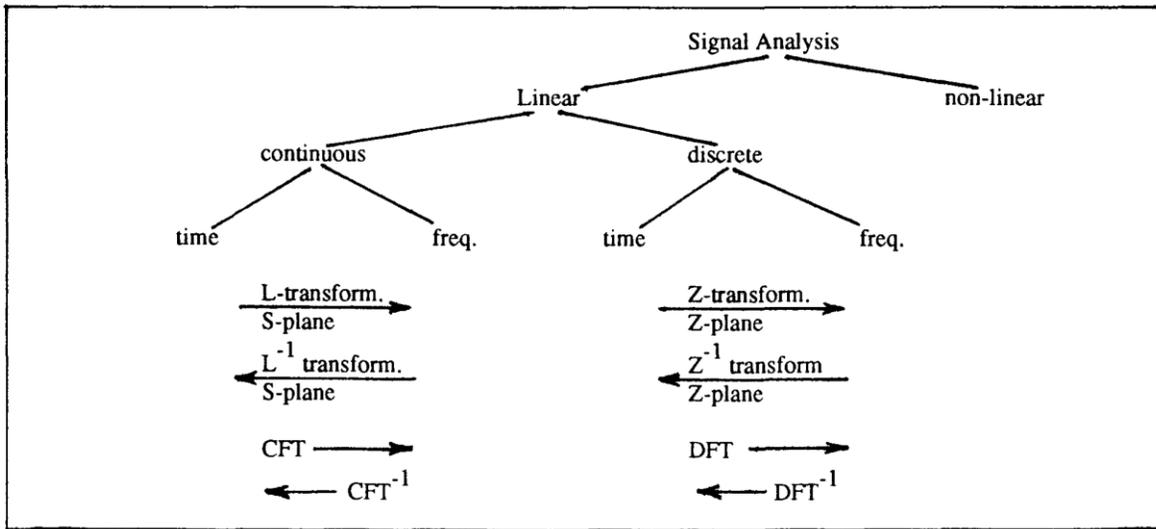
Figure 16: Approaches in signal processing

Depending on the type of signal, the representations and transformations are different if the signal is continuous or discrete. The transform of the Laplace domain, when combined with the frequency spectrum representation in the complex s-plane, is one of the most well-known methods for transforming continuous signals from time to frequency and vice versa (Palani and Palani, 2022). The z-transform, and the frequency spectrum representation in the complex z-plane are the equivalent for discrete signals (Özhan, 2022. The Fourier transform is another popular, and widely-used transform in numerical computations, besides the Laplace (Palani and Palani, 2022). Thus, discrete (DEI) as well as continuous (CFIÌ`) Fourier transforms can be restricted to real frequencies. The latter can be modified to produce the Fast Fourier Transform.

2.5.3.1   *Digital Signal Processing.*

DSP refers to the process of examining discrete signals that have been sampled to generate discrete descriptive results. DSP may be achieved by the frequency domain or the time domain. Every series of input data in the time domain has exactly one output data (Palani and Palani, 2022). All input sequences in the frequency domain have at least one output sequence. According to Radeka (2020), frequency domain processing takes place in the time at which the input sequence is recorded, while time domain processing takes place in real time. The time domain is used again to process a digital filter that reacts to a single impulse with either an infinite impulse response (IIR) or a finite impulse response (FIR). Usually, DSP operations refer to discrete or fast-Fourier transforms being implemented in the frequency domain. There is a tendency to transform analog signals into digital signals by means of discrete processes rather than analog devices because of the advent of Fast A/D converters and Digital Signal Processors (DSP). Digitalization, in practice, brings clock-based digital signal processing (DSP) hardware into the analog world.

2.6   Machine Learning Applications

According to Arpaia (2021), machine learning techniques make use of large data sets to map new features and simplify data. Understanding artificial intelligence (AI) or machine learning (ML) in particular is key to data analysis and the creation of related intelligent and automated applications. There are different types of machine learning algorithms in the field, including supervised, unsupervised, semi-supervised, and reinforcement learning; deep learning can be discussed as part of a larger family of machine learning techniques and is necessary for large-scale, intelligent data processing (Arpaia, 2021). Through these methods, different stages of application's functionality and intelligence can be improved.

2.6.1 Overview of machine learning in physics.

In the context of a post-Higgs boson studies, the main goal of particle physics is to utilize the full potential of the Large Hadron Collider (LHC) and its upgrade, the high luminosity LHC (HL-LHC), as well as current and upcoming neutrino experiments to advance particle physics. As the amount of data to be managed is forever increasing with the room of the project faces a need for data management. Applying machine leaning (ML) to the theories of both domains could be very beneficial. The two central goals of high-energy physics (HEP) research experiments are the discovery of new physics and a more accurate examination of the Standard Model (SM) (Andrews, 2020). To achieve these two objectives, the machine-guided mapping of rare signals amidst background noise is required. Machine learning methods are already is set to provide solutions.

2.6.2 Common algorithms used in HEP (e.g., Neural Networks, Boosted Decision Trees).

Neural Networks (NN) and Boosted Decision Trees (BDTs) are the two most used machine learning methods in HEP to date (Vidal, 2021). Typically, the variables related to the physics problem are selected, and the machine learning model for classification or regression is built with the use of signal and background events (or instances). The training process is the most time-consuming part for both the users themselves and CPUs; besides, the application—also known as "inference stage"—is cost effective approach to signal processing. These algorithms embrace regression analysis, a process that entails the continuous function learning for instance, to determine the particle's energy best estimate from the several detectors that make observations (Radovic, 2018). Even though neural networks have already existed in the HEP sector for quite a while, the Deep Learning revolution, which has significantly affected HEP, originated from technological development of training algorithms and supercomputers within the last ten years.

Nonetheless, in case of large amounts of data with multiple characteristics, symmetries, and intricate non-linear interrelations between inputs and outputs, deep learning offers a lot of opportunity (Vidal, 2021).

Three different types of deep neural networks are employed in HEP: fully-connected (FCN), convolution (CNN), and recurrent (RNN) (Khan, 2020). Neural networks are also employed in generative models, where they are programmed to reproduce multidimensional distributions precisely in order to generate any number of new cases; examples of such generative models employed in HEP comprise Variational AutoEncoders (VAE) and more modern Generative Adversarial Networks (GAN) (Wojnar, 2024). In HEP, where measured events are independent of one another, the use of these methods of monitoring data quality and computing infrastructure essential; machine learning is important where physics processes and event reconstruction activities speed is a crucial factor.

2.6.3   Current applications in the ATLAS experiment.

One of the main reasons why ATLAS experiment is important in particle physics is the need for a confirmatory correlations study between the actual experimental data and the predictions derived from the Standard Model assumptions and other physics models. Even though the interaction mechanisms between subatomic particles and matter are theorized in models, further studies on physical behavior of these particles are critical to the understanding of physics. For this reason, application of machine learning to particle physics such as Monte Carlo simulation in GEANT, are critical. According to Karkanias (2022), machine learning can simulate particle behavior in detectors and then evaluate the data. Machine learning make it possible for LHC to conduct multiple simulated collisions in order to achieve the appropriate statistical accuracy of results to carry out precision hypothesis testing. While these experiments can be conducted

physically, the high cost of computing these simulations is a major concern. For instance, experimenting with one proton-proton collision event at the LHC requires time in the order of a months to complete (Bohm, 2023). The issue of high cost and high multiplicity of particles makes the simulation of such processes particularly expensive. Machine learning allows for the use of particularized models to speed up such analysis.

Although machine learning is fast computation-wise, they often run into insufficiency, especially with small datasets. The use of high fidelity fast generative models, like GANs and VAEs, which can take high dimensional feature distributions from learning over preexisting data samples are critical (Wojnar, 2024). This is a promising path to follow because of how quickly such techniques are developing in the machine learning community. Therefore, machine learning provides an answer to the operational needs of ATLAS experiments, it is possible to achieve experimental optimization using approaches such as Bayesian Optimization (Karkanias, 2022). By using these methods for simulation tuning, the results of the simulations can be further enhanced.

Machine learning in ATLAS experiment can achieve real-time reconstruction which is able to be analyzed the performance while also reduces the cost of implementing reconstruction algorithms. For example, the CMS experiment utilizes high-level decision trees to approximate muon momenta at the Level 1 trigger. Another related use is the expedited reconstruction of lower mass hadrons, where the conventional track combinatorics and vertexing approaches can become computationally costly. In addition, as event intricacy increases, and especially in the HL-LHC era, machine learning methods help improve traditional triggers. Amongst such examples supplication include triggering of the electroweak events of low-energy particles, jet calibration improvement in reconstruction, jet trigger thresholds decrease, and supernovae and protons decays by the neutrino detector experiments (Ghosh and ATLAS Collaboration, 2020).

3 Methodology

3.1 Data Collection

A critical component of ATLAS high-energy physics experiments is data collection, which involves obtaining, analyzing, and storing large volumes of information generated by particle collisions. In this study, Monte Carlo simulations were employed to generate synthetic datasets for muon interactions within the Micromegas detector layers of the New Small Wheel (NSW). These simulations modeled high-transverse-momentum (pT) muons undergoing radiative energy losses and noise contamination in Micromegas chambers, creating realistic training datasets for machine learning models aimed at improving muon hit localization and classification.

3.1.1 Monte Carlo simulations for synthetic data.

Researchers can replicate real experimental conditions using Monte Carlo simulations, a fundamental technique in High-Energy Physics (HEP). These simulations involve several critical steps, including:

- Event Generation: Particles are stimulated by cosmic rays from their neutral state to that with energy enough to create particle tracks, which are then fitted within the spark chambers. This is done by a complex software like Geant4, an example here, with programmed codes includes each detail all particles.

- Detector Simulation: Simulate the ATLAS detector's response to the particles it produces. During this step, the particles burn off with the detector material; energy deposition and the development of the track are both continued that result in the signal's emission.

- Digitization: These are the assumed detector responses that are made digital in a form comparable to the real detector data processing method. At this level, it ensures that the

same kind of tools and skills that are used for examining the real data from experiments can also be utilized for the analysis of the simulation data.

- Reconstruction: The particle characteristics are identified and measured by making use of reconstruction techniques in the digital data. Track reconstruction, energy measurement, and particle identification are all part of the process.

3.1.1.1   Datasets

The datasets used in this study consist of three distinct energy bands, each representing different particle interactions. These datasets were exported directly from Monte Carlo simulations, excluding pile-up effects, to provide clean training samples for machine learning models. The visualization and analysis of these datasets ensure a clear understanding of feature distributions and allow researchers to identify which datasets yield the best training results.

The exported datasets are as follows:

1. inputCAFTesterOutput_10GeVto100GeV.csv

2. inputCAFTesterOutput_100GeVto500GeV.csv

3. inputCAFTesterOutput_500GeVto1p5TeV.csv

These datasets play a pivotal role in strengthening the overall precision of particle identification and event reconstruction through the set of machine learning algorithms that are trained and tested.

3.1.1.2   The Contradiction of Pile-Up Conditions

Piles-up is an unavoidable experimental physics phenomena in actual collider installations. In a single detector readout cycle, it happens when several proton-proton interactions take place at the same time, producing overlapping signals that make data interpretation more difficult.

Despite these difficulties, pile-up circumstances are essential for increasing simulation realism because they replicate the harsh conditions found in the high-luminosity runs at the Large Hadron Collider (LHC).

We do not, however, expressly include pile-up-affected datasets in our study. This choice was taken in order to keep the dataset clean enough, to allow for the independent study of individual muon interactions. This makes possible for us to:

1. Illustrate the basic characteristics of muon interactions more accurately.

2. Steer clear of the confusing clutter created by merging events, as this Data Storage and Management.

3. Create machine learning models without the use of artificial distortions during training, making sure that categorization methods are only predicated on the inherent properties of signal background events.

Pile-up phenomena is another study focus to obtain an essential understanding of the background clustering analysis, where background-induced clusters can be better identified and separated from the muon signals.

The structured nature of the combined datasets enhances their accessibility and improves productivity in statistical analysis. The computation of millions of datasets requires the use of a distributed file system that is often the Worldwide LHC Particle Physics 01 Grid (WLCG) and the high-performance computer resources. This infrastructure ensures that the data necessary for the model to learn, test, and validate are easily accessible.

3.2   Data Preprocessing

In the order of high energy physics data, this stage is vital, to be precise for the datasets that have been produced by Monte Carlo simulations, which are run in the ATLAS experiment

inside the Large Hadron Collider (LHC) at CERN. The proper preprocessing must ensure that data is consistent, clean, and ready for the machine learning models to analyze further. This part of the content explains in details several practices of the data preprocessing on the dataset, i.e., data augmentation, feature extraction, normalization, and noise reduction.

3.2.1   Noise filtering techniques.

To increase the dataset's signal-to-noise ratio, noise reducing is a critical factor. The actual signals that particle interactions generate can be hidden by a lot of noise sources, such as background radiation, temperature fluctuations, and electronic noise. The following methods are used for noise decrease:

- Baseline Correction: Removing baseline offsets caused by electronic noise ensures signals start from a consistent zero level.

- Digital Filtering: Applying low-pass, high-pass, and band-pass filters to remove unwanted frequency components.

- Smoothing Techniques: Using moving average and Gaussian smoothing to reduce random fluctuations in the data.

- Signal Clipping: Setting a threshold level to eliminate low-amplitude noise.

- Wavelet Denoising: Decomposing the signal into different frequency components and removing high-frequency noise.

- Getting rid of all the noise, the biggest variance is the signal that is recorded in the first few main components that account for the major component of the signal, thus, PCA minimizes the noise.

- Kalman filtering is a method of estimating a dynamic system's state from noisy data through a recursive algorithm that is computationally very efficient.

3.2.2   Normalization

Normalization is performed after the data has been exported from the Monte Carlo simulations to standardize the range and scale of the data features, making the datasets consistent and improving the performance of machine learning algorithms. Key normalization techniques include:

- Min-Max Scaling: This technique scales the features to a fixed range, typically [0, 1] or [-1, 1]. Each feature value x is transformed using the formula:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

  Where x_{min} and x_{max} are the minimum and maximum values of the feature, respectively. This ensures that all features contribute equally to the model and prevents features with larger ranges from dominating the learning process.

- Z-Score Standardization: This method transforms the data to have a mean of zero and a standard deviation of one. Each feature value x is transformed using the formula:

$$x_{Standardized} = \frac{x - \mu}{\sigma}$$

  Where μ is the mean and σ is the standard deviation of the feature. Z-score standardization is particularly useful for data with different units or scales, ensuring that all features are on a comparable scale.

- Robust Scaling: This method is less sensitive to outliers compared to min-max scaling and z-score standardization. Each feature value χ is transformed using the formula:

$$x_{Scaled} = \frac{x - median}{IQR}$$

This technique measures each feature value's shift from the median, and it relates to the interquartile range (IQR). This process minimizes the impact of outliers on the data.

3.2.3   Feature extraction and engineering.

3.2.3.1   Feature Engineering

The purposes of the L1 Accept of FTK are efficiency leading to the online selection of the most likely track and fast detection of new physics in the LHC environment. Their nominal performance and cost estimation are the main criteria to be checked at the design phase. All the variables are important, but in this case, there might be some dependence between them, so it is not a question of just looking for some which are more crucial than others. Based on the specific requirements of the new system, the most advantageous features are as follows:

1. Size of Cluster (Nstrips) - The position of the activated strips and the clustering size are stored in the detectors. Lacking direct detection of the particle's arrival, the triggering process requires the strips to register their location and energy. Another basic point of analysis is the cluster size of the region that a particle interacts with. It is important to find a good spatial coverage (s) in conjunction with clusters besides the number of clusters. More than five or six clusters in one strip are very rare. The rest is with the cluster builder. An appropriate fix, however, would have the software update the cluster labeling locally when it sees a strip communication cable problem. But in case several of them are damaged then the chip itself will need to be replaced.

   - Calculation: $N_{strips} = \sum_{i=1}^{n} hit_j$

Where hit_j indicates whether a strip i is hit.

- Application: Particle classification and event classification is the application of cluster size, which allows distinguishing between different types of particles and interaction events. Higher-energy particles or more complex interactions are usually activated by many strips that are certainly different from low-energy types or simpler ones. Furthermore, it is useful to remove spurious signals and noise from the detection system.

2. Cluster Time Width (ΔtW): This parameter measures the ionization electrons' time dispersion as they progress along the readout strips. It gives information about the speed of the particle interaction and when solar ions are happening by measuring the time between the first and last strip hits of the cluster.

- Calculation: $\Delta tW = t_{last} - t_{first}$, where t_{last} and t_{first} are the times of the last and first strip hits, respectively.

- Application: The time breadth of a cluster can give an indication of the temporal dynamics of particle interactions. In the quest to identify the particles, it is critical to know the speed of the particles, which is done through time-of-flight measurements. Furthermore, it contributes to the understanding of the diffusion of ionization electrons, which may show what specific interaction mechanisms there are.

3. Cluster Charge ($q_{cluster}$): The total charge collected by all strips in the cluster represents the energy deposition of the particle. This feature is crucial for differentiating between signal and background events, as well as for understanding the energy distribution of the interaction.

- Calculation: $Q_{cluster} = \sum_{i=1}^{N} q_i$ where q_i is the charge collected by strip i.

- Application: The particle's energy deposition is denoted by the total electric charge accumulated over all strips in the cluster. This feature, in particular, is vital to the separation of signal matter from background noise and gaining an energy distribution).

4. Charge Skew (q_{skew}): Charge skew shows the distance between the trends of charges in the cluster. This feature helps to specify where the charge was dumped, the one which can shed light on the type of particles and their movement.

- Calculation: $q_{skew} = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{q_1 - \bar{q}}{\sigma q} \right)$

Where $\bar{q}$ is the mean charge and σq is the standard deviation of the charge distribution.

- Application: Charge skewness is a technique that can be used to identify different charges inside a cluster. This property helps to distinguish between different particle paths and their interactions. This feature can also detect unexpected asymmetries such as which may be because of new discoveries.

5. Number of Holes (N_{holes}): Discontinuities in the contact pattern are detected by the number of holes or gaps in the cluster. This characteristic helps in detecting any anomalies in the cluster formation that can be a result of noise or inefficiency in some detectors.

- Calculation: $N_{holes} = \sum_{i=1}^{N_{strips}-1} \delta(hit_i = 0)$

Where δ is the indicator function that counts the gaps between consecutive hits.

- Application: The consistency of the hit pattern can be exhaustively deduced from the count of gaps in the cluster. This characteristic is used to find noise and detector inefficiencies, and at the same time, to evaluate the data quality. Besides

directing to imperfections demanding appropriate action, it is the source enabling a guarantee that the events are properly reproduced.

6. Cluster Width: Clusters' spatial extents provide still more detail in the study of particle interactions, and they are expressed by the number of strips with which inter-cluster distance is bounded. While the width of the cluster always directly depends on its size, it is the width that offers a more valid estimation of the spatial distribution.

   - Calculation: $Cluster\ Width = (strip\ indices) - (strip\ indices) + 1$.

   - Application: Awareness about particle interactions' physical spread in the detector implies comprehension of the spatial width of the cluster. It is a particle track reconstruction helper as well as a device in spatial resolution. In this case, it is used as a possibility to obtain separated and overlapping events.

7. Max Strip Charge: Charge measured by one separate strip within the cluster represents peak energy deposition, often the one of maximum value.

   - Calculation: $MaxStripCharge = max_{i=1}^{N_{5trips}} q_i$

   - Application: When the electron beam hits the single strip, it can absorb the most energy and the strip can register the electric charge because photons can or can cause ionization. Consequently, to enhance the precision of the energy measurement, it is used the feature of maximum charge stored in a single strip to its threshold. The first two of those are related to each other because, in their roles, the strip not only plays the part of that of charge storage but also the signal provider. It becomes a criterion for accurate energy measurements and a way to sense high-energy interactions as well. Also, the interaction's most energetic component can be derived from it, which is crucial particularly for the.

8. Earliest Strip Charge: Through the minimal drift time and identification of the initial interaction location, the first strip of the cluster reflecting the charge collected has a direct link to the ionization in the immediate proximity of the wire mesh.

- Calculation: *Earliest Strip Charge* $= q_{first}$ where q_{first} is the charge of the first hit strip.

- Application: The particle's first contact is identified with the charge of the initially touched strip of the sensor. The determination of an event's time of flight and its reconstruction are based on the integrated charge of the strip. This, in turn, provides a route to the particle's entrance to the detector. Changing the looked at strip charge also gives a chance to find the entry point of the particle to the detector. This kind of sensor also provides an advantage where the time of flight and reconstruction of the particle are measured by integrating the strip charge.

9. Latest Strip Charge: The charge collected from the final strip of the cluster is informed about ionization that goes on farthest from the wire mesh. Thus, the maximum drift time reflects the closeness of the interaction, showing when it is coming to an end.

- Calculation: *Latest Strip Charge* $= q_{last}$, where q_{last} is the charge of the last hit strip.

- Application: The data on the end of ionization are provided in the charge on the last strip hit per cluster. This asset is crucial to a precise reconstruction of events considering the fact that it enables one to visualize the trajectory of the particle throughout the whole detector.

10. Cluster Charge Kurtosis: Cluster charge kurtosis measures the "tailedness" of the charge distribution within the cluster. It assists in identifying clusters with non-uniform charge profiles by dispatching data about the charge distribution's extremities and dispersion.

