ΠΑΝΕΠΙΣΤΗΜΙΟ ΔΥΤΙΚΗΣ ΑΤΤΙΚΗΣ
ΣΧΟΛΗ ΜΗΧΑΝΙΚΩΝ
ΤΜΗΜΑ ΗΛΕΚΤΡΟΛΟΓΩΝ ΚΑΙ ΗΛΕΚΤΡΟΝΙΚΩΝ ΜΗΧΑΝΙΚΩΝ
ΤΜΗΜΑ ΜΗΧΑΝΙΚΩΝ ΒΙΟΜΗΧΑΝΙΚΗΣ ΣΧΕΔΙΑΣΗΣ ΚΑΙ ΠΑΡΑΓΩΓΗΣ
http://www.eee.uniwa.gr
http://www.idpe.uniwa.gr
Θηβών 250, Αθήνα-Αιγάλεω 12241
Τηλ: +30 210 538-1614
Διατμηματικό Πρόγραμμα Μεταπτυχιακών Σπουδών
Τεχνητή Νοημοσύνη και Βαθιά Μάθηση
https://aidl.uniwa.gr/

UNIVERSITY OF WEST ATTICA
FACULTY OF ENGINEERING
DEPARTMENT OF ELECTRICAL & ELECTRONICS ENGINEERING
DEPARTMENT OF INDUSTRIAL DESIGN AND PRODUCTION ENGINEERING
http://www.eee.uniwa.gr
http://www.idpe.uniwa.gr
250, Thivon Str., Athens, GR-12241, Greece
Tel: +30 210 538-1614
Master of Science in
Artificial Intelligence and Deep Learning
https://aidl.uniwa.gr/

Master of Science Thesis

Use of Artificial Intelligence and Deep Learning in the Food and Agriculture Domain

Student: Athanasopoulos Iason
Registration Number: MSCAIDL-0001

MSc Thesis Supervisor

Piromalis Dimitrios
Assist. Professor

ATHENS-EGALEO, February 2023

ΠΑΝΕΠΙΣΤΗΜΙΟ ΔΥΤΙΚΗΣ ΑΤΤΙΚΗΣ
ΣΧΟΛΗ ΜΗΧΑΝΙΚΩΝ
ΤΜΗΜΑ ΗΛΕΚΤΡΟΛΟΓΩΝ ΚΑΙ ΗΛΕΚΤΡΟΝΙΚΩΝ ΜΗΧΑΝΙΚΩΝ
ΤΜΗΜΑ ΜΗΧΑΝΙΚΩΝ ΒΙΟΜΗΧΑΝΙΚΗΣ ΣΧΕΔΙΑΣΗΣ ΚΑΙ ΠΑΡΑΓΩΓΗΣ
http://www.eee.uniwa.gr
http://www.idpe.uniwa.gr
Θηβών 250, Αθήνα-Αιγάλεω 12241
Τηλ: +30 210 538-1614
Διατμηματικό Πρόγραμμα Μεταπτυχιακών Σπουδών
Τεχνητή Νοημοσύνη και Βαθιά Μάθηση
https://aidl.uniwa.gr/

UNIVERSITY OF WEST ATTICA
FACULTY OF ENGINEERING
DEPARTMENT OF ELECTRICAL & ELECTRONICS ENGINEERING
DEPARTMENT OF INDUSTRIAL DESIGN AND PRODUCTION ENGINEERING
http://www.eee.uniwa.gr
http://www.idpe.uniwa.gr
250, Thivon Str., Athens, GR-12241, Greece
Tel: +30 210 538-1614
Master of Science in
Artificial Intelligence and Deep Learning
https://aidl.uniwa.gr/

Μεταπτυχιακή Διπλωματική Εργασία

Χρήσεις τής Τεχνητής Νοημοσύνης και τής Βαθειάς Μάθησης στον Αγροδιατροφικό Τομέα

Φοιτητής: Αθανασόπουλος Ιάσων
AM: MSCAIDL-0001

Επιβλέπων Καθηγητής
Πυρομάλης Δημήτριος
Επίκ. Καθηγητής

ΑΘΗΝΑ-ΑΙΓΑΛΕΩ, Φεβρουάριος 2023

This MSc Thesis has been accepted, evaluated and graded by the following committee:

Supervisor	Member	Member
Dimitrios Pyromalis Digitally signed by Dimitrios Pyromalis Date: 2023.05.30 16:42:23 +03'00'	c=GR, l=Athens, o=University of West Attica, ou=Class A - Private Key created and stored in hardware CSP, sn=Papageorgas, givenName=Panagiotis, serialNumber=9462990737, cn=Panagiotis Papageorgas, email=ppapag@uniwa.gr 2023.05.30 11:27:33 +03'00'	Savvas Vasileiadis Digitally signed by Savvas Vasileiadis Date: 2023.05.30 11:40:41 +03'00' Digitally signed by Savvas Vasileiadis Date: 2023.06.03 14:02:02 +03'00'
Piromalis Dimitrios	Papageorgas Panagiotis	Vassiliadis Savvas
Assist. Professor	Professor	Professor
ELECTRICAL & ELECTRONICS ENGINEERING	ELECTRICAL & ELECTRONICS ENGINEERING	ELECTRICAL & ELECTRONICS ENGINEERING
UNIVERSITY OF WEST ATTICA	UNIVERSITY OF WEST ATTICA	UNIVERSITY OF WEST ATTICA

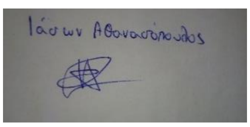
ΔΗΛΩΣΗ ΣΥΓΓΡΑΦΕΑ ΜΕΤΑΠΤΥΧΙΑΚΗΣ ΔΙΠΛΩΜΑΤΙΚΗΣ ΕΡΓΑΣΙΑΣ

Ο/η κάτωθι υπογεγραμμένος/η Αθανασόπουλος Ιάσων του Ευαγγέλου, με αριθμό μητρώου MSCAIDL-0001 μεταπτυχιακός/ή φοιτητής/ήτρια του ΔΠΜΣ «Τεχνητή Νοημοσύνη και Βαθιά Μάθηση» του Τμήματος Ηλεκτρολόγων και Ηλεκτρονικών Μηχανικών και του Τμήματος Μηχανικών Βιομηχανικής Σχεδίασης και Παραγωγής, της Σχολής Μηχανικών του Πανεπιστημίου Δυτικής Αττικής,

δηλώνω υπεύθυνα ότι:

«Είμαι συγγραφέας αυτής της μεταπτυχιακής διπλωματικής εργασίας και κάθε βοήθεια την οποία είχα για την προετοιμασία της είναι πλήρως αναγνωρισμένη και αναφέρεται στην εργασία. Επίσης, οι όποιες πηγές από τις οποίες έκανα χρήση δεδομένων, ιδεών ή λέξεων, είτε ακριβώς είτε παραφρασμένες, αναφέρονται στο σύνολό τους, με πλήρη αναφορά στους συγγραφείς, τον εκδοτικό οίκο ή το περιοδικό, συμπεριλαμβανομένων και των πηγών που ενδεχομένως χρησιμοποιήθηκαν από το διαδίκτυο. Επίσης, βεβαιώνω ότι αυτή η εργασία έχει συγγραφεί από μένα αποκλειστικά και αποτελεί προϊόν πνευματικής ιδιοκτησίας τόσο δικής μου, όσο και του Ιδρύματος. Η εργασία δεν έχει κατατεθεί στο πλαίσιο των απαιτήσεων για τη λήψη άλλου τίτλου σπουδών ή επαγγελματικής πιστοποίησης πλην του παρόντος.
Παράβαση της ανωτέρω ακαδημαϊκής μου ευθύνης αποτελεί ουσιώδη λόγο για την ανάκληση του διπλώματός μου.»

Ο/Η Δηλών/ούσα
Αθανασόπουλος Ιάσων



(Υπογραφή φοιτητή/ήτριας)

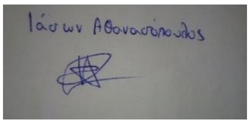
Declaration of the author of this MSc thesis

I, Athanasopoulos Iason of Evangelos with the following student registration number: MSCAIDL-0001, postgraduate student of the MSc programme in "Artificial Intelligence and Deep Learning", which is organized by the Department of Electrical and Electronic Engineering and the Department of Industrial Design and Production Engineering of the Faculty of Engineering of the University of West Attica, hereby declare that:

I am the author of this MSc thesis and any help I may have received is clearly mentioned in the thesis. Additionally, all the sources I have used (e.g., to extract data, ideas, words or phrases) are cited with full reference to the corresponding authors, the publishing house or the journal; this also applies to the Internet sources that I have used. I also confirm that I have personally written this thesis and the intellectual property rights belong to myself and to the University of West Attica. This work has not been submitted for any other degree or professional qualification except as specified in it.

Any violations of my academic responsibilities, as stated above, constitutes substantial reason for the cancellation of the conferred MSc degree.