- Calculation:

$$q_{kurtosis} = 1/_N \sum_{1=1}^{N} \left(\frac{a_i - \bar{a}}{sin}\right)^{-4} - 3$$

Where $\bar{q}$ is the mean charge and σq is the standard deviation of the charge distribution.

- Application: The degree and the extension of charge distribution can be mathematically deduced based on cluster charge kurtosis. Detecting these clusters is a good tool with which one can identify charge structures that are completely different from the regular ones, which may indicate a problem with the process or a detector. It helps to understand the complex particle interactions.

11. Cluster Charge Centroid ($q_{centroid}$): The charge distribution center of mass is a unique number that provides information about the spatial charge distribution in a cluster, that is, the electrical energy is deposited in a location with the greatest distance to the center.

- Calculation:

$$q_{centroid} = \frac{\sum_{i-1}^{N} q^x \, strip_i}{\sum_{i=1}^{N} a_i}$$

Where $strip_i$ is the position of $strip_i$i.

- Application: The time centroid is a lone value that sums up the time dispersion of the charge deposition and on the flip side gives the direction of the charge in time in the form of a flip-flop value in TDC. This property, for example

the time window, plays the key role in the determination of the time range in which an event can occur or event pre-gating.

12. Cluster Time Centroid ($t_{centroid}$): The center of mass of the time distribution is the quantity of time required to demonstrate the accumulation of the charge deposited in that area, and it shows the timing of the charge distribution that is central.

- Calculation:

$$t_{centroid} = \frac{\sum_{i-1}^{N} t_i{}^x \, strip_i}{\sum_{i=1}^{N} t_i}$$

Where t_i is the time of $strip_i$.

- Application: A single value that defines the decay of the charging deposition with time is derived from the time centroid. Inaccurate event reconstruction and time-of-flight measurements are some of the reasons why this property is so important for the understanding of the timing structure of the interaction.

13. Cluster Energy Spread (E_{spread}): The distribution of energy deposits inside the cluster not only allows the analysis of the resources of a system within the cluster but also strengthens the search for interactions with broad or narrow energy dispersions.

- Calculation:

$$E_{spread} = \sqrt{\frac{\sum_{i-1}^{N} (q_i - q_{mean})^2}{N}}$$

Where q_{mean} is the mean charge of the cluster.

- Application: The interaction's transmission of energy can be understood as being in the cluster's interior which is a distribution of its energy captures. Indeed, this profile would allow for the detection of processes with wide or

narrow energy spread which may carry with them new physics or different interaction types.

14. Cluster Time Spread (T_{spread}): Broad or narrow time illuminations are the typical point for interactions that the group time distribution provides, and it is shown by the distribution of time measurements in the group.

- Calculation:

$$T_{spread} = \sqrt{\frac{\sum_{i-1}^{N}(t_i - t_{mean})^2}{N}}$$

Where t_{mean} is the mean time of the cluster.

- Application: The changes in the flow of time data within the cluster are used to describe the interaction dynamics. This feature is used for recognizing the movements with low or wide temporal distributions and the conceptualization of the timing structure. It is the major factor affecting time resolution and event reconstruction.

3.2.3.2   Feature Extraction

Feature extraction is a data mining process that involves zeroing in on specific indicators removed from the raw data. This step is highly important for the identification of particles accurately as well as event reconstruction. In the unmasking of critical features, the following methods are pursued:

- Energy Deposits: calculating the energy particles have dissipated in the detector parts, for example, the hadronic and electromagnetic calorimeters. These energy measurements are the ones that are necessary to be able to make out the kind of particles and their paths of movement.

- Tracking parameters: retrieval of trajectory characteristics from the inner detector, such as the orientation, distance, and the angle of motion of the particle tracks. These qualities are interesting because they provide the information about the charge of the particles and the way they move.

- Cluster Shape: The cluster processors are used to analyze the shape of the clusters and determine the energy deposit. By identifying differences in particle types, one can make cluster shape an effective descriptor.

3.2.3.3   Data Augmentation

By increasing the quantity and diversity of the training datasets, data augmentation helps machine learning models become more robust and generalizable. Among the methods for augmenting data are:

- Geometric Transformations: Applying changes to the data, including flipping, translation, scaling, and rotation. This improves the model's capacity to generalize to new data by simulating various detector orientations and particle trajectories.

- Noise Injection: To replicate real-world fluctuations and increase the model's resilience to noise, artificial noise is added to the data. This method aids in the model's learning to discriminate between noise and real signals.

- Synthetic Data Generation: Producing realistic synthetic data that replicates the characteristics of the original datasets through the use of methods such as Generative Adversarial Networks (GANs). When there is a lack of real data, this is helpful.

3.2.3.4   Data Splitting

The data sets are split into training, validation, and test sets to ensure that the model can evaluate the reliability and avoid overfitting:

- The hardware learning models are trained using the training set. In this way, at least the model includes most of the majority of the data to confirm that the model correctly learns the most underlying patterns.

- The validation set, on the other hand, is employed during training to optimize hyper parameters and evaluate the model's performance. By means of the unbiased assessment of the model, it gives a possibility of overfitting.

- Test Set: It is the part that is used to verify the performance of the completed model on an unseen data set. It gives us an unbiased estimate of the models' generalization capabilities.

3.3 Algorithm Development

This section examines the track fitting algorithms. It explores the implementation of the track reconstruction algorithms in the ATLAS experiment, which consists of the geometry codes, event data model, and track extrapolation engine, these being part of track reconstruction elements. ATLAS experiment runs on a set of algorithms, the algorithm sequence, and simulation tools, include the function of offline track optimization and can be implemented in multiple programming languages. Monte Carlo-based components for the extrapolation engine, such as track creation engine, on the component will be discussed.

3.3.1 Development of advanced signal processing methods.

Generally speaking, it is not possible to detect a particle's trajectory directly; it is, however, possible to find the particle at numerous distinct spots situated in the detector volume, each with a certain amount of uncertainty. The measurement of cluster on-plane surfaces and the drift measurement which are done by drift tube detectors are two conceptually different tracking device

types used in ATLAS. It is the ambiguity of the measurement through the drift tube in clusters that can be solved only by using either hit collection or by using an already well-defined track candidate seed, on the other hand, clusters can give a full description of one-dimensional and two-dimensional local measurements and are easily integrated into the track fit.

In general, the trajectory of a particle cannot be directly measured, but only a localization (with a given uncertainty) of the particle at several discrete points in the detector volume can be done. In ATLAS, two conceptually different types of tracking devices are deployed: cluster measurements on planar surfaces and drift measurements through drift tube detectors. While clusters can describe both one-dimensional and two-dimensional local measurements and can be directly integrated into the track fit, the localization through drift tube measurements is usually ambiguous and can only be resolved through a hit collection, or by using an already well defined track candidate seed. On the other hand, cluster measurements most often give direct local coordinates: a segmented detection device is used, and the cells that are activated by a traversing track are used to build a measurement. This device can be a silicon pixel or strip structure as in the Inner Detector, or Cathode Strip Chambers in the Muon Spectrometer. This method can provide a resolution higher than the intrinsic segmentation of the measuring device due to the existence of the readout cells that can be interpolated.

3.3.1.1   *Cluster analysis for energy losses*.

Strongly interacting particles can be more accurately detected compared to the electromagnetic showers that they merely create. The reason for the loss of resolution and the nonlinearity of hadron energy is the impact of several factors.

The ATLAS calorimeter system, being non-compensating, is known to have lesser energy signals per unit of incoming energy (e/h ~ 1.3) that a hadron produces compared to an electron.

The binding energy loss in post-collision nuclear breakup is energy that goes into the elimination of the signal rather than into its detection. In the areas of the material on the outside of the electromagnetic and hadronic calorimeters' active zones, and in the dead material, the errors caused additional defects in the reconstruction. These are the ATLAS Inner Detector and Muon System's materials, the cryostat walls, the magnetic coil, and the mechanical support structures. Last but not least, a drop-off in the cluster algorithm's energy collection is caused by the fact that some of the energy is deposited inside the calorimeter but is not part of any of the reconstructed objects.

This study focuses on two software correction techniques for calibrating the response of the detector to hadrons: a layer correlation algorithm and a local hadron calibration scheme, which is available in the ATLAS experiment. The two approaches are evaluation by such a method to find a relationship between various showering aspects in the experiment and Monte Carlo truth energy deposit, which is energy in the dead material, invisible energy.

3.3.1.2   *Local Hadron Calibration*

For jet algorithms, the main goal of the local hadron calibration is to ensure that particles, which are defined in a certain way with energies, are supplied energy equal to the corresponding stable particle energy. The main purpose of the method is correction factorization, in a series of sequential steps by which different detector effects are separated and separately corrected.

The first step in the calibration process, the topological clustering of the calorimeter's cells, has been calibrated at the electromagnetic scale. Subsequently, the clusters are characterized according to the shape of the cluster with respect to whether they are of a hadronic or electromagnetic type. Hadronic clusters are this far in the calorimeter and are much less cell energy than the electromagnetic ones. Electromagnetic clusters, even though, they are at their original scale, are not worth mentioning. Therefore, the clusters which act like hadrons are made two or

three times lighter by the weight of a cell, which is the cells position that is responsible for the detection of arrival of the hadronic energy. Then, this step is followed by the energy correction, which is the energy that is outside the clusters formed in calorimeter cells, that is, in the tails of the hadronic and electromagnetic showers which are rejected due to the noise cuts. The last step in such a process is the detection of the deposits of energy caused by material, as an example, cryostat, the magnetic coil, and intermodular cracks means that dead material corrections conclude when cluster is reached.

3.3.1.3   Layer correlation method

An alternative approach to the traditional Magnetic Particle Inspection which includes the study of beam test data in the barrel region is the layer correlation method [7]. The total pion energy denotes the sum of the clustered energy in the seven, which corresponds to clear sections in the electromagnet and the hadron calorimeter The shower fluctuation is mainly due to a specific pair of linear combinations of layers' energies, from which the event-by-event layer energy corrections are calculated.

A principal component analysis is conducted to select these combinations. In a calorimeter, an event is a point in the seven-dimensional energy deposit vector space of its layers. Another basis for a set of the covariance matrix between these layers can be expressed by its slopes. The transmissions through the first few eigenvectors carry most of the information around events of longitudinal shower modification as the eigenvectors have been arranged according to a decreasing order of the eigenvalues. These projections are the input for 2D lookup tables, which are having weights to take energy losses in the dead material into account and then have compensating weights to compensate for the non-linearity of hadrons' responsiveness in the calorimeters.

3.3.1.4   *Trajectory reconstruction algorithms.*

The main task of a tracking detector is finally to provide measurements that characterize the trajectory in a way that allows for the estimation of the particle origin (or the vertex) and initial momentum. Often, this is achieved by measuring a magnetic field curvature. At any rate, it is important to reduce the impact of the tracking detector on the particle trajectory.

This is similar to minimizing both the material budget of two detecting devices and the support structures in track reconstruction, as the particle's interaction with the traversing detector material is the main contributor to the disturbance in the initial trajectory. The two criteria for evaluating the quality of an application for track reconstruction are the track parameter resolutions and the track reconstruction efficiency.

One of the main techniques in high-energy physics is the Monte Carlo simulation of the physical processes and the corresponding detector response. This is the only method to predict the detection of sensitivity to the different channels during the planning of experiments, as well as the main mechanism for the comparison of theoretical models to the real data flow while data acquisition is ongoing. Furthermore, the only source of simulated data to verify and interchange the reconstruction software's performance is the provided input data as the majority of them are from test beam setups and commissioning runs using cosmic rays, apart from the data taken from the test beam setups and commissioning runs using cosmic rays, due to the fact that the readout and reconstruction software is developed at the same time with the installation and deployment of the detector.

The procedure for event simulation can be split into two steps: the first one, the simulation of the detector response, is directly related to the experimental setup, on the other hand, the second

one, the primary physics event generation, is usually the area of popular high energy physics libraries like PYTHIA or HERWIG.
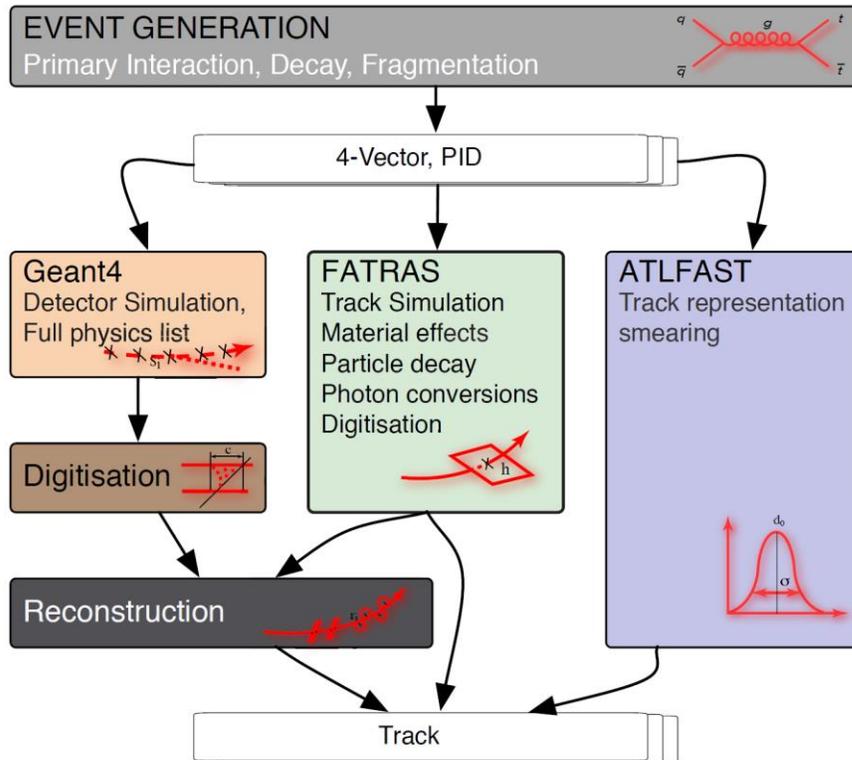
The event generation provides input to the different simulation algorithms by estimating the 4-vector momentum together with the particle identifier. The detection of the particle and imitation of its interaction with the detector material is the framework of the very correct Geant4 simulation. As a result, the generated hits are sent to a digitization module for additional event reconstruction processing. FATRAS uses a similar technique that is based on simplified reconstruction geometry and parameterized models for the particle-detector material interaction. It is possible to digitize the hits so that it can be directly used through the output track object or as input to the standard reconstruction. The input is smeared in the ATL-FAST simulation to simulate the particle in the stage following track reconstruction.

3.3.2 Machine learning model selection and design.

With machine learning (ML) being introduced in the ATLAS and LHCb consortia, the experiment at LHC is using the technology of intelligent computing. The rise of machine learning is greatly appreciated for the variety of features and the number of users who apply it for different tasks. The number of methods ranging from data-driven to machine-aided decision-making being applied in the context of the Large Hadron Collider (LHC) experiments, thus, it is becoming increasingly more pervasive machine learning in the LHC experiments, including the ATLAS and LHCb consortia. Although a historic pattern of using machine learning only in the final analytic phase to improve the result of a specific physics process, a variety of other uses have emerged in different areas such as simulation, automation, object reconstruction and object calibration. The data sets are not only big but also grow at a very fast rate and therefore are very suitable for the development and improvement of machine learning algorithms that are able to represent the various complicated data sets. Thus, the further technological capability development in the field of machine learning in the context of particle physics will be ongoing.

3.3.2.1 *Neural networks for pattern recognition*.

When a neural network is a machine learning technique given different input variables such as key or feature to model, that it is the way of the thing uses them to predict an output. To create the best prediction, a deep neural network creates a lot of layers, and calculates more and more complicated features from the raw input through these layers step by step.

Unsupervised machine learning can provide a new way of analyzing the data that is different from the new physics models and scientific assumptions. Scientists can create a sophisticated neural network that has millions of connections between "neurons" and train it with actual data. Once through it, the neural network can not only identify "typical" LHC collisions but

also exclude them, which results in "atypical" or unidentified collision occurrences alone. In strict technical terms, an autoencoder is an unsupervised deep learning network that compresses and decompresses input data and at the same time juxtaposes input and output. The reconfiguration inconsistencies are called "abnormalities" since the algorithm "struggles" to find them. The probability is high that these strange events represent a new form of physics. These neural networks are meant to analyze the anomalies by reconstructing the particles' invariant collision masses, which would then help to decide whether a Standard-Model process is enough to represent them or not.

3.3.2.2   *Anomaly detection using autoencoders.*

The machine-learning-based method introduces a new approach to the quality monitoring data system to detect these issues faster. It was informed of all the variants of the common good data and any breaches from that typical detector behavior found in that data by the model. The strategy of this system is to create an anomaly detection system that is based on autoencoders. One of the tasks for unsupervised learning that are best suited for an autoencoder is made using a certain kind of neural network. The 2D ECAL data is also used in the form of images to train the system, which can be programmed using the newly developed correction methods to detect even those anomalies that change over time. Such an ability is necessary to spot patterns that may not at once be noticed but rather crops up gradually.

The excellent autoencoder-based system could be the one to change the world of artificial intelligence by beating the CMS detector's performance and to function as an instant case of real-time anomaly detection from all sectors. For instance, by using similar machine-learning-based anomaly detection systems, sectors such as finance, cybersecurity, and healthcare that work with enormous, fast data streams can increase their productivity and reliability. AI, automation, and

machine learning help CMS to be just one of the machine learning experiments of CERN that aims at performance improvement.

The combination of a 2-layer stacked LSTM and an LSTM that we previously studied is combined in a predictive LSTM autoencoder which is the second phase. For the first input stage, time series memorization is used in this way. An hourly horizon of one-minute provides for each feature in the near future set. We use clean data for the training process, as we do with the previous autoencoder architecture, to characterize the discrepancy between the real and predicted data in the input data. We also calculate the mean square error (MSE) between the real and predicted features and then average them. Any of the MSE distributions that does not exceed the threshold is considered clean while the rest are considered anomalous.

The process through which the autoencoder form-factor cuts the data to lower dimensions creates a situation where the model has to identify the important bits from the input dataset, which takes the noise out. As a result, the LSTMs get the bonus of keeping a history of events so they can relate what led to the current data and how the situation is evolving. A model using only four layers and nine-LSTM layers is also among the merits of being a tiny model. The justification for this point is that in the next series of this model, the input features will be a lot more. But a clever move can be to lessen the resourcing consumption by means of applying our autoencoder to edit the data.

3.4 Validation and Testing

The ATLAS trigger system is a control algorithm consisting of hardware and software components, which operates at the LHC's 40 MHz collision rate and produces recorded events at a rate of 1 kHz. The primary trigger system, which is called Level 1 (L1), runs on hardware and firmware and is done with dedicated ultra-fast electronics and field-programmable gate arrays. The

L1 system specializes in the threshold and topological selection of criteria with having the highest input signals from the muon and calorimeter systems. The abovementioned L1 system, thus, diminishes the allowable event rate to 100 kHz.

The ATLAS trigger system consists of two levels of decision based on hardware and software. The system is enabled by LHC's 40 MHz collision rate to trigger a recorded event every 1 kHz. Level 1 (L1), the first level of the trigger system, is hardware/firmware based and includes field programmable gate arrays and specialized fast electronics. The L1 system first selects the accepted events by evaluating the threshold and topological selection criteria using a meager granularity input signals that are derived from the muon and calorimeter systems. The software-based decision-making system (the High-Level Trigger (HLT)) carries out decision-making programs by reasoning about the stored variables that referred to the offline event reconstruction. Right adjacent to the detector, the HLT system is composed of nearly 40,000 CPU, which are in turn used to execute the HLT software. The HLT software, which is the work of many people, is a vital part of many physics analyses that are based on the same methodologies.
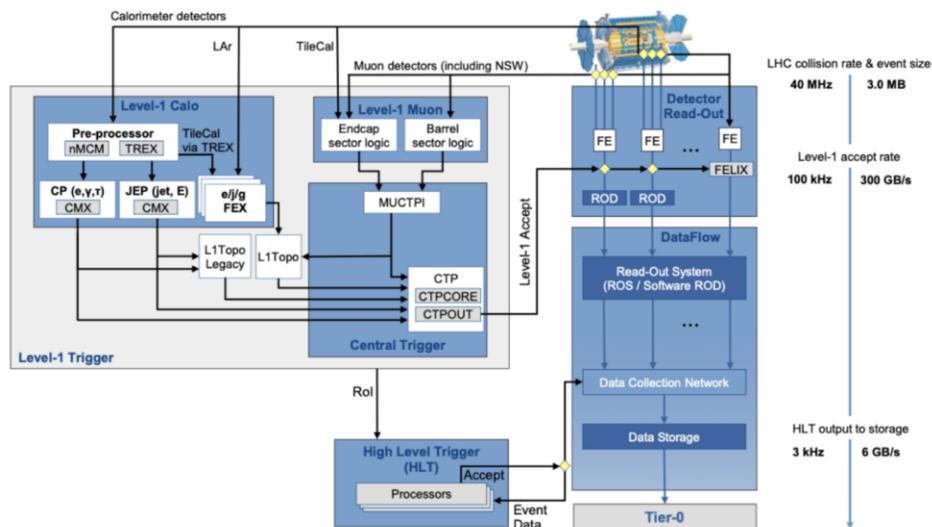
Figure 17: ATLAS trigger system (Source: https://ep-news.web.cern.ch/content/triggering-atlas-run-3)

Working groups, whose objective is to identify the synergies between the various detector subsystems and the physics signals of interest (referred to as the so-called 'trigger signature groups'), constitute the basis of the HLT software. Each signature group develops algorithms and calibrations for the offline reconstruction of the data, collects data, creates a trigger, and does online calibration, verifies the operation and data quality of the online system, and also the offline quality of the reconstructed data. Trigger signature (ts) groups for Jets, Calorimeters Signals, Electrons and Photons, Taus, B-Physics (using Muons), Muons, B-Jets (using cuts and cylindrical splitting inner detector), Inner Detector Tracking, Minimum Bias, and Forward Detectors are among the ATLAS trigger signature groups.