The author
Athanasopoulos Iason



(Signature)

Abstract

The current thesis is an overview of the materials and the technics that are used in the Smart Farming sector. It focuses on the particularities of Smart Farming compared to other Artificial Intelligence applications, hence a basic knowledge of AI constitutes a prerequisite. At the first chapter, a definition and the basic idea of Smart Farming, as well as the necessary conditions for the emergence of this sector and the tasks that it is meant to cope, are represented. In continuation, a brief description of the majority of sensors and platforms (e.g., UAVs, tractors) used in the Smart Farming are analyzed, focusing on the advantages, disadvantages and particularities of each one. Then, a description of the communication technics amongst the nodes is provided, with an emphasis on the Low-power wide area network which is mostly used in agriculture. The thesis describes how software related tasks are tackled, like preprocessing technics and AI models. An object detection algorithm applied on orange fruits is implemented as an example of a Smart Farming application that could be used for autonomous fruit picking. Finally, a social and economic analysis of Smart Farming is provided, along with the obstacles it faces from being adopted by the small-scale farmers.

Keywords

Smart Farming, Precision Agriculture, Object Detection, Internet of Things.

Περίληψη

Η παρούσα διπλωματική εργασία είναι μια επισκόπηση των υλικών και των τεχνικών που χρησιμοποιούνται στον τομέα της Έξυπνης Γεωργίας. Επικεντρώνεται στις ιδιαιτερότητες της Έξυπνης Γεωργίας σε σύγκριση με τις άλλες εφαρμογές τής Τεχνητής Νοημοσύνης, επομένως μία βασική γνώση τής τεχνητής νοημοσύνης αποτελεί προϋπόθεση για την ορθή κατανόηση τής εργασίας. Στο πρώτο κεφάλαιο, παρουσιάζεται ο ορισμός και η βασική ιδέα τής Έξυπνης Γεωργίας, καθώς και οι απαραίτητες προϋποθέσεις για την ανάδυση αυτού του κλάδου, αλλά και τα προβλήματα που προορίζεται να επιλύσει. Στη συνέχεια, γίνεται μια σύντομη περιγραφή τής πλειονότητας των αισθητήρων και των πλατφορμών (π.χ. UAV, τρακτέρ) που χρησιμοποιούνται στην Έξυπνη Γεωργία, εστιάζοντας στα πλεονεκτήματα, τα μειονεκτήματα και τις ιδιαιτερότητες του καθενός. Στη συνέχεια, παρέχεται μια περιγραφή των τεχνικών επικοινωνίας μεταξύ των κόμβων, με έμφαση στο Low-power wide area network που χρησιμοποιείται κυρίως στη γεωργία. Η διατριβή περιγράφει πώς αντιμετωπίζονται εργασίες που σχετίζονται με το λογισμικό, όπως τεχνικές προεπεξεργασίας και μοντέλα τεχνητής νοημοσύνης. Ένας αλγόριθμος ανίχνευσης αντικειμένων που εφαρμόζεται σε πορτοκάλια εφαρμόζεται ως παράδειγμα εφαρμογής Έξυπνης Γεωργίας που θα μπορούσε να χρησιμοποιηθεί για αυτόνομο μάζεμα φρούτων. Τέλος, παρέχεται μια κοινωνική και οικονομική ανάλυση της Έξυπνης Γεωργίας, μαζί με τα εμπόδια που αντιμετωπίζει η υιοθέτησή της από τους μικροκαλλιεργητές.

Λέξεις – κλειδιά

Έξυπνη Γεωργία, Γεωργία Ακριβείας, Ανίχνευση Αντικειμένων, Διαδίκτυο των Πραγμάτων.

Table of Contents

Acronym Index **10**

INTRODUCTION **11**

1 CHAPTER 1: PRECISION AGRICULTURE **13**

2 CHAPTER 2: SENSORS **15**

3 CHAPTER 3: PLATFORMS **20**

4 CHAPTER 4: COMMUNICATION **25**

5 CHAPTER 5: DATA PREPROCESSING **27**

6 CHAPTER 6: MODELS **29**

7 CHAPTER 7: USE CASE: ORANGE OBJECT DETECTION **31**

8 CONCLUSIONS **42**

Bibliography – References – Online sources **43**

Acronym Index

AI: Artificial Intelligence

SF: Smart Farming

NTC: Negative Temperature Coefficient

IC: Integrated Circuit temperature

GNSS: Global Navigation Satellite System

GPS: Global Navigation System

RTK: Real Time Kinematic

PPK: Post Process Kinematic

UAV: Unmanned Aerial Vehicle

UAS: Unmanned Aerial System

LPWAN: Low-power wide area network

VI: Vegetation Indexes

NDVI: Normalized Difference Vegetation Index

CWSI: Crop Water Stress Index

IoU: Intersection over Union

INTRODUCTION

Agriculture has been the major source of food and an important sector of human economy since the beginning of humanity. Therefore, it is necessary to find ways to improve the efficiency of the arable lands. Of course, cultivation is a tough process with a variety of tasks. Every time humans face a problem, they tend to use all the existing technologies in order to solve it. One application of technology in agriculture is the use of Artificial Intelligence (AI). AI is a tool that has contributed significantly to this sector and is promising more results in the near future. In the past, this technic wasn't feasible due to low computational power, absence of suitable platforms and high sensors' cost. Thanks to the development of the Internet of Things (IoT) and the autonomous vehicles on the one hand, and the increase of computational power on the other, getting data from crops and applying a model to evaluate them has become much easier.

The purposes of AI in agriculture domain are to automatize processes, decrease costs, increase the precision of the work that are required in the field, increase profit, but also to decrease the environmental impact. Amongst the most common agricultural activities are watering, sowing, harvesting, weed detection and removal, crop and animal disease identification, mapping, pest attack identification, plant phenology analysis, crop yield prediction, crop classification, fruit counting, and spraying. Some applications are designed for actions after the production of the final product, these can be the price prediction, the traceability of poisonous products or the connection between sellers and buyers. The application of AI in any agricultural activity is called Smart Farming (SF).

The majority of SF applications follow three basic steps which are to: 1) get data from the crop (or any other relative source), 2) apply a model and acquire results, 3) and optionally, if the results are not utilized by traditional means of agriculture, to use some actuators to deal with any problem that is emerged. If it is used a machine learning model, there is one more important step in the whole process, which is not observable in the final product of the procedure, but it is one of the most difficult to accomplish, namely the model training. In agriculture usually we want to optimize a certain value (e.g., yield or profits), thus most applications use supervised learning. In order to train a model in supervised learning, we need independent and dependent data, i.e., the factors that affect the crop and the features of the crop that will be used as label data. Starting to collect data, we have to define the purpose of our work, in other words, the features of our crop we want to optimize. Moreover, it is necessary to find a way to measure the selected feature. Of course, there can be many features. In the first step, apart from the label data, we need data from at least one factor of the crop, preferably as many as possible, so a correlation can be found. Then, depending on our task and the available data we have to choose an AI model that is suitable. This description is an overgeneralization and many variants can exist. Many examples also make use of traditional AI which requires an expert to program the model instead of the model training process, while there was little research that made use of unsupervised learning.

The major obstacles that SF has to deal with, compared with other AI applications, are the changing climate conditions, the uneven terrain, the complex plans' shape and position, the unspecified yields color and shape, and generally the complexity of living being. These features can create challenging tasks not only on the software and the AI models, but mainly to the hardware which will be exposed to this environment. There are cases where the raw data are not collected directly from crop, but instead a sample from the crop is gotten and it is analyzed in the lab. In this case, the problem of selecting the correct sample emerges, but then everything is done in a controlled environment.

With this thesis I will try to examine all the aspects of SF. The following chapter describes the heterogeneity of crops, the natural phenomenon that emerged the precision agriculture, which is the sector of agriculture that has many aspects in common with SF. Then the main part of the thesis describes summarily all the technical aspects of SF, starting from the sensors, which is the first point of the information's route. Then follow the platforms, which get the information from the sensors. Then follow the communications, which are used to transfer the information from the platforms to a central computer and backwards. At the end, there is the preprocessing and the final processing (the AI model) of the information. This thesis ends with a conclusion that presents the social and economic barriers of the adoption of SM from small scale farmers, and suggests a solution to this problem.

1 CHAPTER 1: PRECISION AGRICULTURE

The fields are not homogeneous, even in small sized crops variance is observed. Of course, this was well known to the farmers around the globe over the centuries at least at some level. Despite the fact of the knowledge of the heterogeneous nature of crops, it was not feasible to handle this heterogeneity due to high cost of measurements. As a result, crops were treated as homogenous and generally every action was applied to the whole crop. In rare cases, where the farmers did not treat the crop as homogeneous, the accuracy of the actions that were taken on the crop was low. To deal with this challenge, a sector of agriculture was developed, the so-called precision agriculture.

Precision agriculture is the sector of agriculture that copes with the spatial and temporal variability of all the factors that affect crop production. Precision agriculture requires two types of measurements: 1) environmental factors that affect the crop production and 2) the features of the crop. These two types of measurements are affected by two dimensions that cause change; these are time and space. Furthermore, given the list of measurements that can be applied in order to have an excellent perception of the crop is enormous, it is practically impossible to cover all the space-time continuum. A few of the most common factors and features that are measured during the application of precision agriculture are: temperature (air and soil), humidity, moisture, solar radiation, wind, type of soil, nutrient of the soil, declination of earth, pests, weeds, emitted radiation of the plants, canopy size, number of fruits and weight of yield.

It is worth stressing that these factors do not have the same variation in time and space. For instance, earth declination has an imperceptible variation in time, meanwhile solar radiation has a smaller variation in space. Farmers need to factor in the variability, both in time and space, of each measurable quantity in order to diminish the cost of any application to a feasible level. These technics could lead to higher production, higher yield quality, lower need for inputs in the crop, better decision for crop selection, and smaller impact to the environment. The advantages are so strong that we can talk about a new era of agriculture.