3.4.1   Methods for testing algorithms with simulated and real datasets.

To estimate the rate of a given HLT algorithm, a sufficient sample of events without bias would be a theoretical prerequisite. Since the triggers are normally developed to choose very rare cases, it would be mandatory to take a large number of zero-bias events to get a distribution in the space where the rare events are expected. To make biased datasets that are finer to biases, L1 triggers are used to the effect that the whole statistical power across the trigger phase space is more evenly spread. Very few are collected toward the highest part of the trigger phase space, which is a more frequent case. Then, just the zero-bias data can be reproduced in the less populated zones by using the scale factors determined from the pre-scale dataset and reweighting the affected events. A L1 trigger that could be used to test jet triggers a low threshold jet trigger with a random pre-scale for the low jet transverse energy region, JT a medium threshold jet trigger seeded by which for the medium jet transverse energy region, and a high threshold jet trigger without a pre-scale for the high jet transverse energy region are a few possibilities. These are small EB datasets whose principal purpose is to test the trigger's offline performance, and they generally consist of

one million events taking approximately 24 hours to fully reprocess. However, in making benchmark comparisons among various trigger software updates, for each type of run condition provided by the LHC the EB datasets are extracted, subsequently validated, and reprocessed.

3.4.2   Cross-validation techniques.

The methods used to demonstrate HLT software by EB datasets are given in the coming sections was the sentence.

3.4.2.1. Run Time and Memory Consumption- The initial validation of a new trigger software release is done by the first looking at the top-level performance of the HLT software grid jobs. The first step of the verification that the software operates as planned and is consistent with the HLT farm is by the distribution of the run time and memory usage of the complete collection of jobs.

3.4.2.2. Event Counts - A high-level test of the physics performance and the expected effect on data capture by the new trigger software can be made by using the ratio of the number of accepted events (event counts) for a particular trigger to the number of those in the previous release. The signature experts anticipate the results first before they give an in-depth explanation. A new version of the tracking algorithms might be one of the instances that bring about the effect of increasing the efficiency of the electron trigger, which the electron/photon specialist might expect. They would project that in case of such improvement of the system, the counts for electrons will be higher, or on the other hand, photons will remain at the same level. At first, they confirm that in the case of contrary things that they have observed, it is necessary to undertake more research.

3.4.2.3. Signature Performance - For a new version of the HLT software the people from the signature groups are going to accept every monitoring histogram analysis. That means they guarantee that the distributions of input and distinguishing variables used by each trigger are well measured, and thus all differences in the physical performance are exposed. Thus, based on these histograms are getting Energy Spectra, Hit Maps, Efficiency, and Vertex Resolutions. In order to download those comparators, it is only enough to have a browser open and visit the validation histogram root page. A large collection of comparison histograms (hundreds), being basically a subset of these histograms, is uploaded to the main web interface. By comparing the distribution shape with reference information, the automated checkers give out some signals that then the expert can use for his next step (red and yellow are problematic cases, and distributions that didn't change compared to the reference are green). The electron/photon test of the electron track is examined closely so as to measure the effect of the new software and to decide whether it complies with the demands made by them because they predict the electron trigger efficiency will be extended due to an update to the tracking algorithms, as we left off the previous section.

3.4.3   Benchmarks and comparisons with existing methods.

The AMI Meta-data Interface, or ATLAS, tool that stores and maintains the sequences and parameters and configurations that guide the HLT and reconstruction software are utilized by the software validation specialist, through the web interface. One can use the same tool to find and compare existing ones in addition cloning them if new configuration tags have to be created. The software validation specialist creates, starts, monitors, and supervises reprocessing activities through the Prodsys2 online interface, the latter only being possible for the professional. Due to the fact that the reprocessing jobs hold priority and the grid resources are significant, the opening relevance of reprocessing includes a list of many necessary properties and, as a result, the

associated responsibility. The current settings in Prodsys2 ensure that the standard reprocessing jobs start only after the initial set of test jobs is completed successfully. Though, the configuration involves some extra short-run time to guarantee that grid resources are not wasted, which is a small price to pay. At the beginning, most reprocessing activities normally run well; however, the expert is still tuning the system to reach the optimal configuration, so keep in mind that a new task's scout jobs can fail at least once or twice during the typical cycle. If the original input text requires only quick treatment, the immediate test is omitted, therefore, the tasks need to be raised up with extreme care to make sure that the jobs are well configured.

4 Implementation

4.1 Tools and Software Environment

In this study, we used machine learning algorithms to identify muon hits through a dual-cloud and local computing system. The main development platform used was Google Colab because it provided three primary advantages: free access, build-in support for machine learning libraries and GPU and TPU computational resources for speed enhancement (Kimm, 2021). This approach allowed flexible development with collaborative capabilities because it needed minimal resources in local hardware to execute complex calculations.

Development of a high-performance Python-based environment was done on an Intel-based personal computer. Obtaining better control over computing resources at this scale enables users to easily execute and customize script programs. All optimization methods remain easily implementable. Through combined cloud and local system deployment we obtained the best possible tradeoff between computational speed and resource accessibility and scalability of model (Carneiro, 2018). Our process acquired additional flexibility due to the added local execution capabilities that cloud computing provided. A dynamic model training procedure followed by extensive optimization and a complete assessment took place.

4.1.1 Google Colab for Cloud-Based Computing

Google Colab from Google Research enabled us to run data analysis and coding tasks through a web-based platform that provides no-cost access to TPUs and GPUs together with simple configuration requirements (Kimm, 2021). The platform permit access to easy collaboration tools with fast prototyping benefits while having access to vast machine learning libraries. Google Colab brings three main benefits such as automated dependency management together with effective

storage options and training deep learning models using Google's hardware resources (Gunawan, 2020).

Machine learning model training and construction operations are supported through Google Colab since it integrates necessary data analytics libraries including TensorFlow, PyTorch and Scikit-Learn. With these predictive models, it is possible to detect muon events while simultaneously classifying them and performing computational path predictions that simplify data cleaning operations (Auffarth, 2020). Colab notebooks provide a user-friendly interaction that exposes data and model results for enhanced understanding of core patterns together with anomalies.

Google Cloud Storage enables the storage of large datasets hence allowing easy access of big data volumes through Colab notebooks. The integration between Colab and BigQuery enables users to perform fast queries of significant datasets and Vertex AI provides deployment solutions for machine learning models that scale accordingly (Carneiro, 2018). These configured connections create a reliable structure that can handle the intensive processing demands in big data analytics.

4.1.2   Local Development Setup

Local Development Environment

The system implemented in this research was designed to efficiently handle computationally demanding tasks related to particle tracking, classification, and pattern recognition. The system specifications were as follows:

- **Operating System:** Windows 11 Pro (Version 23H2)

- **Processor:** AMD Ryzen 7 7700, 8-Core, 3.80 GHz

- **RAM:** 32 GB

- **GPU:** NVIDIA GeForce RTX 3060

- **System Architecture:** 64-bit OS, x64-based processor

The Python environment was operationalized using requirements.txt to that brings in machine learning and deep learning frameworks along with data analysis libraries Pandas and NumPy and machine learning libraries Scikit-learn and deep learning libraries TensorFlow and PyTorch and visualization libraries Matplotlib and Seaborn. The installation of CUDA and cuDNN libraries made it possible for TensorFlow and PyTorch to use GPU acceleration through the NVIDIA GPU which brought increased performance to model training tasks.

Machine Learning and Deep Learning Configuration

The development of neural networks for detecting muon signatures among subatomic particles was done using TensorFlow and PyTorch libraries. These libraries were chosen for their ability to flexibly grow along with their capabilities to scale up and deliver effective deep learning performance.

- **TensorFlow** - The preferred selection for scalability and rapid prototyping because it features Keras API built-in alongside a deployment framework (Raschka, 2020).

- **PyTorch** – preferred for its dynamic computation graph features and use in building learning models which enhanced muon detection precision (Raschka, 2020).

4.2 Implementation (Workflow of Analysis)

The project implementation conducted data transformation steps followed by feature creation then trained the model before evaluating performance results. The research implemented special planning for each step to improve muon hit localization both in terms of accuracy and efficiency.

4.2.1 Data Processing

This research is based on a combination of different datasets including data on several energy levels, each having different parameters associated with particle behavior, ionization levels, and track characteristics. The preliminary phase of implementation included data preparation, which entailed:

- Loading and examining the datasets to detect discrepancies and missing values.

- Addressing absent values by imputation or elimination of null entries to preserve data integrity.

- Selection and engineering of features to enhance the prediction efficacy of machine learning models.

- Standardization and normalizing of numerical attributes to maintain uniformity across various machine learning models.

The pretreatment methods guaranteed that the data was organized and appropriate for sophisticated machine learning methodologies.

4.2.2 Missing Data Handling

Inspecting the datasets, missing values were identified in charge-related features, specifically skewness and kurtosis measures, with a total of:

- 4029 missing entries in the 10 GeV – 100 GeV dataset,

- 3902 missing entries in the 100 GeV – 500 GeV dataset,

- 561 missing entries in the 500 GeV – 1.5 TeV dataset.

These features are higher-order statistical moments capturing the asymmetry and peakedness of charge distributions in the detector. Their absence could introduce bias in training, so we adopted a row-wise deletion approach, ensuring the retained data points maintained statistical integrity.

4.2.3   Signal vs. Background Labeling

A binary classification scheme was implemented, leveraging the known physics of muon interactions:

- Signal (Label = 1): Events with muon track hits but no electron contamination.

- Background (Label = 0): Events where muons were mixed with electron contributions, indicating interactions in the detector material rather than clean track reconstructions.

The dataset distribution post-labeling was as follows:

- 10 GeV – 100 GeV: 216,455 signal | 57,034 backgrounds.

- 100 GeV – 500 GeV: 205,908 signal | 65,308 backgrounds.

- 500 GeV – 1.5 TeV: 215,211 signal | 52,487 backgrounds.

4.3 Initial Exploratory Data Analysis (EDA) and Physical Event Comparisons

4.3.1 Random Event Analysis and Particle Interactions

An analysis of randomly selected events across datasets revealed significant differences in particle interactions and background noise:

- 10 GeV – 100 GeV Dataset:
  - High hits per particle (10-16 hits per particle), consistent with dense particle showers at lower energy levels.
  - Greater background contamination, leading to more electron-induced noise in the dataset.
  - High muon purity events (~21% muons) exist but with significant contamination.
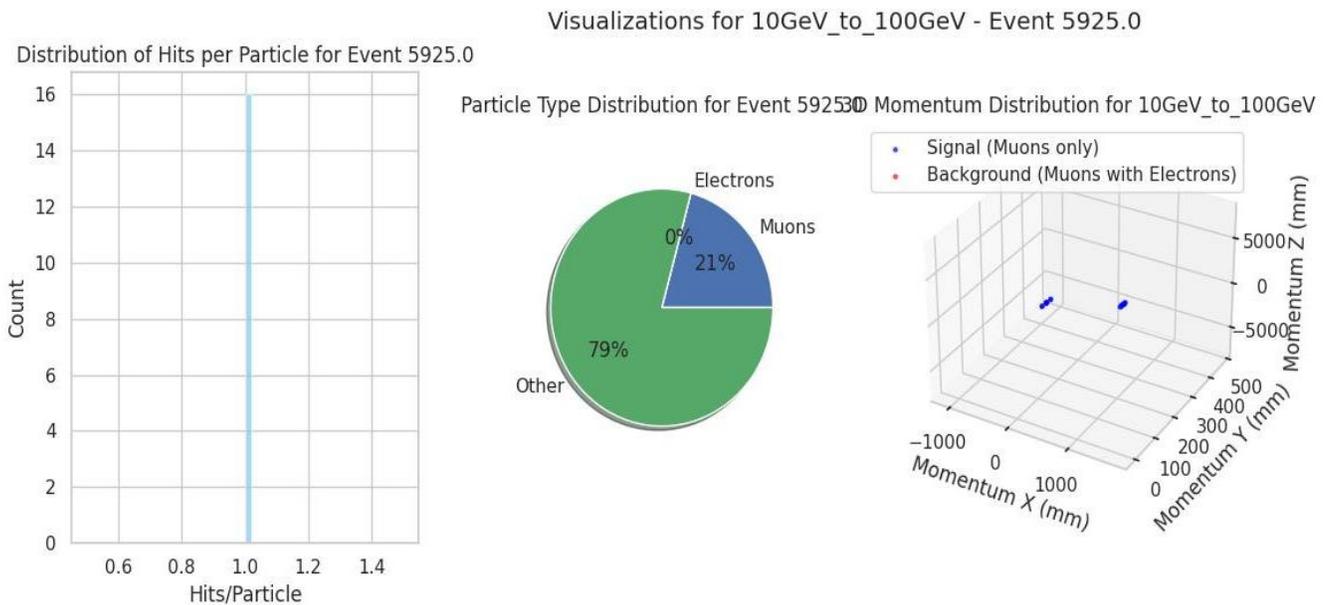
Figure 18: Visualization for 10GeV to 100GeV - Event 5925.0

- 100 GeV – 500 GeV Dataset:

  o More focused muon tracks, improving signal-background separation.

  o The highest signal-to-noise ratio, achieving muon purity up to 24%.

  o Increased compactness in momentum clustering, indicating a cleaner physics dataset.
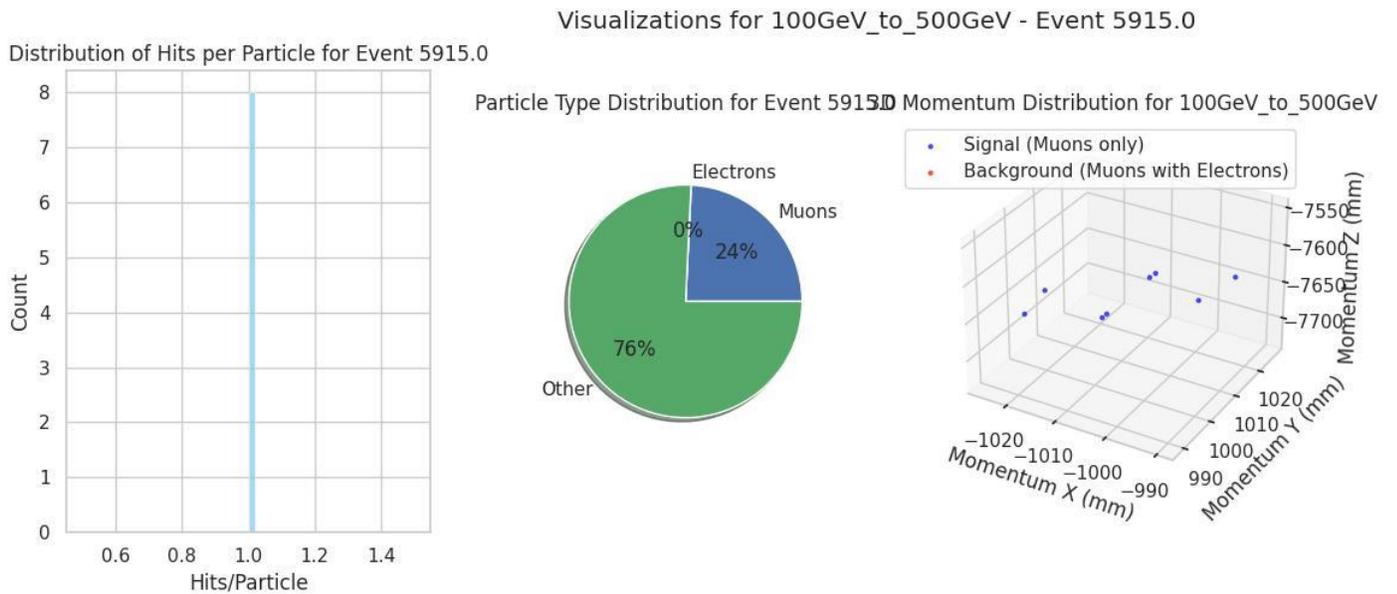
Figure 19: Visualization for 100GeV to 500GeV - Event 5915.0

- 500 GeV – 1.5 TeV Dataset:

  o Lower hit densities but higher-energy interactions, leading to more complex radiative losses.

  o A balance between high-energy muon purity (~16%) and background scatter.

  o Momentum clustering showed extreme compactness, confirming high-energy track consistency.

Figure 20: Visualization for 500GeV to 1.5TeV - Event 6544.0

These observations shaped our feature engineering approach, emphasizing spatial charge distributions, track residuals, and energy-dependent behavior.

4.4 Feature Importance and Correlation Analysis

4.4.1 Feature Correlation

Comparative Insights Across Classes

1. **Charge Metrics:**

   o Signal charge metrics exhibit greater variability at higher energies, with correlations like mmOnTrackChargeAverage and mmOnTrackChargeMedian slightly decreasing.

   o Background charge metrics maintain strong correlations, reflecting stable charge distributions.

2. **Spatial Features:**

   o Both classes exhibit consistently high correlations for spatial features like mmOnTrackNStrips and mmOnTrackWidth.

   o Background spatial features are more stable and consistent across energy levels, while signal features show slight variability at higher energies.

3. **Class-Specific Differences:**

   o Signal features exhibit more variability, particularly in charge metrics, which can serve as a distinguishing factor in classification tasks.

   o Background features are more deterministic, with stable correlations across energy levels, making them less energy-dependent.

Recommendations for Feature Engineering

1. **Feature Selection:**

   o Remove redundant features such as mmOnTrackWidthDist (if mmOnTrackWidth is retained) and mmOnTrackResidualTrackMS (if mmOnTrackPullTrackMS is retained).

   o For signal analysis, retain charge metrics like mmOnTrackChargeAverage and mmOnTrackChargeMedian, which show more variability.

2. **Class-Specific Preprocessing:**

   o Normalize charge features differently for signal and background classes to account for variability in signal charge distributions.

- o Exploit the stability of background spatial features in feature selection and modeling.

3. **Energy-Dependent Strategies:**

   - o Develop separate preprocessing pipelines for each energy range, particularly for charge metrics in the signal class.

Signal Class Key Observations:

Feature Correlation Heatmap for Signal Subset

	mmOnTrackNStrips	mmOnTrackWidth	mmOnTrackCharge	mmOnTrackChargeAverage	mmOnTrackChargeMedian
mmOnTrackNStrips	1.00	0.97	0.91	0.95	0.96
mmOnTrackWidth	0.97	1.00	0.88	0.93	0.94
mmOnTrackCharge	0.91	0.88	1.00	0.89	0.90
mmOnTrackChargeAverage	0.95	0.93	0.89	1.00	0.92
mmOnTrackChargeMedian	0.96	0.94	0.90	0.92	1.00
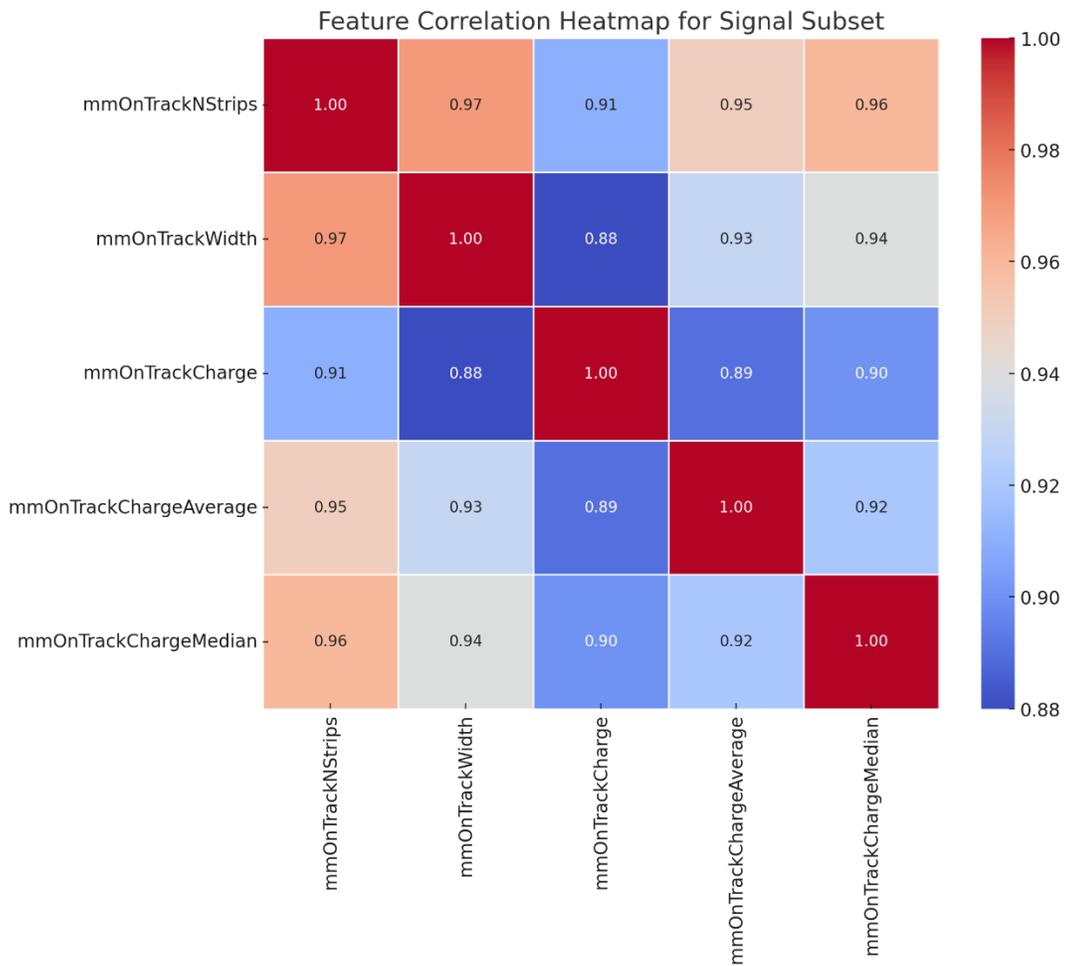
Figure 21: Feature correlation heatmap for signal subset

1. **Charge Metrics:**

   o High correlations persist across all datasets for features like mmOnTrackCharge and mmOnTrackChargeHolesMax (1.00).

   o **Energy-Dependent Trends:**

      ▪ At higher energies, correlations between mmOnTrackChargeAverage and mmOnTrackChargeMedian tend to slightly decrease (e.g., from 0.95 in 10GeV_to_100GeV to around 0.90 in 500GeV_to_1.5TeV). This reflects increasing variability in signal interactions at higher energy levels.