Precision agriculture can be achieved with the traditional agricultural technics, i.e., without the use of AI and SF. Nonetheless, with the implementation of sensors of high spatial and temporal resolution, and of models that can handle huge amounts of data, the precision in the perception and in the interference of the farmer can increase remarkably. Also, a SF application could have no precision at all and treat a crop as homogeneous. Even though SF and precision agriculture are not identical, many times these terms are confused due to their high correlation. [1]

[46] A map with the spatial variability of growth. Similar maps can be made with other aspects of the agricultural process.

2 CHAPTER 2: SENSORS

A sensor is a device which acquires a physical quantity and converts it into a signal. Usually, for AI applications, sensors' outputs are digital so they can be processed directly by computers which handle the models. Sensors are necessary for the majority of smart farming applications because they are the only way to get data directly from a crop.

The selection of the appropriate sensors, both in type and in quantity, is a process that depends on many parameters. In supervised learning, the first objective is to identify a sensor that measures the label data, i.e., the feature of our crop that we want to optimize. Then, we need to measure at least one factor from the ambient so a correlation can be found. Theoretically, the more factors we measure, the correlation we find, if any, will be more accurate. However, in practice, we are submitted to practical restrictions and we need to use our intuition regarding which parameters will have greater impact on the crop.

There are some secondary sensors' characteristics that have to be taken into account. Apart from the physical quantity that a sensor measures, one has to take into consideration the accuracy, the range, the spatial and temporal resolution (the area where each element of the measurement is referred to and the frequency of measurements), the type of output (digital or analog) as well as the need for calibration. Then, depending on the platform that the sensor is equipped with, one has to count the energy consumption, the weight, the climate conditions under which it can function, and many more parameters. Last but not least, the cost of acquisition and maintenance of the sensor is important in every smart farming application, especially when many sensors need to be purchased.

There is a number of sensors that are used in SF. The most common sensors are the following:

Cameras: Each molecule absorbs some frequencies of the electromagnetic spectrum and reflects some others. Also, depending on the temperature, materials emit some electromagnetic energy. These natural phenomena are exploited by cameras and can give us information about the environment by measuring the received electromagnetism of the frequencies that the camera is sensitive to. There are various types of cameras that can be sensitive to various frequencies of the spectrum (e.g., RGB, infrared, multispectral, hyperspectral). A camera is a sensor with very high spatial resolution, which varies with the distance of the measurement and it can be increased further more with the use of focus lens. The selection of the right camera should be based on spectral range and resolution, the spatial resolution, and the frames per second (temporal resolution). It can give us information about the molecules that are present in the crop (usually with multispectral cameras) and about the temperature (with infrared cameras). Camera is used in a huge variety of applications namely: irrigation, soil and plant health assessment, vegetation monitoring, food quality assessment, harvesting, toxin detection, plant classification. The aforementioned list of applications in combination with the rapid results, without any impact to emitting source, makes this sensor on of the most important in the SM domain. Simple RGB cameras can be very cheap, but the price of a hyperspectral camera is relatively expensive which is a barrier for small scale applications. Another barrier of hyperspectral camera is the necessity of high storage volume and computational power. Data preprocessing is also needed, which can be done by premade applications, but sometimes with an extra cost. [2] [3]

Thermometers: These can measure the temperature in both the air and the soil, a parameter that is very important for the plant or animal growth. Apart from the classic ones that produce analog output and have few applications in the AI domain, thermometers can be divided to the ones that need to be in contact with the object and the ones that measure from distance. The first category includes the thermocouple, the resistance temperature devices, the negative temperature coefficient (NTC) thermistors, Integrated Circuit temperature (IC) sensors, and the diodes temperature sensors. Thermocouple is a passive sensor that creates current when there is a difference in temperature between two nodes. The other sensors' principle of function is the change of their electrical properties in function of temperature. These devices must be in contact with the in-measure object and measure only one point, so they have no spatial resolution. While radiation thermometers can measure from distance and some of them can measure multiple points at once. Their principle of function is that warm objects emit Infrared radiation. [4][5]

Humidity sensors: Air can absorb water, which quantity depends on the temperature and the pressure of the gas. A saturation point is called when a gas cannot absorb any more water. Humidity sensors measure the amount of water that is present in a gas. There are three physical quantities associated with the humidity that can be measured: the relative humidity, dew/ frost point, and parts per million. Relative humidity is the percentage of the current vapor partial pressure to the saturation vapor partial pressure at a given temperature and pressure of the gas. Relative humidity is the most important, compared to the other two measurements of humidity, in SF because it has greater influence on the development of plants. Dew/ frost point is the temperature at which a gas starts to dew (or frost if the temperature is below zero) at a given pressure. The parts per million is the mass of water vapor per gas volume. Humidity sensors can be divided by their basic principles of function, the materials that are used (ceramic, semiconductor, and organic polymer), or the type of humidity that sense (relative or absolute). Some of the types that are in use today to measure the relative humidity are: optical ones, that exploit the absorption of some electromagnetic frequencies by the vapor; gravimetric, these sensors measure the difference in the density of the air; capacitive (which are the most common), these are based on the fact that some hygroscopic materials change their dielectric constant when they absorb water; resistive ones instead are based on the change of the resistance of some hygroscopic materials; piezoresistive humidity sensors, which exploit the fact that some hygroscopic material expand with the increase of the absorbed humidity causing the piezoresistive material to change its resistance; and finally magnetoelastic, which have similar principle as the piezoresistive ones, with the difference that they have a magnetoelastic material instead which change its magnetic properties. [6][7][8]

Soil moisture sensors: Soil has the ability to absorb water. The quantity of water that can be absorbed depends on the type of soil (e.g., sand, loam, clay-loam, and clay). The traditional way of measuring the soil moisture is the gravimetric, which can be done by measuring weight of the soil before and after heat drying is applied; this method is very accurate but also very time consuming, so it is used mainly for calibration. Another method exploits the fact that some hygroscopic materials change their dielectric constant or their resistance with the absorption of water. Soil's resistance and dielectric constant (which both can be measured) also change with the humidity content, but it also depends on other factors like temperature, salinity, soil density, soil particle shape, nevertheless the most important factor is the water. Soil’s dielectric constant also affects the velocity of an electromagnetic signal, this principle is used to calculate the moisture with the time and frequency domain reflectometry. Soil moisture can be measured directly with a radioactive source that emits either neutron or γ-ray, the radiation collides with the ions of hydrogen and loses energy. Radioactive materials can be harmful; thus, they have a disadvantage that they cannot be handled by anyone. [9][10]

Other important sensors are: Leaf wetness sensors which measure the wetness of leaves; actinometers which measure the solar irradiance; anemometers which measure wind speed and direction. The list goes on with all possible types of sensors that could measure anything useful, e.g., a scale could be used to measure the weight of yield, a container could be used for measuring the volume of the yield.

Despite the fact of neither measuring a factor nor a feature of the crop, there are sensors which are used for the localization of a platform. These sensors are necessary for the technic of mapping, where each measurement must be located on a map. They are never used alone, but in collaboration with other sensors.

The most important sensor of the kind is the Global Navigation Satellite System (GNSS), also known as Global Navigation System (GPS). The GNSS receiver measures the coordinates of the earth at the point of measurement. The error of the sensor can be 1 to 10 meters, but it can be diminished to less than 30 cm with the correlation of ground bases using the Real Time Kinematic (RTK) or the Post Process Kinematic (PPK) technic. Basic principle of function is the distance measurement from three satellites and subsequently the triangularization. However, due to heterogeneity of the atmosphere, satellites’ signal time travel is not constant, thus ground bases with known coordinates are used to eliminate that error. A noticeable disadvantage of the GNSS is that sometimes it provides inaccurate data or it doesn’t provide any data at all. This anomaly occurs because at some zones the sensor cannot receive the signal from the satellite or it does not receive it directly, thus estimates another position. These zones are called dead zones. Dead zones may occur when obstacles (like large trees or greenhouses) cover the signal. [11][12][13][14]

Other sensors are the Inertial measurement unit (IMU) and odometer. The IMU is a combination of an accelerometer, a gyroscope, magnetometer. The IMU will provide information about the location of the platform based on the previous location using the dead reckoning processes. IMU doesn’t get any information from the external environment and it is a reliable sensor for a small period of time, but it suffers from the accumulated error, so it is usually used in combination with the GNSS to augment the precision and cover the dead zones. The odometer measures the traveled distance of a ground vehicle. Due to the uneven and muddy terrain odometer usually provide inaccurate results, thus it should be always used in collaboration with an IMU. Localization can also be done visually with the use of cameras and the triangularization technic. Visual localization can substitute the GNSS, but it relies heavily on illumination and external features of the surrounding environment.[15][16][17]

Finally, sonar, lidar, and radar are sensors that are used for both purposes: localization and useful features of the crop. These sensors can measure the distance from an obstacle, something that is very useful for the localization and mapping process. Also, they can be used to measure the canopy size of the plants. Especially for the lidar, due to the fact that different types of foliage have different reflecting properties, it can provide information about the plants' species. Radar can also provide some information about the reflected surface, especially when dual polarization is used, because harsh type of soil and generally complicated surfaces change the polarization when reflect the radar signal. [18][19]

3 CHAPTER 3: PLATFORMS

Sensors cannot work alone, but they have to be placed on platforms in order to have energy and the right position for a measurement. Platforms also can handle the sensors' output by storing it or sending it directly away via telecommunications. Each platform has its own features and the selection of the right one depends on the task that we want to accomplish. As with every hardware component, platforms are subjected to acquiring and maintaining costs constrains. The majority of them are manufactured by companies and ready to use, but sometimes we need intervene to make the platform suitable for our purpose. In case of an intervene, we have to pay attention to the payload, the required input-output gates, the required energy and generally with the compatibility of the platform with the sensors and the actuators. Of course, safety issues arise since we deal with heavy moving objects. Some of the most used platforms are the following:

Satellite: Satellites are machines that orbit around the earth at a long distance. They can be divided by their orbital plane and by their distance from earth. Some satellites are free to use, but the ones with the higher performance come with a fee. The price of the data depends on the size of the area of interest. When equipped with cameras they take images of the earth that can be used in smart farming. Usually, each satellite is equipped with many types of cameras (panchromatic, multispectral) with various spectral and spatial resolutions for a variety of tasks. Satellites' spatial resolution is generally low and it slightly depends on the angle between the nadir and the view, closer to the nadir the resolution is higher. A typical resolution may vary from 10 meters to less than a meter, with panchromatic cameras having higher resolution. For example, the satellite "WorldView 2", which is one of the most efficient, has 50cm panchromatic resolution at nadir, 52cm at 20° off nadir, and for the multispectral camera (8 bands) 1.84m and 2.4m respectively. Despite their low spatial resolution, they have ultimate spatial distribution, making them suitable for large crops or case studies. Another issue is the low temporal resolution making them unsuitable for many agricultural activities. The temporal resolution depends on the location of the area of interest and the desired spatial resolution (which depends on the nadir-view angle), data with small nadir-view angle are rarer. Some companies send many identical satellites at the same orbit at different phase to increase the temporal resolution. Farmers on the other hand can get data from many satellites for a specific area in order to have more frequent data. As an example, for the above-mentioned satellite the revisit frequency is 3.7 days for data at 20° off nadir or less, and 1.1 days for data with spatial resolution of 1m or less, which is one of the highest temporal resolutions to be found for SF applications. Apart from the low temporal resolution, satellites are also very vulnerable to weather conditions, especially clouds, thus some data may be useless. For this reason, applications with satellites where the sky is usually cloudy should be avoided. Some satellites are equipped with radars providing radar images, which are immune to weather conditions, but of course have lower resolution due to lower radar's frequencies. Radar imaging can provide information not only by the quantity of the reflected signal, but also by the polarization of the signal. Data from satellites require less data preprocessing, while some companies provide directly the vegetation indexes instead of the raw data. Apart from the data costs, if any, there is no need for hardware maintenance, making satellites a very practical platform. [20][21][45][57]

Unmanned Aerial Vehicle (UAV) or Unmanned Aerial System (UAS): UAVs are flying robots that are controlled from the ground or have a predefined fly route. Based on their aerodynamics, they are divided into fixed-wing, rotary-wing, and hybrid. Rotary-wings are more stable and more flexible (they are omnidirectional) making them suitable for detailed inspection.

While fixed wing ones have higher speed and endurance, which is ideal for large areas. UAVs can also be divided by their weight with different regulation for each category. When UAVs are used for agricultural purposes, they are usually equipped with cameras and more rarely with LiDAR (apart from secondary sensors that are used to locate the vehicle in space and avoid obstacles, like sonar, GNSS etc.). Theoretically, spatial and temporal resolution of UAV's is close to infinity, because spatial resolution can be augmented by flying the vehicle lower, while flying it more often augments the temporal. Of course, both of these technics also augment the cost in time and energy, but nevertheless UAVs are considered to have higher spatial and temporal resolution than satellites. Like satellites, UAVs are also affected by weather conditions. Strong wings and extreme temperatures (both high and low) can diminish flying performance or even prohibit flight. Heavy precipitation, apart from the effect on the flight, can affect the sensors' reliability. Acquiring and maintaining a UAV has a significant cost and also requires a trained and licensed operator to handle it, making it unprofitable for very small-scale farmers. Data from a UAV requires higher data preprocessing, compared to satellites, due to the fact that data are gathered from many points whose location is not a priori known. UAVs are also restricted by law regulations for safety and privacy purposes. UAVs can also be equipped with actuators, usually for spraying liquids (herbicides, pesticides) or fine material (seed, fertilizer), which make them very useful at approaching places that are hard to access, but with the limitation of low payload. [22][23][24]

[47] Rotary wing UAV with a tank that can spray liquids.

Tractors: Tractors are wheeled vehicles that are used for agricultural purposes. Traditionally they were guided by a human, but with the development of autonomous diving the unmanned and the semi-autonomous type has emerged. Autonomous driving in the field has to cope with other challenges compared to flying vehicles. The surface of earth has plenty of obstacles, which makes path planning a remarkable problem in many cases. Even the cultivated plants can be obstacles depending on the type and stage of the crop, as a consequence the decision to use tractors may affect the way plants are planted. In addition to that, the turning radius of the vehicle may be unsuitable for some routes. Tracking is generally not a problem due to slow speed and robustness to weather conditions, although the grip of the tires varies with the soil moisture and the type of soil. Localization any many cases cannot be based completely on GNNS due to the fact that signal may be blocked, especially in green houses. To overcome this problem various sensors are used (e.g., cameras, sonars etc.) but all these have to deal with the seasonal change of the plants and the terrain on the one side, and on the other with the restricted field of view. Despite all these obstacles, it is worth mentioning that autonomous tractors were one of the first autonomous vehicles that were used, which means that in some circumstances (open fields with no obstacles) it can be relatively easy to accomplish. Tractors, due to their proximity to the plants, their stability, and their high payload, can be equipped with a larger variety of sensors compared with UAVs. As an example, tractors can be equipped with sensors that measure the electrical conductivity of the soil while they are moving, which means that, even though the sensor measures at a single point, when implemented to the tractor they gain spatial distribution. Also, tractors can be equipped with a wider variety of actuators which can perform various actions on the crop. A noticeable example, in some types of crops, is harvesting, whose yield can then be measured (either the volume or the weight) and used as label data. Tractors' low speed and plethora of capabilities created the need for interconnectivity between a group of tractors in order to decrease the working time. Apart from the obvious tasks that emerge in the engineering domain, interconnecting a number of tractors creates problems in the legal domain, in case many companies contribute to whole project (and an accident takes place). [25][26]

[48] An autonomous and a semi-autonomous (there is no driver to the blue tractor) collaborating.

[49] A sensor that measures the electrical conductivity of the soil while the tractor is moving.

Ground stations: Ground stations are fixed on a specific point on the crop and all the measurements are done at that point. Some prefabricated ones exist in the market, but it not rare to find hand-made stations by the researchers for a specific task. Ground station main component is an embedded device, which is connected to all the sensors and the actuators. The selection of the right embedded device depends on the number and the type (digital or analog) of inputs and outputs, the memory, the microcontroller, the transceiver, and mainly the energy consumption. Of course, the embedded device has to be protected by the environmental conditions. The energy can be provided from solar panels and stored in batteries. The fact that they don't move means that they cannot provide any spatial distribution along the surface of the earth, but they can get measurements from the deeper layers of the earth. If they are connected with a central computer they can provide live data constantly, meaning that they have practically unlimited temporal distribution and resolution. Ground stations have the advantage that they can be equipped with sensors that need time to get an accurate measurement. Of course, if the project aims at higher precision, then many ground station should be placed to augment the spatial resolution, but as a consequence the sensors' prize becomes a remarkable constraint because each sensor must be purchased multiple times. [27]

[50] A ground station.

4 CHAPTER 4: COMMUNICATION

There are some applications of SF where a single platform gets the data, process them, and acts on the crop in real time. An example is a tractor equipped with a camera and based on the reflected radiation and an index it fertilizes directly if needed. Usually, data must be transferred and stored to a central computer or to a cloud computer, either because the processing power of the platform is not adequate or because interoperability will be applied or because the farmer must take the final decision. Data transferring is also required if commands are sent from the central computer to actuators. When engineers evaluate which technology will be used for data transferring, they have to consider many parameters. Data rate, energy consumption, range, scalability, robustness, payload, latency, directionality (unidirectional or bidirectional), implementation costs, and security to name a few. Data transferring can be categorized into three main categories: by wire, manually after being stored to a memory card, and wireless.

By wire communication is a very robust, safe, and fast way of data transferring but it cannot be applied to moving platforms and the placement of a wire in the field creates obvious problems. Saving data directly to a memory card provides almost the same advantages as by wire connection, but it can also be applied to moving platforms. The major disadvantage is that human intervention is required for transferring so no real time data can be provided. UAVs are usually equipped with them since cameras require huge data flow and there is presence of a UAV operator to remove manually the card. Memory cards can also be used supplementary with wireless communication for data saving in case of disconnection.