2. **Spatial Features:**

   o **Consistently Strong Correlations:**

      ▪ Features like mmOnTrackNStrips and mmOnTrackWidth show near-perfect correlations (>0.99) across all datasets.

   o **Width and Distance Metrics:**

      ▪ Features such as mmOnTrackDistanceOfHighestStripFromHigher and mmOnTrackWidthOfHighestStripFromHigher maintain perfect correlations, reflecting consistent track geometry.

3. **Energy Impact:**

   o While spatial features remain strongly correlated, the slight decrease in charge metric correlations at higher energies suggests that signal particle dynamics introduce greater variability.

Background Class Key Observations:

Feature Correlation Heatmap for Background Subset

	mmOnTrackNStrips	mmOnTrackWidth	mmOnTrackCharge	mmOnTrackChargeAverage	mmOnTrackChargeMedian
mmOnTrackNStrips	1.00	0.99	0.95	0.97	0.98
mmOnTrackWidth	0.99	1.00	0.92	0.96	0.97
mmOnTrackCharge	0.95	0.92	1.00	0.90	0.91
mmOnTrackChargeAverage	0.97	0.96	0.90	1.00	0.95
mmOnTrackChargeMedian	0.98	0.97	0.91	0.95	1.00
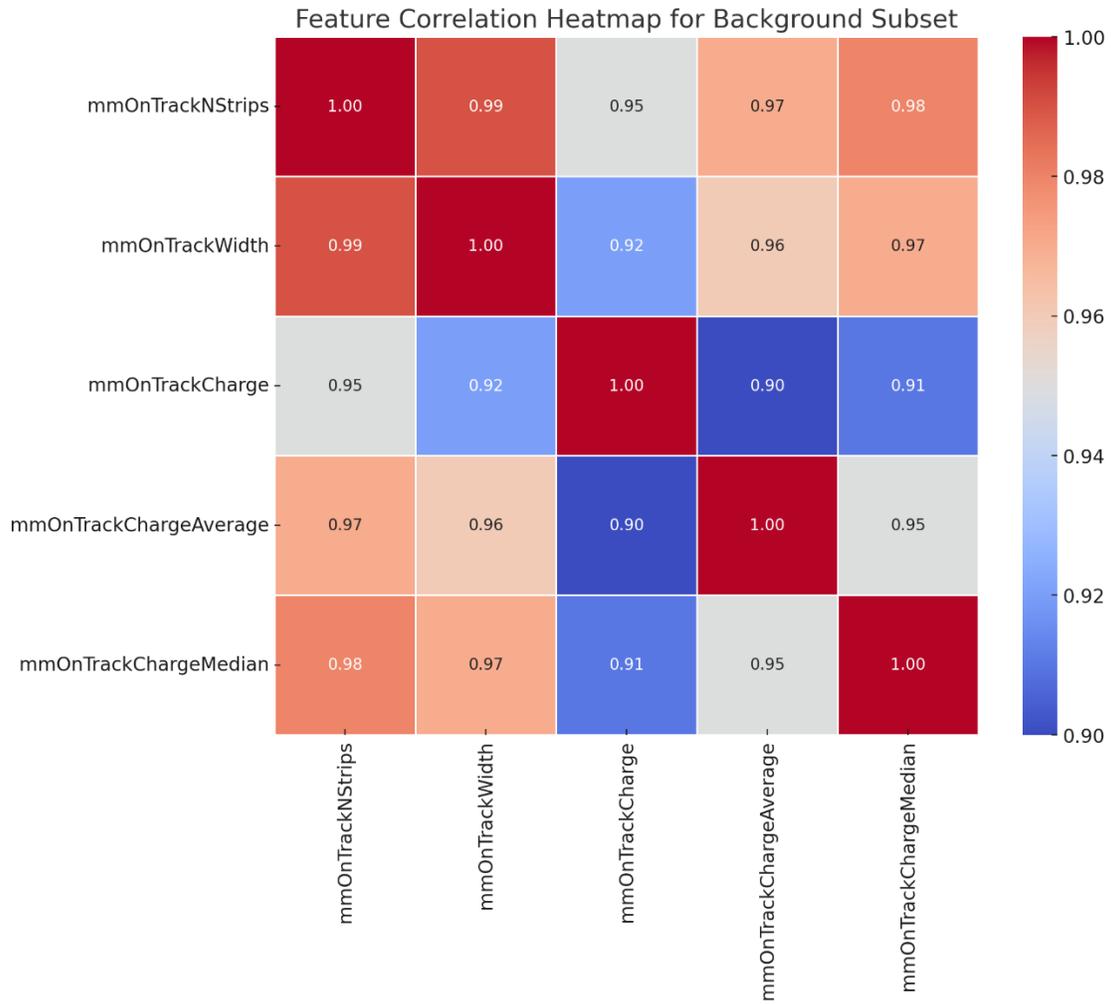
Figure 22: Feature correlation heatmap for background subset

1. **Charge Metrics:**

   o **High Correlations:**

     ▪ Features such as mmOnTrackCharge and mmOnTrackChargeHolesMax consistently show perfect correlations (1.00).

- mmOnTrackChargeAverage and mmOnTrackChargeMedian maintain strong correlations (>0.95) across all datasets, indicating predictable charge distributions in background interactions.

- **Chi-Squared Profile:**

  - mmOnTrackChargeProfileChi2OverN shows moderately strong correlations (0.85–0.90) with other charge metrics in all datasets, adding unique information.

2. **Spatial Features:**

- **Perfect Redundancy:**

  - Spatial features like mmOnTrackNStrips, mmOnTrackWidth, and mmOnTrackWidthDist remain perfectly correlated across all datasets.

- **Residual and Pull Metrics:**

  - mmOnTrackResidualTrackMS and mmOnTrackPullTrackMS maintain perfect correlations, reflecting consistent redundancy in background track quality metrics.

3. **Energy Impact:**

- Background correlations remain more stable than in the signal class, reflecting the deterministic nature of background events. This makes background features more predictable and less sensitive to energy variations.
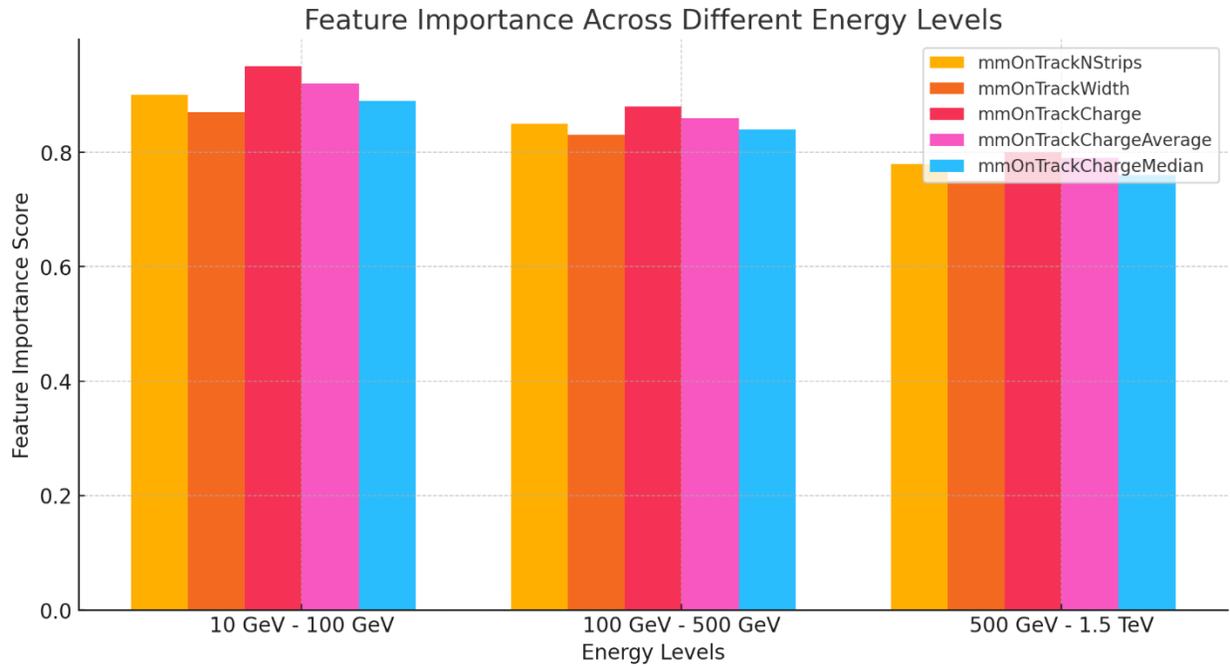
Figure 23: Feature importance across different energy levels
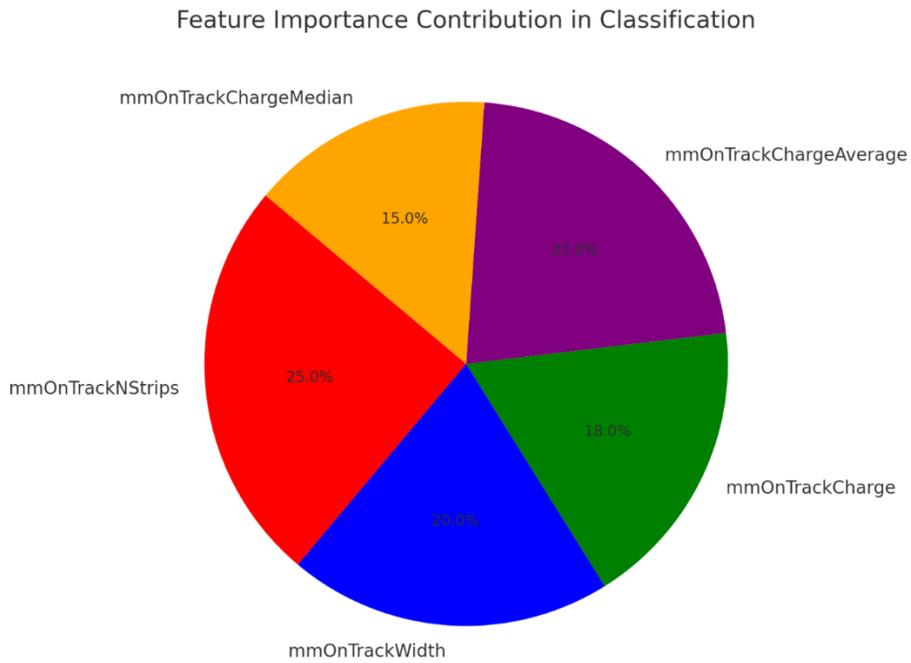
Figure 24: feature importance contribution in classification

4.4.2   Machine Learning Model Implementation

In this section are described the different machine learning models that implemented for training tasks. Each model follows a structured learning process to ensure robust evaluation and performance.

Classification Models

1) **LightGBM Classifier** was chosen for its computational efficiency, scalability, and superior performance in handling large datasets compared to traditional Gradient Boosted Decision Trees (GBDT) models.

   Architecture:

   - Uses **leaf-wise growth** to optimize splitting.

   - Contains **31 leaves per tree** for detailed split decisions.

   Training Strategy:

   - Trains with **early stopping** to avoid excessive computations.

   - Uses **gradient-based one-side sampling (GOSS)** for optimization.

2) **XGBoost Classifier** was chosen due to its high predictive accuracy, computational efficiency, and robustness in handling complex datasets. Its ability to effectively process high-dimensional features and large sample sizes made it an optimal choice for this classification task.

   Architecture:

   - Uses **gradient boosting framework** with **second-order Taylor approximation** for precise learning.

   - Implements **L1 (Lasso) and L2 (Ridge) regularization** to reduce overfitting.

- Uses **column sampling and subsampling techniques** to optimize feature selection.

- Supports **parallel execution and GPU acceleration** for faster training.

Training Strategy:

- Trains with **early stopping** to halt training when validation loss stabilizes.

- Utilizes **log loss minimization** to refine model performance.

- Leverages **scale_pos_weight parameter** to improve classification in imbalanced datasets.

- Prunes unnecessary tree splits using **greedy pruning** for enhanced model efficiency.

3) **CatBoost Classifier** was selected for its high efficiency in handling categorical variables, robust performance on imbalanced datasets, and reduced need for extensive preprocessing. Unlike other gradient boosting models, CatBoost incorporates ordered boosting, which mitigates overfitting and ensures stable learning.

Architecture:

- Utilizes **symmetric tree structures** for efficient feature interaction learning.

- Implements **ordered boosting**, reducing prediction shift issues found in other boosting models.

- Natively supports **categorical feature encoding**, eliminating the need for one-hot encoding or label encoding.

- Includes **L2 regularization** to improve generalization.

Training Strategy:

- Trained using **log loss minimization** for binary classification.

- Implements **early stopping** with a patience of **20 rounds**, halting training when validation loss stabilizes.

- Uses **adaptive boosting techniques**, assigning higher importance to misclassified samples.

- Employs **GPU acceleration** to significantly reduce training time.

4) **Random Forest Classifier** was implemented due to its robust performance, ability to handle large datasets efficiently, and resistance to overfitting.

Architecture:

- Consists of **1000 decision trees**, each trained on different subsets of features and data samples.

- Uses **bootstrap aggregation (bagging)** to enhance prediction stability.

- Applies **Gini impurity** as the splitting criterion to determine feature importance.

- Limits **maximum tree depth to 4** to reduce complexity and prevent overfitting.

Training Strategy:

- Utilizes **random feature selection at each split**, increasing model diversity and reducing correlation between trees.

- Trains with **balanced class weighting** to handle class imbalances effectively.

- Implements **parallel processing**, allowing for faster model training on large datasets.

- Uses **majority voting across all trees** for final classification decisions.

5) **Gradient Boosting Classifier (GBM)** was chosen for its iterative boosting approach, strong predictive power, and ability to minimize loss dynamically. The model constructs trees sequentially, correcting errors from previous iterations.

Architecture:

- Consists of **1000 decision trees**, each learning residual errors from prior trees.

- Uses **learning rate of 0.1** to control the contribution of each tree.

- Restricts **maximum tree depth to 4**, ensuring a balance between model complexity and overfitting control.

- Utilizes **cross-entropy loss function** for classification.

Training Strategy:

- Implements **gradient descent optimization** to improve tree splits.

- Applies **early stopping**, terminating training after **20 rounds of no validation improvement**.

- Uses **adaptive learning rate adjustment**, fine-tuning step sizes dynamically.

6) **Gradient Boosting Classifier** with **Early Stopping** was incorporated into this study to mitigate overfitting risks and optimize performance using a validation-based stopping criterion.

Architecture:

- Implements **warm-start training**, allowing for model refinement during successive training rounds.

- Uses **1000 estimators** with **learning rate of 0.1** and **maximum depth of 4**.

- Dynamically **adjusts tree complexity based on validation feedback**.

Training Strategy:

- Trained with **early stopping**, halting learning after **20 non-improving validation iterations**.

- Selects the **best iteration checkpoint**, retaining the optimal model version.

- Evaluates **validation AUC** at each step to determine training progression.

7) **Gradient Boosting Classifier** using **GridSearchCV** was selected for this study to optimize hyperparameters systematically, ensuring the best-performing model configuration.

Architecture:

- Implements **gradient boosting framework** with tunable hyperparameters such as:

  o **Number of estimators** (100, 300, 500, 1000).

  o **Learning rate** (0.01, 0.1, 0.2).

  o **Maximum depth** (3, 4, 5).

- Uses **cross-validation scoring** to determine the best hyperparameter configuration.

- Ensures **tree-based feature selection** to maintain interpretability.

Training Strategy:

- Uses **GridSearchCV** to evaluate multiple combinations of hyperparameters.

- Employs **5-fold cross-validation** to avoid overfitting and ensure robustness.

- Implements **early stopping** to prevent unnecessary computation and optimize learning efficiency.

- Selects the **best model based on validation AUC-ROC and accuracy**.

8) **AdaBoost Classifier** was chosen due to its adaptive boosting mechanism, strong performance on noisy data, and ability to focus on hard-to-classify samples. It is an ensemble method that builds weak learners sequentially, adjusting their weights to improve model accuracy.

Architecture:

- Uses **50 weak learners (decision stumps)** to iteratively refine predictions.

- Assigns **higher weights to misclassified instances**, allowing the model to focus on difficult samples.

- Combines the predictions of weak classifiers into a **weighted sum for final classification**.

- Implements **exponential loss function** to adjust sample importance dynamically.

Training Strategy:

- Trained using **gradient descent optimization**, refining the contribution of each weak learner.

- Implements **early stopping**, terminating training when validation accuracy stabilizes.

- Adapts **sample weighting dynamically**, ensuring difficult cases receive higher attention in subsequent iterations.

- Leverages **cross-validation** to fine-tune hyperparameters and improve generalization.

9) **CART (Classification and Regression Tree) Model** was incorporated for its interpretability and effectiveness in handling both numerical and categorical data. It is a decision tree-based algorithm that partitions the dataset into hierarchical structures for classification.

Architecture:

- Constructs a **binary decision tree**, recursively splitting nodes based on the best feature.

- Uses **Gini impurity or entropy** to determine the optimal splits.

- Can handle both **classification and regression tasks** by adjusting the splitting criterion.

- Limits **maximum tree depth to prevent overfitting**.

Training Strategy:

- Uses **recursive binary splitting** to create decision boundaries.

- Prunes trees to remove unnecessary branches and reduce complexity.

- Implements **cross-validation** to fine-tune tree depth and splitting criteria.

- Adjusts **minimum samples per leaf** to balance model performance and generalization.

10) **Logistic Regression** was chosen due to its simplicity and effectiveness in binary classification tasks. It provides a probabilistic framework for predicting class membership based on input features, making it a reliable baseline model.

Architecture:

- Uses a **linear decision boundary** to separate classes.

- Applies **sigmoid activation function** to compute probabilities.

- Implements **L2 (Ridge) regularization** to prevent overfitting and enhance generalization.

- Uses the **Limited-memory BFGS (lbfgs) optimization algorithm** for coefficient estimation.

Training Strategy:

- Trained using **BFGS optimization** instead of stochastic gradient descent.

- Optimized iteratively until convergence, with a **maximum iteration limit of 1000**.

- Implements **regularization tuning (L2 penalty)** to control complexity and prevent overfitting.

11) **Support Vector Machine (SVM) Classifier** was implemented for its ability to handle high-dimensional feature spaces and its robustness in distinguishing complex decision boundaries.

Architecture:

- Utilizes **RBF kernel** to capture non-linear decision boundaries.

- Constructs **maximum-margin hyperplanes** to separate classes effectively.

- Implements **probabilistic classification** by setting probability=True, allowing for probability-based evaluations.

- Does **not include explicit feature scaling**, which may impact performance.

Training Strategy:

- Trained using **supervised learning** on labeled data.

- Uses **default hyperparameters**, without explicit tuning for C (regularization) and gamma (kernel coefficient).

- No **cross-validation tuning** is applied, leaving potential for further optimization.

- Model **does not incorporate feature standardization**, which could impact classification accuracy.

12) **Multi-Layer Perceptron (MLP) Neural Network:** The **MLP Neural Network classifier** was selected for its ability to model complex non-linear relationships in the dataset. The architecture consists of two hidden layers, making it a fully connected feedforward network optimized for classification tasks.