Wireless communication is based on radio waves. The connected devices have a transmitter and a receiver (or a transceiver), for emitting signals to send data and receiving signals to get data. The transmitter encodes information by shifting the frequency, the amplitude or the phase of the signal based on a protocol. There is a variety of technologies for wireless communication with a wide range of characteristics. The range of wireless communication can range from less than 10 meters, in the Bluetooth technology for example, to hundreds of meters, such as cellular networks. Similar variations can be found in other features like energy consumption or data rate. For agricultural purposes the category of technologies that drew more attention to the research is the Low-power wide area network (LPWAN). The two advantages of this type of technologies, which are the low power consumption and the wide range, are suitable for agriculture since energy from the node usually comes from batteries, there is need for communication for long period of time, and the fields cover a large area. Meanwhile, LPWAN technologies, in order to achieve the aforementioned levels of communication, lag in terms of data rate, which is a deficiency that can be tolerated by many SF applications. Some common LPWAN technologies are: Long Range Wide Area Network (LoRaWAN), Narrow-Band IoT (NB-IoT) and Sigfox. Wireless communication emerges new challenges that are not present in the other forms of communication. Wireless communication performance is affected by harsh environmental factors, like temperature, humidity, and rainfall. Also, plant growth, greenhouses and any other obstacle can diminish the communication range in manner that varies in time. Interference between the devices may occur since interoperability among devices that operate in the same band is common, creating the need for more robust communication. Like any other IoT application, cyber security issues emerge, which makes state level or any other extremely large application forbidden due to possible agroterrorism attacks that could lead to famine. State laws on radio frequency regulations also must be considered because some frequencies are under license and require payment or are forbidden to use, and it should be mentioned that these regulations vary from state to state. [28][29][30]

Data may not be transferred directly to the computer which they will be processed, but usually passthrough networking devices such as bridges and gateways. In this case we can combine various communication technics and exploit the advantages of each one. Also, possible physical obstacles that make difficult the communication between two nodes can be overcome. Networking devices cannot be necessary fixed, as exact obstacles vary on a crop, for example in case of disconnection of some nodes in remote areas a UAV can be used to gather data from the nodes. Of course, topology problems arise and occasions where a device stops working or lose connection should be considered.

Then data are transferred to a local computer or to a cloud for final processing and storage. The cloud requires internet connection, but this is usually granted due to the advantages that it could offer to the whole project. Connection to the internet can provide data from meteorological stations, satellites and any other data that is not accessible from the crop. In addition, data can be transmitted to all the farmer's end devices (e.g., phone) and commands in real time can be sent in case where actuators are implementer to the project. Cloud computing requires less energy for processing, which in many cases is not abundant in the vicinity of a crop. Combining the fact that cloud computing costs less, it is usually preferred as an option. [31]

5 CHAPTER 5: DATA PREPROCESSING

Before the application or the training of an AI model, data preprocessing is required. Data from sensors are never ready to fit to a model either due to some malfunction of the sensor or due to data's feature (e.g., type, shape, dimension). The first type of preprocessing technic is data cleaning. Sensors may send noisy data (inaccurate, useless or redundant data) or don't send any data at all for a period of time. This may happen due to loss of connection, interruption of power supply or a sensors' reconfiguration that follows the interruption, weather conditions (especially clouds for satellites). There is not a universal way of dealing with missing and noisy values, the engineer has to use his intuition and based on the nature of the phenomenon that was measured, the way which varies in space and time, and the accurate values that possesses he can substitute the values. An average, a mean or a most common value can be used from previous and following measurements of the same sensor, or measurements from neighbor sensors can be used with bi-linear interpolation technic to fill the missing values and substitute the extreme ones. For higher accuracy, complex models that are designed for that purpose can be used. Then a smoothing process can be applied to remove noise. The technics for smoothing are common as with other AI applications.

Unless the data are processed and an action is directly taken, the processing of mapping is necessary. During this process the engineer has to locate each measurement on a map of the field, this can be done by knowing the exact place that it was taken for the sensors that measure in contact and for those that measure in distance the point where the measurement is referred, in case of sensors with spatial resolution this process must be done for each element (e.g., pixel). The location of the platform in open fields can be found with the use of GNSS and the sensors that are mentioned in the corresponding chapter, while in some green houses where GNSS is denied or inaccurate, fix points can be used as place of reference and through triangulation the location can be found. Once the location of the platform is known, sensors that measure in contact can be locate directly, while for sensors that measure in distance the direction of the sensors is required. In the case of cameras, the distance from the emitting source, the resolution and the field of view are required to associate each pixel with the corresponding space. When the camera is equipped to a moving platform, there is an overlapping area between the images, not only for being sure that the whole area is covered, but also for associating with the neighbor pictures and making more accurate localizations, resulting in a very high overlap area (90% in some cases). Fix points of reference with known coordinates can also be used for higher precision.

Some data do not provide any important information unless some features are extracted. A noticeable example in the Smart Farming domain is the reflected radiation from the plants. The reason why reflected radiation need extra preprocessing is because it strongly depends on the intensity of the incident light, which is completely independent from the plant status. To overcome this problem, Vegetations Indexes (VI) are applied. VI is a formula that combines at least two spectral bands of the reflected (or emitted) waves. By combining two spectral bands, the reflected quantity of one band can be calculated in proportion of the other, in this way we can estimate the quantity of molecules that absorb only one of the two mentioned bands, theoretically independent from the solar radiation. Of course, the bands are chosen in a way which one is absorbed by the molecule that we want to estimate and other is not. There are many VIs of whom the most famous is the NDVI (Normalized Difference Vegetation Index) with the formula: $(NIR - RED)/(NIR + RED)$ which estimates the quantity of chlorophyll in plants, since chlorophyll reflects the NIR but absorbs the RED. The right selection of which Index to use depends on a series of questions. Firstly, the engineer has to decide what does he want to measure. For example, as said before NDVI is for the levels of chlorophyll, meanwhile for measuring the crop water stress conditions the Crop Water Stress Index (CWSI) is suitable. The right decision should also be based on the type of crop, the growing stage, and the background (exposed soil). Even though VIs shouldn't be affected by the solar conditions, in practice, intensity, zenith angle and proportion of diffused light affects the VIs, with some of them being more robust to changes. Another deficiency that has to be taken into account when selecting an index is the saturation, after a certain threshold VIs stop being sensitive to variations of the molecule that are meant be sensitive at. Lasty, each vegetation index varies differently in variation of the under-measurement molecule, making some indexes more sensitive to a specific range. [22][32][33]

Another form of preprocessing, that cameras usually are submitted, is dimensionality reduction, in case of cameras it can be called more accurately spectral reduction. It is very common in multi or hyper spectral cameras. In open fields, the atmosphere absorbs some frequencies, thus measuring those is pointless and augments the complexity of the project. Furthermore, some frequencies behave the same to all classes of data, thus they have little to no variation and they don't provide any data. The technics for reducing the dimensions that are used in agriculture are similar to other applications of AI.

Data from different sources have various spatial and temporal resolutions. In order to find a correlation, data must be formed in a way that they will refer to the same time and space, in other words data must have the same resolution. An engineer can augment or diminish the data's resolution with various ways to deal with that problem, with an augmentation in the error when the resolution is augmented of course. The final data's resolution, both temporal and spatial, should be high enough to deal with the task we want, but not higher because it will add useless complexity, and of course should be close to the resolution of the raw data. For example, a weed monitoring system would require high spatial and low temporal resolution (e.g., $100cm^2$ and 3 days) since weed development is slow, while an auto irrigation system would be the contrary. As with data cleaning, there is not a universal way to change the resolution of a type of data. In the case of augmentation, the technics are similar to the ones in the case of missing values. For augmenting the spatial resolution, data from neighbor sensors should be used to evaluate the true value with technics like the weighted mean, the bipolarization technic, the value of the closest sensor or some other technic. The same thing must be done for the temporal resolution with the use of previous and following measurements. While in case of degradation of the resolution a mean can be used or a more complicated model that extracts higher level of information. In both cases, perception of the natural phenomenon is needed and knowledge of how this varies in the time-space domain, e.g., an evaluation of temperature at a specific time should be based on measurements that were taken at similar hours of the day with similar weather conditions. [34][35]

6 CHAPTER 6: MODELS

After the preprocessing the data are ready to fit in a model. Various machine learning algorithms have been used for agricultural purposes, both in simple machine learning and in the deep learning domain, but also traditional AI technics. Generally deep learning achieves higher accuracy than the other technics, but it is not always the most preferred. There are some technical purposes why someone would avoid complex models, which are the limited or absolute absence of data for training, lower computational time and power, and ease of implementation. Simpler AI models are also used because they are white boxes, which means they are transparent on how they come to their conclusions. Using a white box is very important when the role of the model is advisory and the final decision will be taken by a farmer, this can take place in agriculture when a decisive importance decision must be taken, e.g., the selection of pesticide, which could be harmful if consumed. [36][37]

Some tasks require high complexity that cannot be dealt with traditional AI. In this case Deep Learning (DL) is used. Various DL models exist with different characteristics. In order to select the right one, the engineer has to understand the nature of the problem that he is dealing with and how it depends on other factors. For time sequence, which is very common in agriculture, RNNs are preferred, while for image recognition a CNN should be used. The major disadvantage of DL is that it requires a significant amount of data for training. At this point, it should be mentioned that the input data could derive from four sources: from the sensors on the crop, from the internet, manually uploaded by the farmer, and from another model. In case a machine learning model is used, some labeled data are needed for training, which can be derived from all the above-mentioned sources, whom I want to emphasize the internet, where public datasets are available which can tackle the training problem. Usually, many models are used for the same task and are evaluated with various metrics for the right one to be found, since the cost of implementing a model is minimal. [38]

Even though it not so common, some applications make use of unsupervised learning. Unsupervised learning can be used for extracting information about variations in climate, in crop features, or in the agricultural activities. This information can be very useful when is represented to an expert. Unsupervised learning is also used for detecting and predicting animals' health problems and pathogenic bacteria in food products. An advantage that unsupervised learning has compared with other supervised learning technics is that farmers and breeders, probably unconsciously, make the data unpresentable due to bias towards the better ones. [39][40][41][42]

As mentioned before, input data may derive from other model's outputs. The combination of many models was mentioned in the data cleaning and in the equation of the data's spatial- temporal resolution. By using many models, we can exploit the advantages of each one. Of course, it is not mandatory to input all the data to a model and subsequently to another. Some data can be inputted to a model to extract useful information which will be inputted with other raw data to another model and get the final result. In this way we can make complex architectures of models. [51]

Finally, data and results must be represented to the farmer. Representation of the overall situation is obligatory when the final decision is made by the farmer, but it is also recommended in all cases because it is important for the farmer to supervise the crop and intervene if necessary.