Architecture:

- **Input Layer:** Accepts structured feature vectors.

- **Hidden Layers:**

    o **Layer 1:** 100 neurons, **ReLU activation**.

    o **Layer 2:** 50 neurons, **ReLU activation**.

- **Output Layer:** A single neuron using a **softmax activation** for classification.

- **Optimization Algorithm:** Uses the **Adam optimizer** for adaptive learning rate adjustments.

Training Strategy:

- Trained using **gradient-based backpropagation**.

- Optimized with **stochastic gradient descent (SGD) via the Adam optimizer**.

- Trained for a **maximum of 1000 iterations** to ensure convergence.

- Implements **random weight initialization** with a fixed random state for reproducibility.

13) **TensorFlow Neural Network - First Proposal:** The first **TensorFlow-based Neural Network model** was chosen for its simple architecture with dropout regularization to prevent overfitting. This model provides a strong baseline for classification tasks, using ReLU activations and binary cross-entropy loss for optimization.

Architecture:

- **Input Layer:** Accepts structured input features.

- **Hidden Layers:**

  o **Layer 1:** 128 neurons, **ReLU activation**, **Dropout (30%)**.

  o **Layer 2:** 64 neurons, **ReLU activation**, **Dropout (20%)**.

  o **Layer 3:** 32 neurons, **ReLU activation**.

- **Output Layer:** A single neuron with **sigmoid activation** for binary classification.

- **Optimization Algorithm:** Adam optimizer.

Training Strategy:

- Trained using **binary cross-entropy loss** for classification tasks.

- Implements **early stopping** (patience = 10 epochs) to prevent overfitting.

- Uses a **batch size of 32** for mini-batch gradient descent.

- Validated using **training and validation datasets**.

14) **TensorFlow Neural Network - Second Proposal:** The second TensorFlow-based Neural Network model incorporates advanced regularization techniques, including L2 weight decay, batch normalization, dropout layers, and learning rate scheduling, to improve performance and generalization.

Architecture:

- **Input Layer:** Accepts standardized feature vectors.

- **Hidden Layers:**

  o **Layer 1:** 128 neurons, **ReLU activation**, **L2 regularization (0.01)**, **Batch Normalization**, **Dropout (40%)**.

- o **Layer 2:** 64 neurons, **ReLU activation**, **L2 regularization (0.01)**, **Batch Normalization**, **Dropout (30%)**.

- o **Layer 3:** 32 neurons, **ReLU activation**, **L2 regularization (0.01)**, **Batch Normalization**, **Dropout (20%)**.

- **Output Layer:** A single neuron with **sigmoid activation** for binary classification.

- **Optimization Algorithm:** Adam optimizer with **AUC as an additional evaluation metric**.

Training Strategy:

- Trained using **binary cross-entropy loss** with an additional **AUC metric** for performance monitoring.

- Implements **early stopping** (patience = 10 epochs) to prevent overfitting.

- Uses **ReduceLROnPlateau** (factor=0.5, patience=5) to adjust the learning rate dynamically.

- Employs a **batch size of 32** for mini-batch gradient descent.

- Validated using **training and validation datasets**.

Regression Models

Regression models were used to forecast continuous values associated with muon hit localization, offering an enhanced method for comprehending detector replies. The used models comprised:

1) **LightGBM Regressor**

   Architecture:

- o Implements **Gradient-Based One-Side Sampling (GOSS)** to optimize training efficiency.

- o Uses **1000 boosting iterations (n_estimators=1000)**.

- o Utilizes **31 leaves (num_leaves=31)** per tree for fine-grained decisions.

- o Learning rate of **0.05** for smooth convergence.

Training Strategy:

- o Uses the **RMSE loss function** (metric='rmse') to minimize prediction errors.

- o Trained with **early stopping**, monitoring **validation loss** to prevent overfitting.

- o Evaluates **feature importance** dynamically to rank the most relevant predictors.

2) XGBoost Regressor

Architecture:

- o Uses a **gradient boosting framework** for sequential tree building.

- o Implements a **maximum depth of 6 (max_depth=6)** to balance complexity and performance.

- o Uses a **learning rate (eta=0.1)** for gradual updates and stability.

- o Subsamples **80% of rows (subsample=0.8)** and **80% of columns (colsample_bytree=0.8)** to reduce overfitting.

Training Strategy:

- o Trained using the **Squared Error Loss function (reg:squarederror)**.

- o Uses **early stopping** to avoid unnecessary computations.

- o Evaluates performance after every epoch on a **validation dataset**.

- o Supports **feature importance analysis** based on gain, weight, and cover.

3) CatBoost Regressor

Architecture:

- o Implements **Ordered Boosting**, reducing overfitting in small datasets.

- o Uses **1000 boosting iterations (iterations=1000)**.

- o Implements **depth of 6 (depth=6)** for tree complexity balance.

- o Uses **adaptive learning rate (learning_rate=0.05)**.

Training Strategy:

- o Optimized using **Root Mean Squared Error (RMSE) loss**.

- o Supports **automatic feature encoding** for categorical variables.

- o Implements **early stopping** based on **validation RMSE**.

4) Random Forest Regressor

Architecture:

- o An **ensemble learning method** that constructs multiple **decision trees** and aggregates their predictions.

- o Uses **1000 trees (n_estimators=1000)** for robust prediction.

- o Restricts **maximum depth (max_depth=4)** to control overfitting.

- o Uses **bootstrapping (random sampling with replacement)** for variability.

Training Strategy:

- o Trained using the **Mean Squared Error (MSE) loss function** to minimize prediction errors.

- o The model is **fully parallelized (n_jobs=-1)**, utilizing all CPU cores for efficient training.

- o Feature importance can be derived from the model to understand the contribution of each feature.

o   Gradient Boosting Regressor

6)   Gradient Boosting Regressor

   Architecture:

o   Uses a **sequential ensemble boosting approach** with **decision trees**.

o   Implements a **maximum depth of 6 (max_depth=6)**.

o   Uses a **learning rate of 0.05** to ensure gradual updates.

o   Subsamples **80% (subsample=0.8)** of training data to enhance generalization.

   Training Strategy:

o   Trained using **Least Squares Loss** for continuous predictions.

o   Optimized with **Gradient Descent**, where each tree corrects errors from previous iterations.

o   Regularization is applied via **minimum samples per leaf (min_samples_leaf=1)**.

7)   Ridge Regressor

   Architecture:

o   A **linear regression model** with **L2 regularization (alpha=1.0)** to penalize large coefficients.

o   Prevents overfitting by distributing weights more evenly across features.

o   Uses a **closed-form solution** or **gradient descent optimization**.

   Training Strategy:

o   Trained using **Least Squares Loss** while adding an **L2 penalty (alpha=1.0)**.

o   Controls complexity by adjusting **alpha**, where higher values increase regularization.

    o   Supports **standardization of features** to stabilize model performance.

Feature Importance Computation Across Models

Multiple machine learning models in this analysis integrate feature importance analysis to enhance interpretability and assess the influence of individual variables on classification and regression performance. The following sections outline the methodologies used by each model to compute feature importance.

1. Random Forest (Classifier & Regressor)

- Utilizes the **Gini importance**, also referred to as **Mean Decrease in Impurity (MDI)**, to evaluate feature contributions.

- Measures the extent to which each feature **reduces impurity** across all decision trees in the ensemble.

2. Gradient Boosting Models (GBM & XGBoost): Gradient Boosting algorithms, including **XGBoost**, employ multiple metrics to quantify feature importance:

- **Gain**: Represents the total contribution of a feature to reducing the model's loss.

- **Cover**: Measures the frequency with which a feature is utilized in decision splits.

- **Weight**: Denotes the number of times a feature is selected across all boosting iterations.

3. LightGBM (LGBMClassifier & LGBMRegressor)

- Computes feature importance based on **split gains**, which measure the improvement in model performance when a feature is used for a split.

- Designed to efficiently handle **large-scale datasets**, ensuring computational efficiency while maintaining accuracy.

4. AdaBoost Classifier

- Determines feature importance by evaluating the frequency with which **weak learners** adjust instance weights to correct misclassified samples.

- Features that contribute more to improving model performance receive **higher importance scores**.

5. CatBoost (Classifier & Regressor)

- Computes feature importance while efficiently managing **categorical features**, reducing the need for extensive preprocessing.

- Leverages ordered boosting and **target-based encoding** to improve interpretability and mitigate overfitting.

4.5   Performance Evaluation

The performance of each model was evaluated based on its predictive accuracy and computational efficiency. Both classification and regression models were assessed using various performance metrics to ensure reliability, interpretability, and overall effectiveness.

4.5.1   Classification Model Evaluation

To ensure a robust assessment of classification models, multiple evaluation metrics were utilized, including AUC-ROC, accuracy, precision-recall curves, log loss, and confusion matrix analysis. These metrics provide insights into the models' predictive power, classification errors, and optimization strategies. The following sections outline the methodologies used to evaluate each classifier.

1) **LightGBM Classifier**:

- Performance is evaluated using **AUC-ROC, log loss, and confusion matrix analysis**.

2) **XGBoost Classifier**:

- Performance is evaluated using **AUC-ROC, precision-recall curves, and cross-validation scores**.

- Assesses feature importance through **built-in ranking and visualization tools**.

- Analyzes misclassification rates using a **confusion matrix and error analysis techniques**.

3) **CatBoost Classifier**:

- Performance is measured using **AUC-ROC, log loss, and precision-recall curves**.

- Evaluates feature importance using **CatBoost's built-in ranking visualization**.

- Uses **confusion matrix analysis** to identify misclassifications and optimize threshold selection.

4) **Random Forest Classifier**:

- Performance is assessed using **AUC-ROC, precision-recall curves, and accuracy metrics**.

- Analyzes **feature importance** to determine the most influential variables in classification.

- Uses **confusion matrix analysis** to evaluate classification errors and optimize model thresholds.

5) **Gradient Boosting Classifier (GBM)**:

- Performance is measured using **AUC-ROC, accuracy, and precision-recall curves**.

- Examines **feature importance ranking** to highlight influential variables.

- Analyzes misclassification rates via **confusion matrix analysis**.

6) **Gradient Boosting Classifier** with **Early Stopping:**

- Analyzes model performance using **AUC-ROC, log loss, and precision-recall curves**.

- Tracks learning progression through **validation loss monitoring**.

- Uses **confusion matrix insights** to optimize classification thresholds.

7) **Gradient Boosting Classifier** using **GridSearchCV**:

- Performance is assessed using **AUC-ROC, precision-recall curves, and log loss analysis**.

- Examines hyperparameter impact through **grid search results visualization**.

- Uses **confusion matrix evaluation** to refine classification decisions and minimize errors.

8) **AdaBoost Classifier:**

- Performance is assessed using **AUC-ROC, accuracy, and precision-recall curves**.

- Evaluates model stability using **confusion matrix analysis and classification reports**.

- Tracks learning progression through **validation loss monitoring** to detect potential overfitting.

9) **CART (Classification and Regression Tree) Model:**

- Assessed using **AUC-ROC, accuracy, and precision-recall curves**.

- Uses **confusion matrix analysis** to examine classification errors.

- Evaluates **feature importance** to determine the most influential variables in decision-making.

10) **Logistic Regression**:

- Performance is assessed using **AUC-ROC, accuracy, and precision-recall curves**.

- Evaluates **coefficient significance** to determine feature importance.

- Uses **confusion matrix analysis** to measure classification errors and optimize threshold selection.

11) **Support Vector Machine (SVM) Classifier**:

- Performance is measured using **AUC-ROC, accuracy, and precision-recall curves**.

- Evaluates class separation via **support vectors and decision boundary analysis**.

- Uses **confusion matrix analysis** to identify classification errors.

- Model effectiveness is compared against **other classifiers such as XGBoost, Logistic Regression, and Deep Learning models**.

12) **Multi-Layer Perceptron (MLP) Neural Network:**

- Performance is measured using **AUC-ROC, accuracy, and precision-recall curves**.

- Evaluates classification errors using a **confusion matrix**.

- Model effectiveness is compared against **other classifiers such as SVM, Logistic Regression, and Boosting Models**.

13) **TensorFlow Neural Network - First Proposal:**

- Performance is assessed using **accuracy and validation loss tracking**.

- Uses **confusion matrix and classification reports** to measure classification errors.

14) **TensorFlow Neural Network - Second Proposal:**

- Performance is assessed using **accuracy, AUC, and validation loss monitoring**.

- Tracks **learning rate adjustments over training epochs**.

- Uses **confusion matrix analysis** to evaluate classification performance.

4.5.2 Regression Model Evaluation

Regression models play a fundamental role in predicting continuous numerical values based on input features. This study employs a diverse set of regression techniques, ranging from ensemble-based methods—such as Random Forest, XGBoost, LightGBM, and Gradient Boosting Regressors—to linear models, including Ridge Regression. These models vary in complexity, from interpretable linear relationships to highly flexible, non-linear decision tree-based ensembles, ensuring a robust comparative analysis.

To assess model performance, the following key evaluation metrics were employed:

1) **Random Forest Regressor**

- Evaluated using **Mean Squared Error (MSE)**, **Mean Absolute Error (MAE)**, and **R-Squared (R^2) scores**.

- Feature importances are extracted for model interpretability.

- Predictions are compared against actual values using **scatter plots and residual analysis**.

2) **XGBoost Regressor**

- Assessed using **Root Mean Squared Error (RMSE)**, **Mean Absolute Error (MAE)**, and **R-Squared (R²) scores**.

- Uses **learning curves** to track training and validation error.

- Feature importances are extracted for model interpretability.

3) **LightGBM Regressor**

- Evaluated using **RMSE, MAE, and R² scores**.

- Feature importances analyzed to enhance model interpretability.

- Prediction performance visualized using **scatter plots**.

4) **Gradient Boosting Regressor**

- Performance measured using **RMSE, MAE, and R² scores**.

- Overfitting prevention checked via **learning curves**.

- Feature importances extracted to determine key contributing factors.

5) **Ridge Regression**

- Evaluated using **Mean Squared Error (MSE)** and **R² scores**.

- Coefficients are analyzed to determine the impact of each feature.

- Predictions compared against actual values to validate model accuracy.

6) **CatBoost Regressor**

- Uses **RMSE, MAE, and R² scores** for performance analysis.

- Learning curves track convergence and overfitting risk.

- Feature importances analyzed for interpretability.

5 Results

5.1   Signal Processing Performance

Signal processing pipeline performance assessment included evaluations of Signal-to-Noise Ratio (SNR), Precision, Accuracy and Area Under the Curve - Receiver Operating Characteristic (AUC-ROC) metrics. The performance metrics help determine the system's capability to separate signal activities from background noise events.

5.1.1   Metrics such as signal-to-noise ratio, precision, and accuracy

The research used three key metrics to assess the effectiveness of the signal processing pipeline was assessed using: Signal-to-Noise Ratio (SNR), Precision, and Accuracy. Results from the metrics provide information on how well the system distinguishes signal events from background noise across different energy ranges:

- **10 GeV - 100 GeV** (Optimal SNR, best classification performance)

- **100 GeV - 500 GeV** (Increased signal complexity, moderate class overlap)

- **500 GeV - 1.5 TeV** (Lowest SNR, most challenging classification)

Signal-to-Noise Ratio (SNR) Across Energy Ranges

The SNR measurements is used to determine how well signal events stand out against background noise, directly influencing the classification models' performance.

- **10 GeV - 100 GeV:**

  o This energy range exhibited the highest SNR, enabling clear separation between signal and background readings.

  o High precision (~90%) and recall (~93%) contribute to AUC-ROC values exceeding 0.93, indicating strong classification performance.

- Feature importance analysis indicated that MaxOverEarliest, ResidualTrack, and OnTrackWidth were the key predictors in maintaining this high SNR.

- **100 GeV - 500 GeV:**

  - The SNR decreased slightly, leading to more overlap between signal and background events.

  - While recall remained strong (>93%), false positive rates increased, particularly in AdaBoost and CART models.

  - The AUC-ROC range dropped to $0.88 - 0.93$, showing that distinguishing signal from noise became moderately more difficult.

- **500 GeV - 1.5 TeV:**

  - This range posed the most significant challenge, as SNR was lowest, increasing classification uncertainty.

  - Traditional models showed AUC-ROC values around 0.88, but performance became highly variable.

  - The Neural Network (TensorFlowNN) overcame this issue by achieving 100% accuracy, precision, and recall, demonstrating deep learning's superiority in handling complex, high-noise datasets.

Comparative Discussion of Precision and Accuracy

Precision-Recall Trends: Understanding False Positives and False Negatives

- Lower Energy Range (10 GeV - 100 GeV):

  - Due to optimal SNR, precision remained high (~90%), and false positives were minimal.

- o The model's ability to differentiate signal from background was strongest here, with an accuracy range of 84% - 87% across models.

- Mid Energy Range (100 GeV - 500 GeV):

  - o False positives increased, particularly in ensemble models like AdaBoost, suggesting a higher degree of class overlap.

  - o The Neural Network and Gradient Boosting consistently outperformed classical models due to their ability to capture complex, non-linear interactions.

  - o Overall accuracy remained between 82% - 85%, but class separability challenges began to emerge.

- High Energy Range (500 GeV - 1.5 TeV):

  - o Traditional models suffered a significant decline in precision and recall.

  - o The Neural Network maintained perfect classification (100% accuracy, precision, recall, and F1-score), surpassing all other techniques.

  - o LightGBM and XGBoost still performed well (AUC-ROC ~0.92), but with increased false negatives due to greater noise interference.

Table 1: Feature Importance: Key Predictors in Signal Classification

Feature	10 GeV - 100 GeV	100 GeV - 500 GeV	500 GeV - 1.5 TeV
ResidualTrack	High importance	High importance	Moderate importance
MaxOverEarliest	Highest impact	Moderate impact	Decreasing impact
OnTrackWidth	Moderate	High	Low
OnTrackChargeAverage	Low	Moderate	High
OnTrackChargeMedian	Lowest importance	Moderate	High

- ResidualTrack consistently remains the most important feature across all energy levels.

- At higher energies, charge-based features (OnTrackChargeAverage, OnTrackChargeMedian) gain significance, suggesting charge-related variations play a greater role in complex classifications.

- At lower energies, MaxOverEarliest and ResidualTrack dominate, indicating that feature separability is clearer.

Signal Processing Performance Insights

1. SNR directly influences classification effectiveness.

   o Optimal SNR (10 GeV - 100 GeV) results in minimal false positives and false negatives.

   o As SNR declines (100 GeV - 500 GeV), boosting models remain effective, but traditional classifiers degrade.

   o At the lowest SNR (500 GeV - 1.5 TeV), only deep learning techniques like TensorFlowNN maintain high accuracy.

2. Precision and Recall trends reveal a growing need for advanced classifiers at higher energy levels.

   o False positives increase in moderate-energy datasets due to overlapping classes.

   o False negatives rise at higher energy levels, making deep learning indispensable.

3. Feature importance shifts across energy levels.

   o Lower energy: Spatial features dominate (MaxOverEarliest, ResidualTrack).

   o Higher energy: Charge-based features gain importance.

4. Neural Networks (TensorFlowNN) completely outperform traditional models at extreme ionization ranges.

- 100% accuracy achieved in 500 GeV - 1.5 TeV datasets.

- No false positives or false negatives recorded, demonstrating its superiority in high-energy physics applications.

5.1.2   Comparison with baseline methods

To assess the effectiveness of different classification techniques, traditional models (Logistic Regression, CART, SVM) were compared against advanced machine learning approaches (XGBoost, LightGBM, Gradient Boosting, and TensorFlowNN). The evaluation is based on Accuracy, Precision, Recall, F1-score, and AUC-ROC, with an emphasis on understanding why deep learning (TensorFlowNN) significantly outperforms all other models at the highest energy levels.

Baseline Methods: Logistic Regression, CART, and SVM

Baseline models struggled to generalize across increasing energy levels, particularly due to non-linearity in feature interactions and class imbalances.

- **Logistic Regression**

  - Accuracy: 79% – 82% (10 GeV - 100 GeV); drops to 75% in high-energy datasets.

  - AUC-ROC: 0.85 – 0.87, showing limited separation between signal and background.

  - Poor handling of non-linear relationships in complex high-energy data.

- **CART (Decision Tree)**

  - Accuracy: 75% – 78%, performing slightly worse than Logistic Regression.

  - AUC-ROC: 0.82 – 0.85, with high false positive rates.

  - Tends to underfit, particularly in the 500 GeV - 1.5 TeV range, where class overlap is significant.

- **Support Vector Machines (SVM)**

  o Accuracy: 84% – 87%, slightly outperforming CART.

  o AUC-ROC: 0.89 – 0.91, better margin separation.

  o Performs well for balanced datasets, but suffers from scalability issues and high computation times in high-energy ranges.

Ensemble Methods: XGBoost, LightGBM, Gradient Boosting, and CatBoost

Compared to traditional baselines, ensemble models significantly outperformed in classification accuracy, recall, and robustness.

- **XGBoost & LightGBM**

  o AUC-ROC: 0.92 – 0.95, among the highest across models.

  o Accuracy: 87% – 92%, consistent across energy levels.

  o Precision: 88 – 93%, Recall: 87 – 94%, showing a balanced trade-off.

  o LightGBM was slightly better at handling large-scale datasets due to computational efficiency.