There are also premade applications (smart apps) that are available on the internet which can be installed on a smartphone. These applications can deal with various tasks, from the preprocessing to the model implementation, but also hardware associated tasks like route planning. They can also provide general information about our crops, recommendations, and everything else we can imagine. Usually, they have a very good machine-human interface making them very easy to use. Some of them get all data from the internet, meaning they require no hardware to work, which makes them even easier to use. A typical data source from the internet are weather stations, which are used for improving and predicting the final product. But a lot of attention is drawn to applications which are used for selling the final product due to the fact that these increase the profit noticeably and are very easy to use. For example, there are application which work like social networks, whose purpose is to bring in contact sellers and buyers based on the location where they live and the product. [43][44]

7 CHAPTER 7: USE CASE: ORANGE OBJECT DETECTION

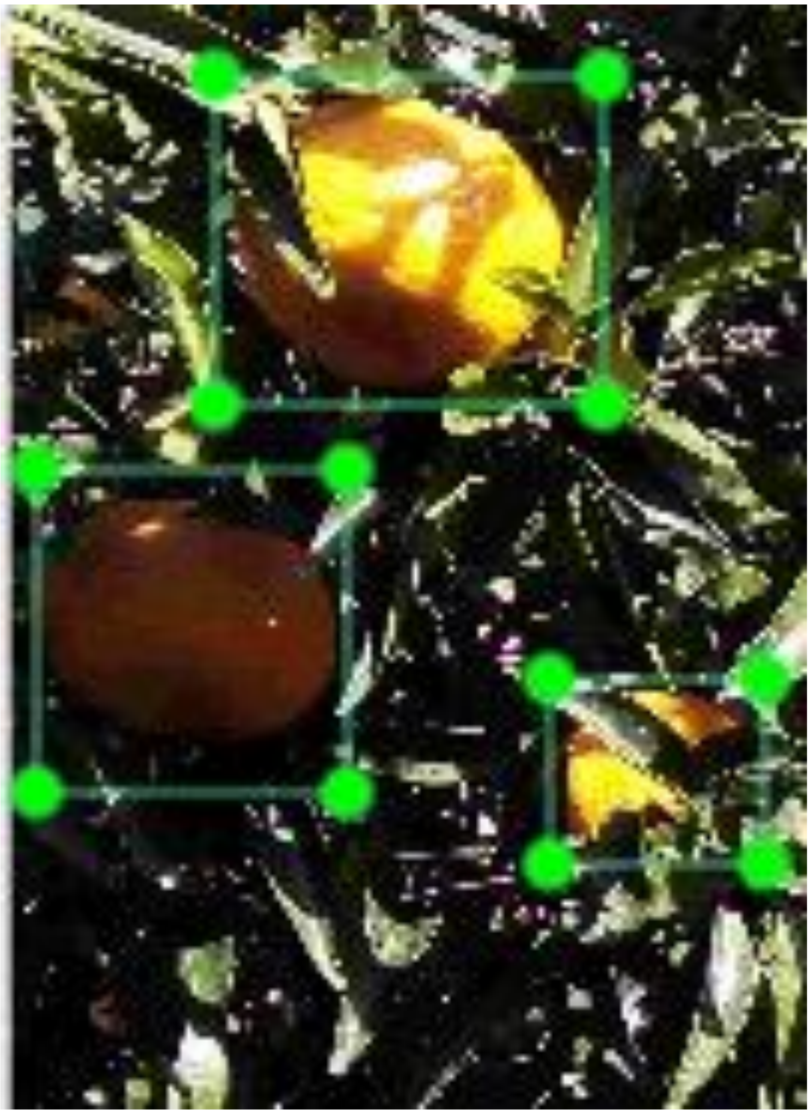
Harvesting is a time and energy consuming task. Various technics have been invented to decrease the costs and the labor time. Towards this direction, SF applications exist that are meant to collect fruits from the trees. For implementing an actuator to pick fruits the localization of the fruit is required. This can be done with object detection. Object detection is a computer vision technic that recognizes and localizes certain classes in the image.

Since object detection belongs to the supervised learning, a labeled dataset is required for training the model. I collected images of orange trees with fruits on them, which I used as training data.


I collected 49 images of which 32 were used for training and 17 for test. The total number of images is not very large, but there are many oranges in every image and the model that I used is pretrained. Also, there were used some data augmentation technics. The dimensions of the raw images are 3120x4208. The size of the raw images is between 4.000KB and 9.000KB, which was very big for the available RAM, so quality reduction was applied and the size of the new images fall between 400KB and 1.000KB maintaining the same resolution. A zoomed picture before and after the quality reduction is shown below:

The next step is the image labeling. For annotating the images, I used a module named labelImg [52]. Labeling an image for object detection means that the coordinates of the bounding boxes and the classes of the objects that are present in the image are annotated. In our case there is only one class. In case of oranges and generally for fruits, labeling is not a banal process. The foliage may cover any percentage of the fruit, creating the dilemma of which fruits should be labeled. Labeling fruits that are barely seen or not labeling a fruit that it can be seen clearly, would create a bad dataset which will confuse the model. Similar problems I encountered with the reflected light, some oranges were under the shadow causing their color to be closer to the leaf's color than the one of the other oranges. Lastly, the distance of the fruit created similar dilemmas, since the further it is located the smaller it looks.

An annotated image.



Three fruits can be seen. The top one should be undoubtedly annotated. While one is very dark and the other is mostly covered.

The model training was done in a “google research colab” [53] based on the “tensorflow object detection api tutorial” [54] with the help of this example [55]. I used the transfer learning technic, which means that I use a pre-trained model and I adapt it to my dataset. I tested on two models which I got from “TensorFlow 2 Detection Model Zoo” [56]. The two models are the “SSD ResNet101 V1 FPN 640x640 (RetinaNet101)” and the “EfficientDet D1 640x640”. Both models output boxes which is a necessary condition for object detection. These two models change the resolution of the input image to 640x640, which I found after I testing to some images that it is a resolution that the oranges can be seen clearly, thus higher complexity would probably be useless. Also, at lower resolutions(320x320) some oranges could hardly be distinguished by the human eye. Finally, these models have good speed, and amongst the highest accuracies at this resolution. The first one has a speed of 57ms and accuracy of 35.6%, which makes it the third best in terms of accuracy, while the second model achieved 54ms in speed and 38.4% in accuracy, hence making it the best in the list. At this resolution, the second best accuracy is succeeded by the “Faster R-CNN Inception ResNet V2 640x640” which is 37.7%, but with a noticeably lower speed of 206ms, thus I did not choose it. All the parameters of the model can be tuned from the pipeline that can be found on [54]. The losses that I achieved on the ResNet101 were:

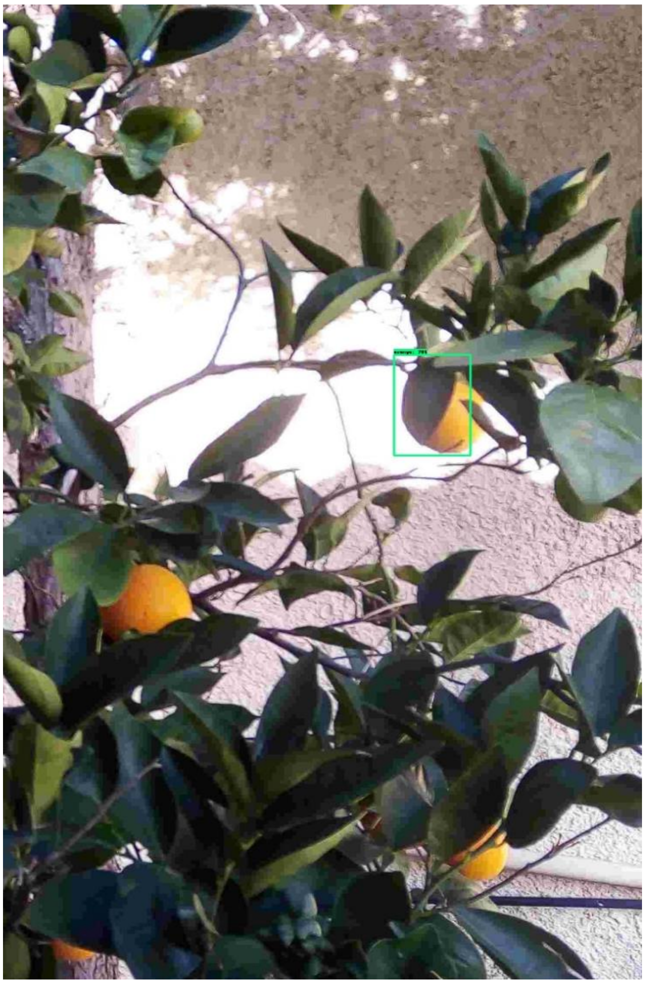
Num. of training steps	17,000	21,400
Classification loss	0.034605272	0.021624524
Localization loss	0.0036916514	0.0010708789
Regularization loss	0.19457465	0.037390664
Total loss	0.23287158	0.060086068

While the losses for the EfficientDet were:

Num. of training steps	13,000	15,000
Classification loss	0.06827974	0.034605272
Localization loss	0.0014643676	0.0036916514
Regularization loss	0.03541752	0.19457465
Total loss	0.10516163	0.23287158

The models were training for 4 to 5 hours each time. It can be seen from the ResNet101 that more training is required, but there were no processing units available.