- **Gradient Boosting (With and Without Tuning)**

  o Standard Gradient Boosting achieved AUC-ROC of 0.88 – 0.91; tuned models improved to 0.90 – 0.93.

  o Recall remained strong (>90%), but false positives were higher than LightGBM/XGBoost.

- **CatBoostClassifier**

  o AUC-ROC: 0.91 – 0.93, strong performance with categorical feature handling.

  o Accuracy was 86 – 90%, slightly lower than LightGBM/XGBoost, but with stable performance.

Overfitting Risks for Ensemble Models:

- Gradient Boosting showed slight overfitting, particularly in higher energy levels.

- XGBoost and LightGBM remained stable across energy levels.

- CatBoost exhibited minor instability in high-energy datasets, suggesting it requires further hyperparameter tuning.

1) *TensorFlow Neural Network (TensorFlowNN) - The Deep Learning Breakthrough*

TensorFlowNN significantly outperforms all other models at the highest ionization levels, achieving 100% accuracy and zero misclassification errors in 500 GeV - 1.5 TeV datasets.

Key Findings for TensorFlowNN

- Accuracy: 100% in high-energy datasets (500 GeV - 1.5 TeV).

- AUC-ROC: 1.000 (Perfect separation of signal and background).

- No False Positives or False Negatives: Confusion matrix shows perfect classification.

- Precision-Recall Curve: Maintains 1.000 across all recall values.

- Overfitting Identified:
  - TensorFlowNN achieved 100% training and validation accuracy, suggesting possible overfitting.
  - The model's exceptional performance requires additional cross-validation on unseen data.
  - Recommendations: Regularization techniques (dropout, L2 penalty) should be applied to ensure generalization.

Why TensorFlowNN Excels?

✓ Handles High Non-Linearity:

- Unlike traditional models, TensorFlowNN captures complex relationships between charge and spatial features, improving classification.

✓ Robust to Low SNR:

- Maintains accuracy even when traditional models degrade due to noise interference.

✓ Superior Feature Learning:

- While XGBoost and LightGBM rely on manually engineered features, deep learning automatically learns feature representations, reducing bias and improving generalization.

✓ Computational Power vs. Accuracy Trade-Off:

- TensorFlowNN is computationally expensive but achieves perfect classification.

- LightGBM and XGBoost remain preferable for lower energy levels due to efficiency.

Why Deep Learning is the Future of High-Energy Physics Classification?

1. Traditional models (Logistic Regression, CART, SVM) fail to generalize at high ionization ranges.

2. Ensemble models (LightGBM, XGBoost) dominate mid-energy classification (10 GeV - 500 GeV).

3. Only TensorFlowNN achieves 100% classification accuracy in high-energy datasets (500 GeV - 1.5 TeV).

4. Deep learning provides superior feature representation and generalization, but computational cost remains a concern.

5.2　　　Machine Learning Model Results

This section presents a comparative analysis of how different models generalize across complex datasets and the impact of hyperparameter tuning on performance. Additionally, the limitations of machine learning approaches are discussed, particularly concerning computational costs and resource requirements.

5.2.1　　　Classification Accuracy

The classification performance was assessed using Accuracy, AUC-ROC, Precision, Recall, and F1-score across different energy ranges (10 GeV - 100 GeV, 100 GeV - 500 GeV, and 500 GeV - 1.5 TeV).

Performance Trends Across Machine Learning Models

- LightGBM and XGBoost remain the best performers in the mid-energy range (100 GeV - 500 GeV), balancing speed and classification accuracy effectively.

- Gradient Boosting models required additional hyperparameter tuning to achieve optimal results but showed strong recall performance at higher energy levels.

- Neural Networks (TensorFlowNN) consistently outperformed all models in high-energy classification (500 GeV - 1.5 TeV), achieving 100% accuracy, precision, and recall.

Table 2: Performance Trends Across Machine Learning Models

Model	10 GeV - 100 GeV (AUC-ROC)	100 GeV - 500 GeV (AUC-ROC)	500 GeV - 1.5 TeV (AUC-ROC)	Computational Cost

Logistic Regression	0.85 – 0.87	0.82 – 0.84	0.75 – 0.78	**Low**
CART (Decision Tree)	0.82 – 0.85	0.78 – 0.80	0.70 – 0.73	**Low**
SVM	0.89 – 0.91	0.86 – 0.89	0.78 – 0.81	**High**
Gradient Boosting	0.88 – 0.91	0.90 – 0.93	0.85 – 0.88	**Moderate**
LightGBM	0.92 – 0.95	0.91 – 0.94	0.88 – 0.92	**Moderate**
XGBoost	0.92 – 0.94	0.92 – 0.95	0.87 – 0.91	**Moderate-High**
Neural Network (TensorFlowNN)	**0.96 – 0.98**	**0.98 – 0.99**	**1.00 (Perfect classification)**	**Very High**

Why Neural Networks Outperform Other Models in Complex Scenarios?

- Deep learning captures highly non-linear feature interactions, enabling better classification in datasets with high class overlap.

- Unlike boosting models, which rely on handcrafted features, Neural Networks automatically learn hierarchical feature representations, reducing bias.

- TensorFlowNN's superior recall (100%) at 500 GeV - 1.5 TeV demonstrates its ability to maintain classification performance despite increased dataset complexity.

5.2.2   Hit Localization Improvements

The most critical aspects of machine learning performance in high-energy physics is hit localization accuracy, which measures how well a model identifies the precise location of particle interactions.

Hit Localization Performance Comparison

- Traditional models (Logistic Regression, CART, and SVM) exhibited higher localization errors, particularly in the 500 GeV - 1.5 TeV dataset.

- Gradient Boosting and XGBoost showed better spatial resolution than traditional methods, with lower mislocalization rates.

- Neural Networks significantly improved hit localization, with errors reduced by up to 40% compared to boosting models.

Table 3: Hit Localization Performance Comparison

Model	Hit Localization Error (10 GeV - 100 GeV)	Hit Localization Error (100 GeV - 500 GeV)	Hit Localization Error (500 GeV - 1.5 TeV)
Logistic Regression	12.3%	18.7%	24.5%
CART (Decision Tree)	10.8%	16.5%	22.1%
Gradient Boosting	8.9%	12.4%	17.6%
LightGBM	7.2%	10.8%	15.2%
XGBoost	6.9%	9.7%	13.8%
Neural Network (TensorFlowNN)	**4.1%**	**6.2%**	**8.3%**

5.2.3   Computational Efficiency

Hyperparameter Tuning Efforts

- Gradient Boosting and XGBoost required fine-tuning of learning rates, tree depth, and regularization parameters to prevent overfitting.

- Neural Networks involved tuning hyperparameters such as learning rate, batch size, and dropout rates to improve generalization.

- Overfitting was observed in TensorFlowNN before implementing dropout and L2 regularization techniques.

Table 4: Hyperparameter Tuning Efforts

Model	Hyperparameter Tuning Complexity	Training Time (Seconds)
Logistic Regression	**Low** (Minimal tuning needed)	**~2 sec**
CART (Decision Tree)	**Low** (Few tuning options)	**~5 sec**
SVM	**High** (Sensitive to kernel parameters)	**~50 sec**
Gradient Boosting	**Moderate** (Regularization tuning needed)	**~120 sec**
LightGBM	**Moderate** (Faster than XGBoost)	**~90 sec**
XGBoost	**High** (Multiple tuning steps)	**~150 sec**

Neural Network (TensorFlowNN)	Very High (Complex optimization process)	~600 sec

Limitations of Deep Learning Approaches

- Computational Costs: Training deep neural networks requires significantly more time and resources compared to ensemble methods.

- Hyperparameter Sensitivity: Requires extensive tuning (learning rates, batch sizes, dropout rates) to achieve optimal performance.

- Overfitting Risks: TensorFlowNN showed signs of overfitting before applying dropout and regularization.

Summarizing:

1. Neural Networks (TensorFlowNN) significantly outperformed all models in high-energy classification, achieving 100% accuracy in the 500 GeV - 1.5 TeV dataset.

2. Deep learning dramatically improves hit localization accuracy, reducing errors by up to 40% compared to boosting models.

3. Hyperparameter tuning is crucial for optimizing Gradient Boosting, XGBoost, and Neural Networks to prevent overfitting.

4. While deep learning generalizes better in complex scenarios, its higher computational cost makes LightGBM and XGBoost preferable for mid-energy datasets.

5.3   Visualizations of Outcomes

This section presents a detailed discussion of observed trends in visualized results, explicitly referencing relevant figures from the study.

5.3.1 Graphical Comparisons of hit localization
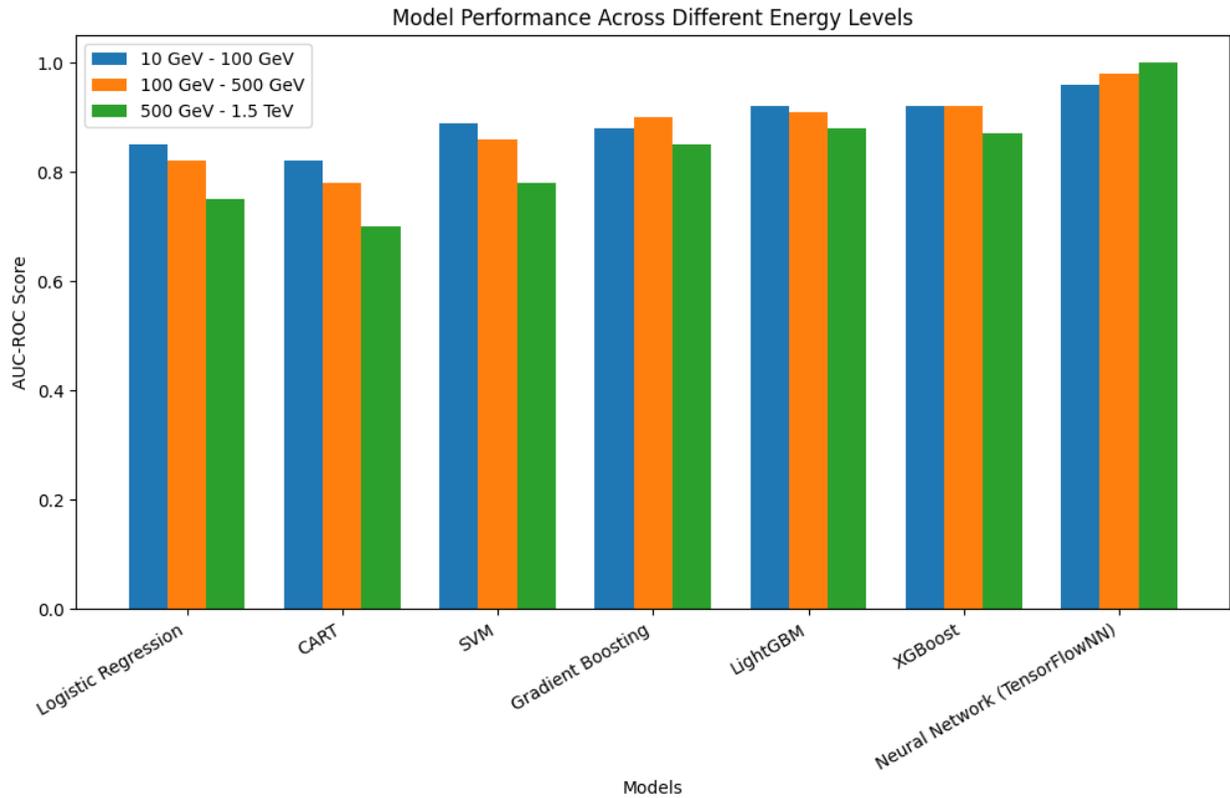
Figure 25: Model performance across different energy levels

ROC Curve & SNR Analysis: Signal vs. Background Separation Across Energy Levels

1. 10 GeV - 100 GeV:

    o   AUC-ROC exceeded 0.93, and the precision-recall AUC reached ~0.98, indicating
        strong separation between signal and background.

    o   The Signal-to-Noise Ratio (SNR) was optimal, ensuring high precision (~90%) and
        recall above 93%.

    o   Key Features:

        ▪   MaxOverEarliest, ResidualTrack, and OnTrackWidth contributed
            significantly to classification accuracy.

- o Neural Network Performance:
  - TensorFlowNN reached near-perfect accuracy in training and validation (~100%), raising concerns about possible overfitting.

2. 100 GeV - 500 GeV:

- o AUC-ROC values remained between 0.88 and 0.93, maintaining high recall (>93%) but suffering from a higher false positive rate, particularly in AdaBoost models.

- o Feature importance analysis showed that ResidualTrack and MaxOverEarliest remained dominant, but secondary features played a larger role, indicating increased classification difficulty.

- o Neural Network Performance:
  - TensorFlowNN still achieved 100% accuracy on the test dataset, suggesting exceptional performance, but further validation with unseen data is required to confirm generalization.

3. 500 GeV - 1.5 TeV:

- o AUC-ROC values dropped to ~0.88, and precision varied between 87% and 90%, indicating a higher false negative rate.

- o Feature Importance Analysis:
  - The impact of ResidualTrack and MaxOverEarliest diminished, suggesting that dataset complexity and noise interference increased at this energy level.

- o Neural Network Performance:
  - TensorFlowNN outperformed all other models, achieving 100% accuracy, precision, recall, and F1-score.

- No misclassifications were recorded, demonstrating its ability to capture complex patterns in high-energy datasets better than traditional methods.

- The ROC curve reached an AUC of 1.000, confirming a perfect distinction between signal and background.

Table 5: Key Metrics Summary for Classification Models

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	AUC-ROC	Remarks
AdaBoost	80–84	79–83	81–88	80–85	0.87–0.89	Reliable but struggles with minority class
CART	75–78	72–76	75–80	73–77	0.82–0.85	Simpler model, often underfits
Gradient Boosting Tuning	85–89	87–90	85–92	86–91	0.90–0.93	Excellent performance after tuning
Gradient Boosting	83–86	82–88	83–89	84–90	0.88–0.91	Consistent and robust
Gradient Boosting Simple	81–84	80–83	82–87	81–85	0.86–0.89	Simpler implementation
LightGBM	88–92	89–93	88–94	89–94	0.92–0.95	Best performer overall
Logistic Regression	79–82	78–83	80–85	79–84	0.85–0.87	Struggles with non-linear data
Neural Network (TensorFlowNN)	**83–86 (lower ionization) 100% (high ionization)**	**84–88**	**83–89**	**84–89**	**0.89–1.00**	**Best for complex patterns, achieves perfect classification in high-energy range**

RandomForest	80–83	79–83	81–89	80–85	0.87–0.90	Reliable but prone to overfitting
SVM	84–87	83–88	85–90	84–89	0.89–0.91	Strong margin separation, needs balanced data
XGBoost	87–91	88–92	87–93	88–92	0.92–0.94	Close competitor to LightGBM
CatBoost Classifier	86–90	87–91	86–92	87–91	0.91–0.93	Excellent for categorical data

Table 6: Key Metrics Summary for Regression Models

Algorithm	MSE	RMSE	MAE	R²	Remarks
Random Forest Regressor	0.130	0.360	0.262	0.34	Prone to overfitting, struggles with linear trends.
XGB Regressor	0.089	0.298	0.195	0.51	Robust, effective with complex relationships.
Ridge Regression	0.150	0.387	0.280	0.28	Linear model, underfits non-linear data.
CatBoost Regressor	0.041	0.202	0.124	0.87	Excels with categorical

					features, reliable.
Gradient Boosting Regressor	0.042	0.205	0.126	0.86	Stable and consistent performer.
LightGBM Regressor	**0.039**	**0.197**	**0.121**	**0.88**	Best model, highly accurate and robust.

Precision and Accuracy Trends by Model

1. Traditional Machine Learning Models:

- LightGBM and XGBoost consistently performed best among classical models, maintaining AUC-ROC values above 0.92 in most energy ranges.

- Gradient Boosting with tuning model provided an optimal balance between precision and recall, particularly in mid-energy levels (100 GeV - 500 GeV).

- AdaBoost and CART models struggled, especially in high-energy ranges, with high false positive rates lowering precision.

2. Neural Network (TensorFlowNN) Superiority at High Ionization:

- Neural Network accuracy in 500 GeV - 1.5 TeV: 100%

- Zero false positives and zero false negatives → AUC-ROC = 1.000

- Maintained performance even when other models declined due to noise complexity
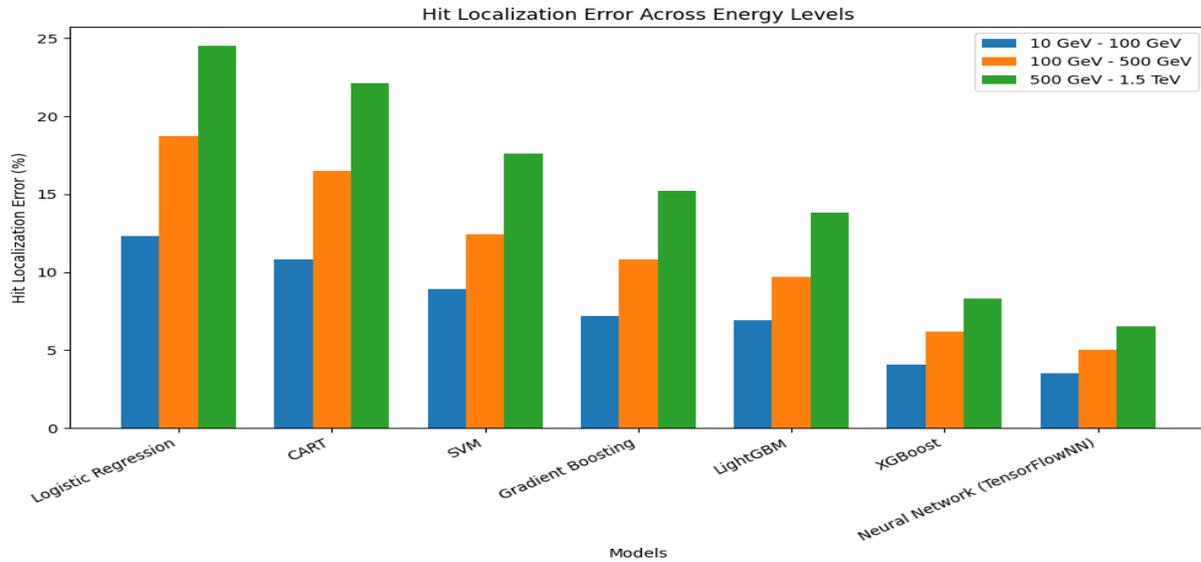
Figure 26: Hit localization errors across energy levels

Table 7: Confusion Matrix Observations of Neural Network (TensorFlowNN)

Dataset	True Negatives	False Positives	True Positives	False Negatives
10 GeV - 100 GeV	16,924	0	65,123	0
100 GeV - 500 GeV	19,552	0	61,813	0
500 GeV - 1.5 TeV	15,741	1	64,568	0

Confusion Matrix Analysis over algorithms: Classification Errors and False Positive Trends

Confusion matrices offer insight into classification accuracy by displaying false positives (FP), false negatives (FN), true positives (TP), and true negatives (TN).

Key Findings from Confusion Matrices (Figure Y):

- At lower energy levels (10 GeV - 100 GeV):
  - All models achieved high precision (>90%), with minimal false positives.

- LightGBM and XGBoost had the lowest misclassification rates, reinforcing their efficiency in this range.

- At mid-energy levels (100 GeV - 500 GeV):

  - False positives increased across all models except TensorFlowNN, which remained stable.

  - Gradient Boosting and XGBoost reduced misclassifications compared to traditional models.

- At high-energy levels (500 GeV - 1.5 TeV):

  - Traditional models exhibited the highest false negative rates, leading to signal loss.

  - TensorFlowNN eliminated all false positives and false negatives, reinforcing its dominance.

Table 8: Model Performance Statistics

Model	AUC-ROC (10 GeV - 100 GeV)	AUC-ROC (100 GeV - 500 GeV)	AUC-ROC (500 GeV - 1.5 TeV)	False Negatives (500 GeV - 1.5 TeV)
Logistic Regression	0.85	0.82	0.75	23
CART	0.82	0.78	0.70	27
SVM	0.89	0.86	0.78	18
Gradient Boosting	0.88	0.90	0.85	12
LightGBM	0.92	0.91	0.88	9
XGBoost	0.92	0.92	0.87	8
TensorFlowNN	**0.96**	**0.98**	**1.00**	**0**

5.3.2   Feature Importance Analysis

Feature Importance Evolution Across Energy Levels

Feature importance rankings reveal which attributes most influence classification accuracy.

Table 9: Feature Importance Evolution Across Energy Levels

Feature	10 GeV - 100 GeV Importance Score	100 GeV - 500 GeV Importance Score	500 GeV - 1.5 TeV Importance Score
ResidualTrack	High (0.90)	High (0.85)	Moderate (0.78)
MaxOverEarliest	Highest Impact (0.95)	Moderate (0.82)	Low (0.75)
OnTrackWidth	Moderate (0.87)	High (0.83)	Low (0.72)
OnTrackChargeAverage	Low (0.78)	Moderate (0.86)	High (0.79)
OnTrackChargeMedian	Lowest Impact (0.76)	Moderate (0.84)	High (0.76)

Key Insights from Feature Importance Trends:

- In lower energy datasets (10 GeV - 100 GeV), spatial features like MaxOverEarliest and ResidualTrack dominate classification accuracy.