Then, I tested the models at some of the images. At some of them the models were accurate even though they didn't manage to find all the oranges (high precision):



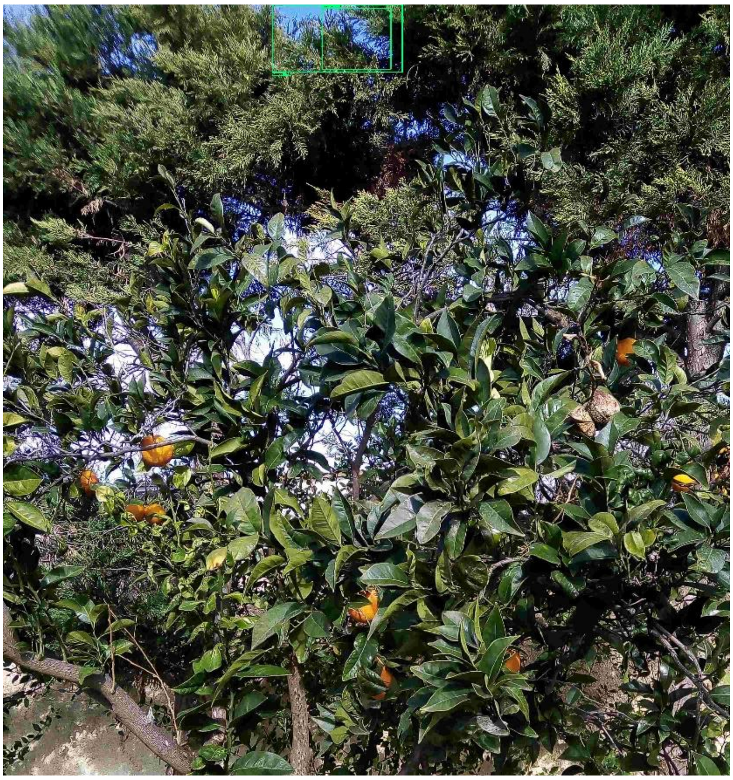
78% confidence

93% and 99% confidence

With some pictures the models did both accurate and inaccurate detections:

57% confidence for the leaf and 66% for the orange

While in some cases the models were completely inaccurate or did not make any prediction at all:



It detects the sky twice with confidence 59% and 79%

Finally, I retrained the EfficientDet D1 640x640 for 10,000 and 15,000 steps and evaluate the model on a metric function. The metrics that I used are the "coco detection metrics". This metric is used in the “Microsoft COCO challenge”. Also, it has been used numerous times and it is the dominant metric for object detection [58]. The primary metric function of the coco detection metrics is the Average Precision with IoU 0.50 to 0.95 with step 0.05, but it also calculates some other metrics, too. The full list of metrics and the results for both training steps is the following:

	IoU	Area	Max Detections	Training Steps: 10,000	Training Steps: 15,000
Average Precision	0.50:0.95	All	100	0.363	0.370
Average Precision	0.50	All	100	0.787	0.797
Average Precision	0.75	All	100	0.269	0.256
Average Precision	0.50:0.95	Medium	100	0.023	0.197
Average Precision	0.50:0.95	Large	100	0.378	0.376
Average Recall	0.50:0.95	All	1	0.089	0.092
Average Recall	0.50:0.95	All	10	0.383	0.385
Average Recall	0.50:0.95	All	100	0.469	0.459
Average Recall	0.50:0.95	Medium	100	0.375	0.325
Average Recall	0.50:0.95	Large	100	0.473	0.464

According to the primary metric (first row) the model did slightly better when it was trained for 15,000 steps (0.7% better), but with some other metrics the model did better with 10,000 training steps. The only metric that showed noticeable difference is the Average Precision with IoU 0.50:0.95 for Medium Area detections (fourth row), with the average precision increasing from 2,3% to 19,7%. This difference was probably caused because the majority of the objects in the data set are of medium size.

The code that I used in google colab is the following:

```
#Unzip the folder structure, the data, and the label map that I have
uploaded
!unzip /content/train_demo.zip -d /content

import tensorflow as tf
print(tf.__version__)

!git clone https://github.com/tensorflow/models.git

cd /content/models/research

!protoc object_detection/protos/*.proto --python_out=.

!git clone https://github.com/cocodataset/cocoapi.git

cd cocoapi/PythonAPI

!make

cp -r pycocotools /content/models/research

cd /content/models/research

cp object_detection/packages/tf2/setup.py .

!python -m pip install .

# A test that checks if everything is installed correctly
!python object_detection/builders/model_builder_tf2_test.py

cd /content/train_demo/pre-trained-models

#Downloads the SSD ResNet101 V1 FPN 640x640
#!wget
http://download.tensorflow.org/models/object_detection/tf2/20200711/ss
d_resnet101_v1_fpn_640x640_coco17_tpu-8.tar.gz

#Downloads the EfficientDet D1 640x640
!wget
http://download.tensorflow.org/models/object_detection/tf2/20200711/ef
ficientdet_d1_coco17_tpu-32.tar.gz

# Unzip the SSD ResNet101 V1 FPN 640x640
#!tar -xvf ssd_resnet101_v1_fpn_640x640_coco17_tpu-8.tar.gz

#Unzip the EfficientDet D1 640x640
!tar -xvf efficientdet_d1_coco17_tpu-32.tar.gz

cd /content/train_demo
```

```
# Transforms xml files to tfrecord
!python generate_tfrecord.py -x /content/train_demo/images/train -l
/content/train_demo/annotations/label_map.pbtxt -o
/content/train_demo/annotations/train.record
!python generate_tfrecord.py -x /content/train_demo/images/test -l
/content/train_demo/annotations/label_map.pbtxt -o
/content/train_demo/annotations/test.record

#Model training based on the pipeline's configurations
!python model_main_tf2.py --
model_dir=/content/train_demo/models/my_resnet101 --
pipeline_config_path=/content/train_demo/models/my_resnet101/pipeline.
config

#Coco Detection Metrics
!python model_main_tf2.py --
model_dir=/content/train_demo/models/my_resnet101 --
pipeline_config_path=/content/train_demo/models/my_resnet101/pipeline.
config --checkpoint_dir=/content/train_demo/models/my_resnet101

#Exporting the model for testing
!python exporter_main_v2.py --input_type image_tensor --
pipeline_config_path
/content/train_demo/models/my_resnet101/pipeline.config --
trained_checkpoint_dir /content/train_demo/models/my_resnet101 --
output_directory /content/train_demo/exported-models/my_model

#Testing the model on an image
import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'
import pathlib
import tensorflow as tf
import cv2
import argparse
from google.colab.patches import cv2_imshow
gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
    tf.config.experimental.set_memory_growth(gpu, True)
# Path to image directory
IMAGE_PATHS =
'/content/train_demo/images/train/IMG_20230114_123524.jpg'
# Path to the exported model directory
PATH_TO_MODEL_DIR = '/content/train_demo/exported-models/my_model'
# Path to label map
PATH_TO_LABELS = '/content/train_demo/annotations/label_map.pbtxt'
MIN_CONF_THRESH = float(0.60)
import time
from object_detection.utils import label_map_util
from object_detection.utils import visualization_utils as viz_utils
PATH_TO_SAVED_MODEL = PATH_TO_MODEL_DIR + "/saved_model"
print('Loading model...', end='')
start_time = time.time()
```

```
category_index =
label_map_util.create_category_index_from_labelmap(PATH_TO_LABELS,
use_display_name=True)
import numpy as np
from PIL import Image
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
def load_image_into_numpy_array(path):
    return np.array(Image.open(path))
print('Running inference for {}... '.format(IMAGE_PATHS), end='')
image = cv2.imread(IMAGE_PATHS)
image_rgb = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
image_expanded = np.expand_dims(image_rgb, axis=0)
input_tensor = tf.convert_to_tensor(image)
input_tensor = input_tensor[tf.newaxis, ...]
detections = detect_fn(input_tensor)
num_detections = int(detections.pop('num_detections'))
detections = {key: value[0, :num_detections].numpy()
               for key, value in detections.items()}
detections['num_detections'] = num_detections
detections['detection_classes'] =
detections['detection_classes'].astype(np.int64)
image_with_detections = image.copy()
# A threshold for the confidence of the prediction, predictions with
# confidence below the the threshold will not be shown
viz_utils.visualize_boxes_and_labels_on_image_array(
      image_with_detections,
      detections['detection_boxes'],
      detections['detection_classes'],
      detections['detection_scores'],
      category_index,
      use_normalized_coordinates=True,
      max_boxes_to_draw=200,
      min_score_thresh=0.5,
      agnostic_mode=False)
print('Done')
cv2_imshow(image_with_detections)
```

8 CONCLUSIONS

SM is the new agricultural era. Inevitably, in the future almost all farmers will have some form AI in their process due to the advantages that it offers, exactly like farmers intergraded fertilizers, tractors and other important technologies that introduced a new era. The main barriers for the incorporation of the SF technologies are the prerequisite knowledge, initial costs and data for training. From the side of the farmers there is also ignorance for the advantages of SF. On the other side, engineers who have the knowledge cannot easily make profit from it, because they cannot collaborate with farmers and consequently lacking of training data. These barriers are broken down for large scale farmers because the profits that these technologies offer to a single farm are high enough. Also, large farms have higher diversity, making PA even more efficient.