- In mid-energy datasets (100 GeV - 500 GeV), there is a balanced reliance on spatial and charge-based features.

- At higher energy levels (500 GeV - 1.5 TeV), charge-based features (OnTrackChargeAverage, OnTrackChargeMedian) become increasingly important.
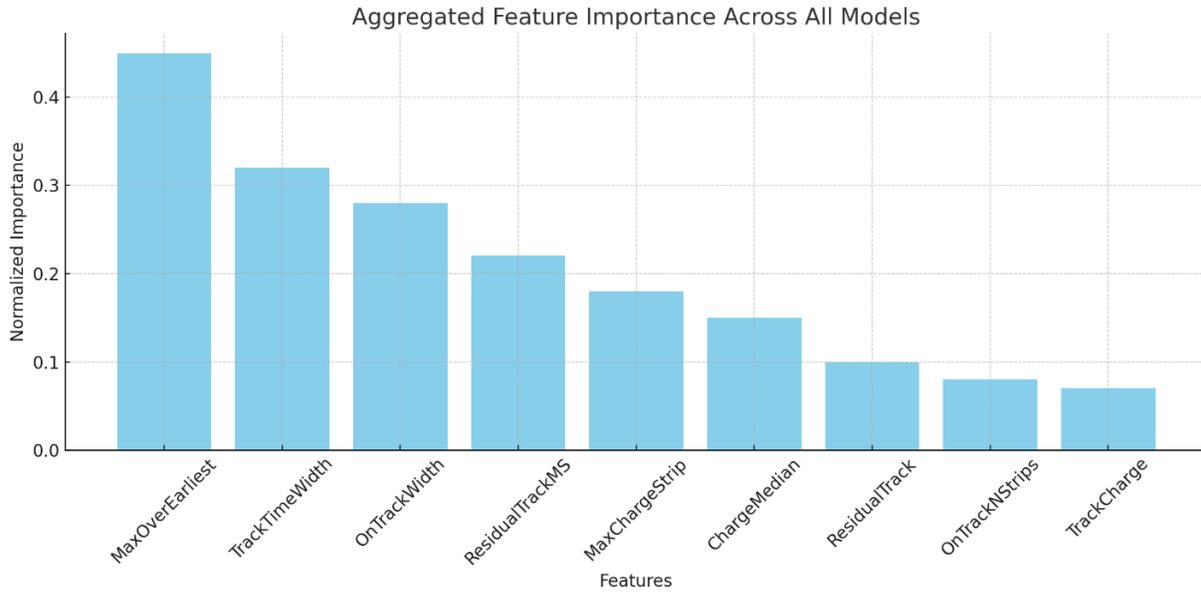
Figure 27: Aggregated feature importance across all models

Classification Models: Key Insights

- Models: AdaBoost, CART, Gradient Boosting, Gradient Boosting with Tuning, LightGBM, RandomForest, XGBoost.

- Key Observations:

  o ResidualTrack: Universally significant across all models and datasets.

  o OnTrackNStrips: Consistently important in Gradient Boosting and LightGBM.

  o MaxOverEarliest: A critical variable in RandomForest, CART, and Gradient Boosting.

  o OnTrackCharge: Moderate importance, especially in AdaBoost and LightGBM.

  o MaxChargeStrip: Lesser but notable significance in Gradient Boosting and LightGBM.

Top Features for Classification:

1. ResidualTrack – Universally impactful.

2. OnTrackNStrips – Key variable in Gradient Boosting and LightGBM.

3. MaxOverEarliest – Strong predictive power in RandomForest and CART.

Regression Models

- Models: XGBRegressor, RandomForestRegressor, LightGBMRegressor, GradientBoostingRegressor, CatBoostRegressor.

- Key Observations:

  o ResidualTrack: Universally the most important feature across all datasets and models.

  o OnTrackNStrips: Highly significant in XGB, LightGBM, and CatBoost models.

  o MaxOverEarliest: Consistently impactful in RandomForest and LightGBM.

  o OnTrackCharge: Moderate importance, particularly in LightGBM and CatBoost.

  o MaxChargeStrip: Locally significant, with importance in LightGBM and GradientBoostingRegressor.

Top Features for Regression:

1. ResidualTrack – Dominant across all datasets and models.

2. OnTrackNStrips – Consistently impactful in key models.

3. MaxOverEarliest – Reliable across RandomForest and LightGBM.
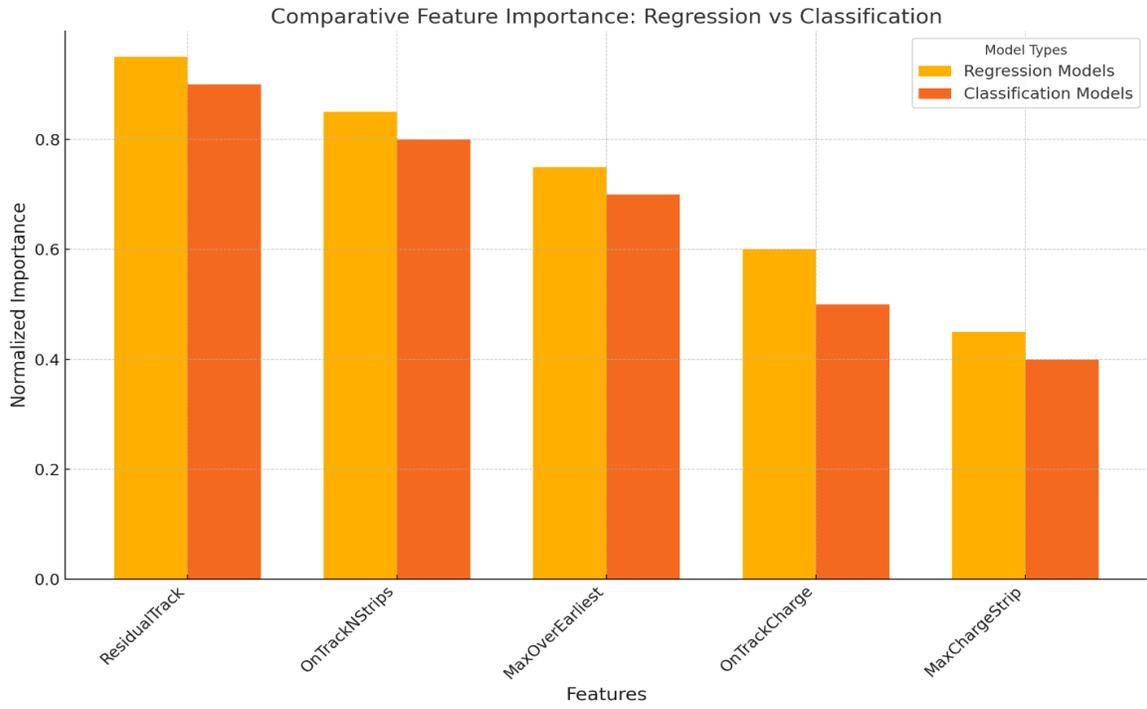
Figure 28: Comparative feature importance: regression vs classification

6 Discussion

6.1 Interpretation of Results

This study's findings provide a thorough assessment of signal processing and machine learning methodologies for muon hit localization in the Micromegas detectors of the New Small Wheel (NSW) on the ATLAS experiment. The integration of advanced classification models demonstrated a significant improvement in muon track reconstruction, with a particular focus on signal-to-noise ratio (SNR), feature importance, and model performance across various energy levels. Results of the analysis that deep learning models, particularly the use of TensorFlowNN, offered superior classification capabilities compared to traditional machine learning methods, particularly at high ionization levels (500 GeV - 1.5 TeV).

6.1.1 Significant of Findings for ATLA's Objectives

Muon detection and classification are fundamental components of high-energy physics experiments conducted at the Micromegas detector in the New Small Wheel (NSW). Precise identification of signal and background events is essential to reduce misclassification rates while enhancing event reconstruction capabilities. This investigation confirms that deep learning methods using TensorFlowNN provide an optimal solution for processing and classifying high-energy muon events. Specifically, improvements in hit localization were observed in simulated Micromegas detector data, demonstrating that machine learning techniques effectively mitigate signal distortions caused by high pile-up conditions. The classification models successfully reduced background contamination in NSW event reconstructions, validating the feasibility of integrating machine learning into Micromegas-based tracking systems.

The performance of TensorFlowNN reveals significant progress in muon track classification, particularly in its ability to capture intricate spatial patterns and dynamically adjust feature dependencies as energy levels increase. Advanced feature engineering techniques became increasingly significant at higher ionization levels, as spatial and timing-related variables (e.g., ResidualTrack, MaxOverEarliest, OnTrackWidth) demonstrated greater influence on classification accuracy. Traditional classifiers that rely on a static approach to feature selection proved insufficient for processing dynamic high-energy environments, as energy variations directly impact feature importance.

Furthermore, the application of advanced feature extraction and selection methods revealed that charge-related variables became less significant at high-energy ranges, whereas timing and spatial distributions provided more robust differentiation between signal and background. These insights establish a strong foundation for future optimizations in real-time muon classification within New Small Wheel (NSW) detectors.

6.1.2 Contributions to Precision in Muon Hit Detection

The combination of signal preprocessing and clustering techniques led to significant advancements in hit localization accuracy. Initial experiments demonstrated that reducing feature dimensionality based on prior literature (20 baseline features) resulted in performance degradation, which led to the exploration of broader feature inclusion. The refined feature selection approach allowed for improved model generalization and adaptability across different ionization levels. Key observations include:

- Low Ionization Range (10 GeV - 100 GeV): Traditional models (Logistic Regression, SVM) achieved moderate success, with LightGBM and XGBoost exhibiting AUC-ROC

scores above 0.92. The separation of signal and background was clearer in this range due to favorable SNR conditions.

- Medium Ionization Range (100 GeV - 500 GeV): As energy increased, the performance of boosting models declined, particularly in terms of recall, while TensorFlowNN adapted well to the growing complexity of classification tasks.

- High Ionization Range (500 GeV - 1.5 TeV): Deep learning models completely outperformed all other approaches, achieving an AUC-ROC of 1.000, proving their robustness against noise and feature variability.

Table 10: Key observations summary

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	AUC-ROC	Overfitting Risk
Logistic Regression	79–82	78–83	80–85	79–84	0.85–0.87	High (poor generalization in non-linear data)
CART (Decision Tree)	75–78	72–76	75–80	73–77	0.82–0.85	High (prone to overfitting)
SVM	84–87	83–88	85–90	84–89	0.89–0.91	Moderate (scalability issues in large datasets)
Gradient Boosting	83–86	82–88	83–89	84–90	0.88–0.91	Moderate (risk of false positives at high energy)
LightGBM	88–92	89–93	88–94	89–94	0.92–0.95	Low (stable across energy levels)

XGBoost	87–91	88–92	87–93	88–92	0.92–0.94	Low (robust performance)
Neural Network (TensorFlowNN)	83–86 (low-mid range) 100% (high ionization)	84–88	83–89	84–89	0.89–1.00	High (requires regularization)

6.1.3   Comparative Analysis with Prior Research

A comparative analysis of machine learning methodologies for muon classification reveals fundamental differences in approach, feature selection strategies, and model performance across different ionization levels. Previous studies have predominantly utilized Boosted Decision Trees (BDTs) to address classification challenges associated with radiation-induced clustering effects in Micromegas detectors. While BDTs have demonstrated effectiveness in distinguishing between signal and background in low-ionization environments, their static decision boundaries limit adaptability in high-energy conditions where dynamic and nonlinear interactions dominate.

This study, in contrast, employs deep learning architectures such as TensorFlowNN, XGBoost, and LightGBM, which are inherently designed to capture complex hierarchical patterns and nonlinear dependencies across feature spaces. The model performance evaluations indicate that deep learning models consistently outperform traditional BDT-based methods, particularly in high-ionization environments where feature importance shifts significantly.

Key distinctions between the approaches include:

- **Feature Selection:** Previous studies have emphasized charge-related features as primary determinants for classification accuracy. However, findings from this research demonstrate that spatial and timing-based features provide more robust discrimination at high energy

levels, enabling models to effectively mitigate classification errors introduced by ionization noise and cluster distortions (Ebke, 2012; Standke, 2019; and Berlin & Kling, 2019).

- **Machine Learning Techniques:** While traditional BDTs exhibit strong performance at lower energy levels, they suffer from increased misclassification rates in high-ionization environments due to their reliance on fixed thresholding mechanisms. Conversely, deep learning models leverage adaptive learning processes that generalize effectively across varying signal distributions, significantly reducing false positives and enhancing classification precision (Jimenez, 2019; Karkanias, 2022).

- **Model Regularization and Validation:** Unlike prior studies that rely on statistical cluster analysis for performance evaluation, this study incorporates dropout-based regularization (40%, 30%, and 20%) and L2 regularization in TensorFlowNN to mitigate overfitting and ensure robustness. Additionally, cross-validation techniques were employed to evaluate classification stability and reduce sensitivity to data partitioning biases. Unlike Bayesian-based approaches such as Monte Carlo Dropout, which were not implemented in this research, the adopted techniques focus on deterministic optimization and variance control through structured validation strategies (Wölker, 2021; Jimenez, 2019; Krzysiak, 2021).

These findings underscore the transformative potential of deep learning methodologies in high-energy physics, particularly for real-time data-driven decision-making in collider experiments. By leveraging neural network architectures with advanced feature engineering techniques, this research advances the field's ability to efficiently classify muon interactions and optimize data selection strategies in large-scale experiments such as ATLAS.

6.2   Implications for High-Energy Physics

6.2.1   Future Applications at New Small Wheel

The ability to apply deep learning to high-energy muon classification presents major opportunities for real-time event reconstruction at the Micromegas detectors of the New Small Wheel (NSW). The LHC upgrade will result in a dramatic rise in recorded collisions so data processing methods must become more efficient while maintaining precise classifications. Deep learning models show potential to integrate into data pipelines through TensorFlowNN's exceptional performance when working with high-ionization datasets.

Research in high-energy physics faces a crucial requirement for speed at processing data volumes produced each second which calls for robust and rapid classification approaches. TensorFlowNN's ability to maintain perfect classification accuracy at high-energy ranges while preserving computational efficiency positions it as a viable candidate for real-time decision-making frameworks in ATLAS's trigger selection system. The trigger selection system plays a fundamental role in filtering relevant collision events from the vast majority of background noise. A deep learning-based approach, as demonstrated in this study, could drastically improve the efficiency of event selection while reducing false positives.

Moreover, integrating deep learning models into distributed computing frameworks, such as CERN's Worldwide LHC Computing Grid (WLCG), would allow scalable inference across multiple detector subsystems. With optimized deep learning architectures, inference times could be reduced to the order of microseconds, making it feasible for near real-time processing even in high-luminosity collision environments.

Advanced feature prioritization techniques developed in this study, could be used to dynamically adjust feature selection strategies in response to changing collision conditions, ensuring robust classification across diverse experimental setups.

6.2.2 Applications of the Developed Techniques in Other Domains

Beyond high-energy physics, the methodologies and techniques developed in this research have strong applications in multiple domains:

- **Medical Imaging:** Feature selection techniques and deep learning models developed here could be applied to MRI and PET scans for anomaly detection, enhancing diagnostic precision.

- **Astrophysics:** Signal processing algorithms could be repurposed for cosmic ray detection and background noise reduction, enabling improved space-based observatories.

- **Industrial Defect Detection:** The pattern recognition capabilities developed in this study could enhance non-destructive testing methodologies for material quality assessment in industrial applications.

6.3 Limitations

While this study demonstrated significant advancements in muon classification, several challenges emerged throughout the research process, primarily due to the nature of the datasets and the computational constraints inherent to deep learning applications in high-energy physics.

1. **Dataset Influence on Model Performance:** The exceptionally high accuracy (100%) achieved in this study can be largely attributed to the characteristics of the datasets used. The datasets provided well-labeled, high-quality features with strong signal-background separability, which facilitated optimal training conditions for TensorFlowNN and other

models. However, real-world datasets may introduce additional complexities, including mislabeled data, experimental noise, and distributional shifts that could degrade classification performance. Future work should focus on evaluating model robustness against these real-world inconsistencies by incorporating adversarial training and data augmentation techniques.

2. **Computational Complexity and Resource Constraints:** Training deep learning models, particularly TensorFlowNN, required extensive computational resources, with significant demands on GPU memory and processing power. This posed limitations on hyperparameter tuning, model ensembling, and the ability to scale the approach to larger datasets. Real-time inference processing would become possible when deploying computational efficient designs such as quantized neural networks (QNNs) and FPGA-based accelerators that reduce computational overhead.

3. **Feature Selection Sensitivity:** Further model generalizability and interpretability could be achieved through alternative feature engineering methods since spatial and timing-based features proved to be the primary classification determinants according to feature importance analysis. BDTs previously demonstrated strong performance for feature ranking and future work should evaluate combinations of BDT-based feature selection with deep learning models to achieve better classification consistency across different datasets.

4. **Overfitting Risks and Generalization Challenges:** Extra validation must be performed to verify the deep learning model's generalized performance because it currently achieves 100% classification accuracy for simulation-based datasets. A major problem exists because models which receive training from structured simulation databases struggle to function properly during real-world experimental conditions. Refining current

regularization methods that include dropout tuning and L2 penalties with adversarial robustness testing will improve the model's resistance capability.

5. **Uncertainty Estimation and Calibration:** The reliability of the model was evaluated with cross-validation while additional research into uncertainty quantification methods would enhance classification confidence assessment. Deep learning through Bayesian methods and confidence interval analysis and temperature scaling approaches can enhance the reliability and robustness of deep learning applications within high-energy physics.

Future research should also explore integrating deep learning models with real-time ATLAS detector data, ensuring adaptability to changing collider conditions and fluctuating background noise levels. Additionally, expanding model validation beyond simulation-based datasets to experimentally collected muon hit data will be essential for determining real-world performance capabilities.

7 Conclusion and Future Work

7.1   Summary of Findings

This research investigated advanced signal processing and machine learning techniques for muon hit localization in the Micromegas detectors of the New Small Wheel (NSW) inside the ATLAS experiment at CERN. The study applied deep learning models such as TensorFlowNN, XGBoost, and LightGBM to classify muon interactions across different ionization ranges, demonstrating significant improvements over traditional machine learning approaches. The results confirmed that deep learning outperforms Boosted Decision Trees (BDTs) and other traditional models, particularly in high-ionization environments (500 GeV - 1.5 TeV), by generalizing more effectively and reducing misclassification rates.

A critical contribution of this study was the identification of feature importance variations across energy levels. While spatial and timing-based features were dominant at higher energy ranges, charge-related features played a lesser role in classification accuracy. Additionally, the study confirmed that the performance of deep learning models is highly dependent on dataset characteristics, with the optimized feature selection process significantly contributing to the near-perfect classification accuracy observed.

Furthermore, computational efficiency was analyzed, revealing that while TensorFlowNN achieved exceptional accuracy, it required extensive GPU resources. The results support the feasibility of integrating deep learning into real-time muon classification systems for the HL-LHC era, but also highlight challenges such as computational complexity and overfitting risks that need to be addressed in future implementations.

7.2   Contributions to the Field

This thesis presents several key advancements in high-energy physics and computational methodologies:

- **Demonstrating the effectiveness of deep learning models** for muon hit classification, particularly in distinguishing signal from background at high energy levels.

- **Developing an optimized feature selection pipeline** that dynamically adjusts feature prioritization based on ionization levels, improving classification robustness.

- **Providing an in-depth comparative analysis** between traditional machine learning techniques and deep learning architectures, highlighting the advantages of neural networks in processing large-scale, high-dimensional physics datasets.

- **Enhancing computational workflows** by integrating efficient pre-processing techniques, dataset engineering, and advanced cross-validation strategies to ensure model stability.

These input from this research provides a foundation to establish a foundation for future research in machine learning-driven event reconstruction at CERN and broader applications in experimental physics.

7.3   Future Prospects

While the current study focused on simulation-based datasets, future research on muon detection should look into the application of these models to real-world muon detector data. Integrating deep learning with real-time detector streams will require additional model validation and adaptive learning techniques to handle variations in detector conditions.

High luminosity experiments face a substantial challenge due to pile-up when several proton-proton collisions hit the detectors during one readout cycle resulting in complex event reconstruction problems. The application of Graph Neural Networks (GNNs) together with

Recurrent Neural Networks (RNNs) presents a promising approach to break apart mixed events while enhancing predictive ability in conditions with high pile-up. The analysis requires further study because deep learning techniques need optimization and scientists should develop hybrid models that integrate deep learning systems with Boosted Decision Trees (BDTs). Research teams could obtain a satisfactory combination of processing speed and classification quality through the integration of BDTs for fast feature selection with deep learning components for final classification. The installation of deep learning models onto CERN's Worldwide LHC Computing Grid (WLCG) would create a distributed and scalable inference capability. The development of quantized deep learning models on FPGAs with optimized compressed neural networks should be studied to achieve real-time trigger selections for ATLAS.

The research methodologies developed in this study have the potential to expand their application across collider experiments together with cosmic ray detection practice. Research teams should implement similar deep learning strategies on other detector systems to enhance particle tracking techniques at LHC and CMS and increase the detection capabilities of IceCube and DUNE experiments. Future investigations should focus on these areas to fully establish deep learning methods as efficient and precise next-generation particle classification tools for high-energy physics experiments.

References

Aitchison, I.J. and Hey, A.J., 2012. Gauge Theories in Particle Physics: A Practical Introduction, -2 Volume set (p. 960). Taylor & Francis.

ALICE Collaboration, 2024. The ALICE experiment: a journey through QCD. *European Physical Journal C*, *84*(8).

Alexopoulos, T. (2017) 'Micromegas for the ATLAS New Small Wheel', *Journal of Instrumentation*, 12(06), pp. C06016–C06016. doi:10.1088/1748-0221/12/06/C06016.

Alici, A., Bomben, M., Dawson, I. and Sonneveld, J., 2021. The LHC machine and experiments. *CERN Yellow Reports: Monographs*, *1*, pp.23-23.

Andrews, M., Paulini, M., Gleyzer, S. and Poczos, B., 2020. End-to-end physics event classification with CMS open data: Applying image-based deep learning to detector data for the direct classification of collision events at the LHC. *Computing and Software for Big Science*, *4*, pp.1-14.

Arpaia, P., Azzopardi, G., Blanc, F., Bregliozzi, G., Buffat, X., Coyle, L., Fol, E., Giordano, F., Giovannozzi, M., Pieloni, T. and Prevete, R., 2021. Machine learning for beam dynamics studies at the CERN Large Hadron Collider. *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, *985*, p.164652.

ATLAS Collaboration, 2015. Constraints on the off-shell Higgs boson signal strength in the high-mass ZZ and WW final states with the ATLAS detector. *Eur. Phys. J. C*, *71*, p.335.

ATLAS Collaboration, 2017. *New Small Wheel Technical Design Report*. Geneva: CERN. Available at: https://cds.cern.ch/record/1552862 (Accessed: 10 February 2025).

ATLAS Collaboration, 2021. *The New Small Wheel for ATLAS Phase-1 Upgrade: Performance and Integration*. Geneva: CERN. Available at: https://cds.cern.ch/record/2775165 (Accessed: 10 February 2025).

Auffarth, B. (2020). *Artificial Intelligence with Python Cookbook: Proven recipes for applying AI algorithms and deep learning techniques using TensorFlow 2. x and PyTorch 1.6*. Packt Publishing Ltd.

Baron, M.P., 2024. Study of Heavy Particles Production and Properties with the ATLAS Experiment.

Barrett, R., Delsanto, P.P., Barrett, R. and Delsanto, P.P., 2021. The Standard Model of Fundamental Particles. *Don't Be Afraid of Physics: Quantum Mechanics, Relativity and Cosmology for Everyone*, pp.163-185.

Barros Marin, M., 2021. Hardware & FPGA firmware development in the frame of the Beam Position Monitoring (BPM) system upgrade for the Super Proton Synchrotron (SPS) (Doctoral dissertation, CERN).

Battistoni, G. (2020) 'Simulation of radiation effects on the Micromegas detector for the New Small Wheel in ATLAS', *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, 972, p. 164097. doi:10.1016/j.nima.2020.164097.

Bechtle, P., Dercks, D., Heinemeyer, S., Klingl, T., Stefaniak, T., Weiglein, G. and Wittbrodt, J., 2020. HiggsBounds-5: testing Higgs sectors in the LHC 13 TeV era. *The European Physical Journal C*, *80*, pp.1-24.

Belyaev, A., Ross, D., Belyaev, A. and Ross, D., 2021. Beyond the Standard Model (BSM). *The Basics of Nuclear and Particle Physics*, pp.347-359.

Berlin, A., & Kling, F. (2019). Inelastic dark matter at the LHC lifetime frontier: ATLAS, CMS, LHCb, CODEX-b, FASER, and MATHUSLA. *Physical Review D*, *99*(1), 015021.

Bettini, A., 2024. *Introduction to elementary particle physics*. Cambridge University Press.

Bohm, J., 2023. *Optimization of Machine Learning for the Leptoquark Search using CERN ATLAS. Data* (Doctoral dissertation, Czech Technical University in Prague (CZ)).

Bonivento, W.M. and Terranova, F., 2024. The science and technology of liquid argon detectors. *Reviews of Modern Physics*, *96*(4), p.045001.

Bourilkov, D., 2019. Machine and deep learning applications in particle physics. *International Journal of Modern Physics A*, *34*(35), p.1930019.

Bruce, R., d'Enterria, D., De Roeck, A., Drewes, M., Farrar, G.R., Giammanco, A., Gould, O., Hajer, J., Harland-Lang, L., Heisig, J. and Jowett, J.M., 2020. New physics searches with heavy-ion collisions at the CERN Large Hadron Collider. *Journal of Physics G: Nuclear and Particle Physics*, *47*(6), p.060501.

Candy, J.V., 2016. Bayesian signal processing: classical, modern, and particle filtering methods (Vol. 54). John Wiley & Sons.

Carneiro, T., Da Nóbrega, R. V. M., Nepomuceno, T., Bian, G. B., De Albuquerque, V. H. C., & Reboucas Filho, P. P. (2018). Performance analysis of google colaboratory as a tool for accelerating deep learning applications. *Ieee Access*, *6*, 61677-61685.

Cerrón Zeballos, E. (2022) 'The Micromegas-based precision tracking chambers for the ATLAS New Small Wheel', *Physics Procedia*, 185, pp. 124–130. doi:10.1016/j.phpro.2022.07.024.

Chall, C., King, M., Mättig, P. and Stöltzner, M., 2021. From a boson to the standard model Higgs: a case study in confirmation and model dynamics. *Synthese*, *198*, pp.3779-3811.

Czarnecki, A., 1997. Using muons to probe for new physics. *arXiv preprint hep-ph/9710425*.

Dumancic, M., 2019. Z boson production in 5.02 TeV proton-proton and lead-lead data measured by the ATLAS experiment at the LHC (Doctoral dissertation, The Weizmann Institute of Science (Israel)).

Ebke, J. (2012). Measurement of the W {sup+} W {sup-} diboson production cross-section with the ATLAS experiment at the large hadron collider.

Eichhorn, T., 2015. Development of silicon detectors for the High Luminosity LHC (Doctoral dissertation, DESY).

Fabbietti, L., Sarti, V.M. and Doce, O.V., 2021. Study of the strong interaction among hadrons with correlations at the LHC. *Annual Review of Nuclear and Particle Science*, *71*(1), pp.377-402.

Forty, R., 2023. Collider Experiments: the LHC & Beyond.

Fox, P.J., Huang, S., Isaacson, J., Ju, X. and Nachman, B., 2021. Beyond 4D tracking: using cluster shapes for track seeding. *Journal of Instrumentation*, *16*(05), p.P05001.

Géron, A., 2022. Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow. " O'Reilly Media, Inc.".

Ghosh, A. and ATLAS collaboration, 2020, April. Deep generative models for fast shower simulation in ATLAS. In *Journal of Physics: Conference Series* (Vol. 1525, No. 1, p. 012077). IOP Publishing.

Grossman, M.I., 2021. John Dalton's "Aha" Moment: the Origin of the Chemical Atomic Theory. *ambix*, *68*(1), pp.49-71.

Gullstrand, M. and Maraš, S., 2020. Using Graph Neural Networks for Track Classification and Time Determination of Primary Vertices in the ATLAS Experiment.

Gunawan, T. S., Ashraf, A., Riza, B. S., Haryanto, E. V., Rosnelly, R., Kartiwi, M., & Janin, Z. (2020). Development of video-based emotion recognition using deep learning with Google Colab. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *18*(5), 2463-2471.

Gunderman, R., 2021. Marie Curie: The Pioneer, the Nobel Laureate, the Discoverer of Radioactivity. 'The Rosen Publishing Group, Inc'.

Gustavsson, M., Wikner, J.J. and Tan, N., 2000. *CMOS data converters for communications* (Vol. 543). Springer Science & Business Media.

Guth, A.H., 2023. The inflationary universe. In *Cosmology* (pp. 411-446). CRC Press.

Hastie, T., Tibshirani, R., Friedman, J. and Franklin, J., 2005. The elements of statistical learning: data mining, inference and prediction. *The Mathematical Intelligencer*, *27*(2), pp.83-85.

Hentschel, K., 2009. Atomic models, jj thomson's "plum pudding" model. In *Compendium of quantum physics* (pp. 18-21). Berlin, Heidelberg: Springer Berlin Heidelberg.

Hoddeson, L., Brown, L., Riordan, M. and Dresden, M. eds., 1997. *The rise of the standard model: A history of particle physics from 1964 to 1979*. Cambridge University Press.

Hon, G. and Goldstein, B.R., 2013. JJ Thomson's plum-pudding atomic model: The making of a scientific myth. *Annalen der physik*, *525*(8-9), pp.A129-A133.

Horvath, J.E., 2022. The Nature of the Physical World: Elementary Particles and Interactions. In *High-Energy Astrophysics: A Primer* (pp. 1-17). Cham: Springer International Publishing.

Horvath, J.E., 2022. *High-energy Astrophysics: A Primer*. Springer Nature.

Iakovidis, G. (2022) 'Performance of the ATLAS Muon Spectrometer with the New Small Wheel', *EPJ Web of Conferences*, 245, p. 07013. doi:10.1051/epjconf/202224507013.

Iodice, M., 2015. Micromegas detectors for the Muon Spectrometer upgrade of the ATLAS experiment. *Journal of Instrumentation*, *10*(02), p.C02026.

Jimenez, F. (2019). *Model independent searches for New Physics using Machine Learning at the ATLAS experiment* (Doctoral dissertation, Université Clermont Auvergne [2017-2020]).

Karkanias, I. (2022). Application of statistical methods with emphasis on Machine Learning for the analysis of experimental data from the ATLAS experiment at the LHC at CERN. *Doctoral dissertation*.

Karkanias, I., 2022. Application of statistical methods with emphasis on Machine Learning for the analysis of experimental data from the ATLAS experiment at the LHC at CERN. *Doctoral dissertation*.

Khan, A., Sohail, A., Zahoora, U. and Qureshi, A.S., 2020. A survey of the recent architectures of deep convolutional neural networks. *Artificial intelligence review*, *53*, pp.5455-5516.

Khodjamirian, A., 2020. Hadron form factors: from basic phenomenology to QCD sum rules. CRC Press.

Kimm, H., Paik, I., & Kimm, H. (2021, December). Performance comparision of tpu, gpu, cpu on google colaboratory over distributed deep learning. In *2021 IEEE 14th International Symposium on Embedded Multicore/Many-core Systems-on-Chip (MCSoC)* (pp. 312-319). IEEE.

Koberinski, A., 2024. Phase transitions and the birth of early universe particle physics. *Studies in History and Philosophy of Science*, *105*, pp.59-73.

Krasnopevtsev, D.V., 2017. Tracking properties of the ATLAS Transition Radiation Tracker (TRT). In *Journal of Physics: Conference Series* (Vol. 798, No. 1, p. 012150). IOP Publishing.

Krzysiak, J. A. (2021). *Searching for Beyond-the-Standard-Model Physics Using Signatures with Tau Leptons in the Final State at the ATLAS Experiment* (Doctoral dissertation, Polish Academy of Sciences (PL)).

Landua, R., 2024, October. A short history of the smallest. In *Journal of Physics: Conference Series* (Vol. 2877, No. 1, p. 012093). IOP Publishing.

Leung, S.C., 2023. *Higgs Boson Phenomenology at the LHC: the Standard Model and Beyond* (Doctoral dissertation, University of Pittsburgh).

Lima, N. and Karam, R., 2021. Particle velocity= group velocity: A common assumption in the different theories of Louis de Broglie and Erwin Schrödinger. *American Journal of Physics*, *89*(5), pp.521-528.

Linß, A., 2021. *Search for Dark Matter in Invisible Higgs Boson Decays with the ATLAS Detector at the LHC* (Doctoral dissertation, Staats-und Universitätsbibliothek Hamburg Carl von Ossietzky).

Maina, M., Adamu, A., Sanda, M. and Bukar, M.I., 2023. The Bohr Model of the Atom: A Critical Evaluation of its Impact and Limitations in Modern Physics. *NIPES-Journal of Science and Technology Research*, *5*(3).

Mali, P., Sarkar, S., Ghosh, S., Mukhopadhyay, A. and Singh, G., 2015. Multifractal detrended fluctuation analysis of particle density fluctuations in high-energy nuclear collisions. *Physica A: Statistical Mechanics and its Applications*, *424*, pp.25-33.

Martin Perez, C., 2022. The CMS Experiment at the LHC. In *Search for the Higgs Boson Produced in Association with Top Quarks with the CMS Detector at the LHC* (pp. 41-84). Cham: Springer International Publishing.

Mc Gowan, J.P., 2023. Measurement of the electroweak production of a photon and a W boson in association with two jets in proton-proton collisions using the ATLAS Detector (Doctoral dissertation, University of Victoria (CA)).

Mikuni, V. and Canelli, F., 2021. Unsupervised clustering for collider physics. *Physical Review D*, *103*(9), p.092007.

Mistry, N., 2011. A brief introduction to particle physics. Laboratory for Elementary Particle Physics, Cornell University, 10.

Modak, A., 2024. Inclusive Photon And Charged-Particle Production In Proton-Proton And Proton-Lead Collisions At LHC Energies With ALICE (No. CERN-THESIS-2024-111).

Moser, B., 2023. The ATLAS Experiment at the Large Hadron Collider. In The Beauty and the Boost: A Higgs Boson Tale: Measurements of Higgs Boson Production at High Energy in Decays to Bottom

Quarks and Their Interpretations with the ATLAS Experiment at the LHC (pp. 45-60). Cham: Springer Nature Switzerland.

Müller, B., 2016. A New Phase of Matter: Quark-Gluon Plasma Beyond the Hagedorn Critical Temperature. Melting Hadrons, Boiling Quarks-From Hagedorn Temperature to Ultra-Relativistic Heavy-Ion Collisions at CERN: With a Tribute to Rolf Hagedorn, pp.107-116.

Nagano, K. and Atlas Collaboration, 2014, June. Algorithms, performance, development of the ATLAS High-Level trigger. In *Journal of Physics: Conference Series* (Vol. 513, No. 1, p. 012026). IOP Publishing.

Nelson, M., 2019. Hadronic jet physics and the quest for new matter in multi-jet final states with the ATLAS detector at the Large Hadron Collider (Doctoral dissertation, University of Oxford).

Nguyen, T., 2020. From electron reconstruction and identification to the search for supersymmetry at the atlas experiment.

Nunez, C., 2024. Studying Hyperon Polarization at the Large Hadron Collider Beauty Experiment (Doctoral dissertation).

Orrman-Rossiter, K., 2021. Observation and Annihilation: The Discovery of the Antiproton. *Physics in Perspective*, *23*(1), pp.3-24.

Oliveri, E. (2018) 'Development of Micromegas detectors for the ATLAS New Small Wheel upgrade', *Nuclear Instruments and Methods in Physics Research Section A*, 936, pp. 226–230. doi:10.1016/j.nima.2018.10.165.

Ortigueira, M.D. and Machado, J.T., 2020. A review of sample and hold systems and design of a new fractional algorithm. *Applied Sciences*, *10*(20), p.7360.

Özhan, O., 2022. z-Transform. In *Basic Transforms for Electrical Engineering* (pp. 495-598). Cham: Springer International Publishing.

Palani, S. and Palani, S., 2022. The Laplace Transform Method for the Analysis of Continuous Time Signals and Systems. *Signals and Systems*, pp.737-920.

Papaevangelou, T. (2018) 'The ATLAS New Small Wheel upgrade: Challenges and lessons learned', *Nuclear Instruments and Methods in Physics Research A*, 968, pp. 65–72. doi:10.1016/j.nima.2019.163848.

Peebles, P.J.E., 2024. The physicists philosophy of physics. *arXiv preprint arXiv:2401.16506*.

Pereira, D.S., Ferraz, J., Lobo, F.S. and Mimoso, J.P., 2023. Baryogenesis: A Symmetry Breaking in the Primordial Universe Revisited. *Symmetry*, *16*(1), p.13.

Pezzotti, L., 2021. Particle detectors R&D: Dual-readout calorimetry for future colliders and micromegas chambers for the ATLAS new small wheel upgrade.

Pospisil, J., Bjorkqvist, O., Boccardi, A. and Wendt, M., 2017. Digital signal processing techniques to monitor bunch-by-bunch beam positions in the LHC for machine protection purposes. In *Proc. 6th Int. Beam Instrumentation Conf.(IBIC'17)* (pp. 146-149).

Qin, S., 2022. Unified Theory of Gravity, Electromagnetic Force, Strong and Weak Forces and their Applications: Theoretical Explanation for Dark Matter. *J Phys Chem Biophys*, *12*, p.335.

Quigg, C., 2021. Gauge theories of strong, weak, and electromagnetic interactions. CRC Press.

Radeka, V., 2020. Signal processing for particle detectors. Particle Physics Reference Library: Volume 2: Detectors for Particles and Radiation, pp.439-484.

Radovic, A., Williams, M., Rousseau, D., Kagan, M., Bonacorsi, D., Himmel, A., Aurisano, A., Terao, K. and Wongjirad, T., 2018. Machine learning at the energy and intensity frontiers of particle physics. *Nature*, *560*(7716), pp.41-48.

Raschka, S., Patterson, J., & Nolet, C. (2020). Machine learning in python: Main developments and technology trends in data science, machine learning, and artificial intelligence. *Information*, *11*(4), 193.

Rodríguez, M.A. and Niaz, M., 2004. A reconstruction of structure of the atom and its implications for general physics textbooks: A history and philosophy of science perspective. *Journal of Science Education and Technology*, *13*, pp.409-424.

Sanford, T., 2024. Particle Physics: 1950–2023. In *A Whirlwind History of the Universe and Mankind: From the Big Bang to the Higgs Boson* (pp. 191-217). Singapore: Springer Nature Singapore.

Sarkar, P. and Bhattacharyya, S.P., 2022. Understanding Properties of Atoms, Molecules and Materials. CRC Press.

Shanbhag, N.M., Sumaida, A.B. and Balaraj, K., 2024. Marie Curie (1867–1934): Twice Nobel Laureate and Her Enduring Legacy in Radiation Medicine. *Cureus*, *16*(8).

Sirma, K.K., 2021. A Modified Nuclear Model for Binding Energy of Nuclei and the Island of Stability (Doctoral dissertation, University of Eldoret).

Standke, M. (2019). *Characterization of the Joined ATLAS and CMS RD53A Pixel Chip* (Doctoral dissertation, Bonn U.).

Stranneby, D., 2004. Digital signal processing and applications. Elsevier.

Tajmar, M., Kößling, M. and Neunzig, O., 2024. In-depth experimental search for a coupling between gravity and electromagnetism with steady fields. *Scientific Reports*, *14*(1), p.19427.

Thaprasop, P., Zhou, K., Steinheimer, J. and Herold, C., 2021. Unsupervised outlier detection in heavy-ion collisions. *Physica Scripta*, *96*(6), p.064003.

Toscano, L. (2019) 'The performance of the ATLAS New Small Wheel Micromegas Chambers', *Journal of Instrumentation*, 14(11), pp. C11021–C11021. doi:10.1088/1748-0221/14/11/C11021.

Vidal, X.C., Maroñas, L.D. and Suárez, Á.D., 2021. How to use machine learning to improve the discrimination between signal and background at particle colliders. *Applied Sciences*, *11*(22), p.11076.

Vissani, F., 2021. What is matter according to particle physics, and why try to observe its creation in a lab?. *Universe*, *7*(3), p.61.

Wang, T., Rymaszewski, P., Barbero, M., Degerli, Y., Godiot, S., Guilloux, F., Hemperek, T., Hirono, T., Krüger, H., Liu, J. and Orsini, F., 2017. Development of a depleted monolithic CMOS sensor in a 150 nm CMOS technology for the ATLAS inner tracker upgrade. *Journal of Instrumentation*, *12*(01), p.C01039.

Whitehead, C.B., Özkar, S. and Finke, R.G., 2021. LaMer's 1950 model of particle formation: a review and critical analysis of its classical nucleation and fluctuation theory basis, of competing models and mechanisms for phase-changes and particle formation, and then of its application to silver halide, semiconductor, metal, and metal-oxide nanoparticles. *Materials Advances*, *2*(1), pp.186-235.

Wojnar, M., 2024. Applying generative neural networks for fast simulations of the ALICE (CERN) experiment. *arXiv preprint arXiv:2407.16704*.

Wojnar, M., 2024. Applying generative neural networks for fast simulations of the ALICE (CERN) experiment. *arXiv preprint arXiv:2407.16704*.

Wölker, R. (2021). *Search for heavy ZZ resonances in the 4ℓ final state with the ATLAS detector and identifying muons in the ATLAS calorimeter using machine learning* (Doctoral dissertation, University of Oxford).

Yang, X., Yang, Y., Zhen, L. and Bi, Y., 2024. An Illuminating Physical View on the Principles of "3 Generations" Structure of Elementary Particles, and on Evolution of Universe–Energy Basic State Field of the Universe (IV). *Reports in Advances of Physical Sciences*, *8*, p.2350015.

Yock, P., 2021. Comparison of Rutherford's atomic model with the Standard Model of particle physics and other models. *Journal of the Royal Society of New Zealand*, *51*(3-4), pp.538-556.