Of course, this does not mean that SF is useless for small farmers. The problem is that small farmers as individuals, both engineers and farmers, will not find any significant profit from adopting SF, if we count in the starting cost and the required time and effort. For this reason, in places where there are many small farmers, an institution could change the structure of the agricultural sector in order to adapt to the new era. An analogy of many farmers that collaborate with few engineers is a combination that could break the majority of barriers. The starting costs will decrease, since less hardware per application would require, for example, a single UAV could be used for many applications making this platform more cost efficient. The prerequisite knowledge would not be a problem because the engineers would need little training and would be few in number. Also, engineers would have access to a lot of data because they would collaborate with many farmers, these data would be more representative than those found on the internet since they would derive from the same area. Finally, if all these changes take place, the engineers and their applications would adapt to the farmers' problems and would make SF even more efficient.

Consequently, the society should establish and finance a team of engineers and urge farmers to collaborate with them. SF will not only benefit farmers with higher yields and lower inputs, but it will also reward the whole society due to the lower impact to the environment.

Bibliography – References – Online sources

[1] S. Fountas, and T. Gemtos, "Γενική Εισαγωγή Γεωργία Ακριβείας," In Γεωργία ακριβείας, Kallipos, Open Academic Editions, 2015 pp: 8-45. Accessed: Jan. 23, 2023 [Online]. Available: https://hdl.handle.net/11419/2670

[2] M. Mahajan and S. Kamalapur, "Spectral Imaging," International Journal of Modern Electronics and Communication Engineering (IJMECE), vol. 7, no. 1, pp. 144–148, Jan. 2019, Accessed: Jan. 23, 2023. [Online]. Available: https://www.researchgate.net/publication/334645235

[3] M. Eady, "Potential for spectral imaging applications on the small farm: a review," Journal of Spectral Imaging, Oct. 2022, doi: 10.1255/jsi.2022.a8.

[4] S. P. PANCHANGAM and V. N. A. NAIKAN, "RELIABILITY ANALYSIS OF TEMPERATURE SENSOR SYSTEM," International Journal of Reliability, Quality and Safety Engineering, vol. 20, no. 01, p. 1350003, Feb. 2013, doi: 10.1142/s0218539313500034.

[5] R. S. T. M. Sohn, "Understanding the Radiation Thermometers," Journal of Physics: Conference Series, vol. 1826, no. 1, p. 012031, Mar. 2021, doi: 10.1088/1742-6596/1826/1/012031.

[6] Z. Chen and C. Lu, "Humidity Sensors: A Review of Materials and Mechanisms," Sensor Letters, vol. 3, no. 4, pp. 274–295, Dec. 2005, doi: 10.1166/sl.2005.045.

[7] C.-Y. Lee and G.-B. Lee, "Humidity Sensors: A Review," Sensor Letters, vol. 3, no. 1, pp. 1–15, Jan. 2005, doi: 10.1166/sl.2005.001.

[8] H. Farahani, R. Wagiran, and M. N. Hamidon, "Humidity Sensors Principle, Mechanism, and Fabrication Technologies: A Comprehensive Review," Sensors (Basel, Switzerland), vol. 14, no. 5, pp. 7881–7939, Apr. 2014, doi: 10.3390/s140507881.

[9] A. Garg, P. Munoth, and R. Goyal, "APPLICATION OF SOIL MOISTURE SENSORS IN AGRICULTURE: A REVIEW," in Proceedings of International Conference on Hydraulics, Water Resources and Coastal Engineering (Hydro2016), CWPRS, Dec. 2016, pp. 1662–1672.

[10] L. Yu et al., "Review of research progress on soil moisture sensor technology," International Journal of Agricultural and Biological Engineering, vol. 14, no. 3, pp. 32–42, 2021, doi: 10.25165/j.ijabe.20211404.6404.

[11] N. V. Nguyen, W. Cho, and K. Hayashi, "Performance evaluation of a typical low-cost multi-frequency multi-GNSS device for positioning and navigation in agriculture – Part 1: Static testing," Smart Agricultural Technology, vol. 1, p. 100004, Dec. 2021, doi: 10.1016/j.atech.2021.100004.

[12] N. V. Nguyen and W. Cho, "Performance Evaluation of a Typical Low-Cost Multi-Frequency Multi-GNSS Device for Positioning and Navigation in Agriculture—Part 2: Dynamic Testing," AgriEngineering, vol. 5, no. 1, pp. 127–140, Jan. 2023, doi: 10.3390/agriengineering5010008.

[13] J. Guo et al., "Multi-GNSS precise point positioning for precision agriculture," Precision Agriculture, vol. 19, no. 5, pp. 895–911, Mar. 2018, doi: 10.1007/s11119-018-9563-8.

[14] M. Hernández-Pajares et al., "Wide-Area GNSS Corrections for Precise Positioning and Navigation in Agriculture," Remote Sensing, vol. 14, no. 16, p. 3845, Aug. 2022, doi: 10.3390/rs14163845.

[15] N. Gu, F. Xing, and Z. You, "Visual/Inertial/GNSS Integrated Navigation System under GNSS Spoofing Attack," Remote Sensing, vol. 14, no. 23, p. 5975, Nov. 2022, doi: 10.3390/rs14235975.

[16] S. S. Mehta, T. F. Burks, and W. E. Dixon, "Vision-based localization of a wheeled mobile robot for greenhouse applications: A daisy-chaining approach," Computers and Electronics in Agriculture, vol. 63, no. 1, pp. 28–37, Aug. 2008, doi: 10.1016/j.compag.2008.01.013.

[17] A. Elamin, N. Abdelaziz, and A. El-Rabbany, "A GNSS/INS/LiDAR Integration Scheme for UAV-Based Navigation in GNSS-Challenging Environments," Sensors, vol. 22, no. 24, p. 9908, Jan. 2022, doi: 10.3390/s22249908.

[18] D. Ho Tong Minh et al., “Deep Recurrent Neural Networks for Winter Vegetation Quality Mapping via Multitemporal SAR Sentinel-1,” IEEE Geoscience and Remote Sensing Letters, vol. 15, no. 3, pp. 464–468, Mar. 2018, doi: 10.1109/lgrs.2018.2794581.

[19] W. D. Kissling et al., “Laserfarm – A high-throughput workflow for generating geospatial data products of ecosystem structure from airborne laser scanning point clouds,” Ecological Informatics, vol. 72, p. 101836, Dec. 2022, doi: 10.1016/j.ecoinf.2022.101836.

[20] N. Alahacoon and G. Amarnath, “Agricultural drought monitoring in Sri Lanka using multisource satellite data,” Advances in Space Research, vol. 69, no. 11, pp. 4078–4097, Jun. 2022, doi: 10.1016/j.asr.2022.03.009.

[21] M. Moradizadeh and P. K. Srivastava, “A new model for an improved AMSR2 satellite soil moisture retrieval over agricultural areas,” Computers and Electronics in Agriculture, vol. 186, p. 106205, Jul. 2021, doi: 10.1016/j.compag.2021.106205.

[22] S. Alexandris et al., “Integrating Drone Technology into an Innovative Agrometeorological Methodology for the Precise and Real-Time Estimation of Crop Water Requirements,” Hydrology, vol. 8, no. 3, p. 131, Sep. 2021, doi: 10.3390/hydrology8030131.

[23] “DJI Agriculture,” DJI. https://ag.dji.com/

[24] A. Kumar et al., “An innovative drones technology in agriculture: A review,” The Pharma Innovation Journal, pp. 279–286, Dec. 2022, Accessed: Jan. 30, 2023. [Online]. Available: https://www.researchgate.net/publication/365991586_An_innovative_drones_technology_in_agriculture_A_review

[25] M. Corno, S. Furioli, P. Cesana, and S. M. Savaresi, “Adaptive Ultrasound-Based Tractor Localization for Semi-Autonomous Vineyard Operations,” Agronomy, vol. 11, no. 2, p. 287, Feb. 2021, doi: 10.3390/agronomy11020287.

[26] A. A. Rodriguez et al., “Review of control on agricultural robot tractors,” International Journal of Combinatorial Optimization Problems and Informatics, vol. 11, no. 3, Dec. 2019, Accessed: Jan. 31, 2023. [Online]. Available: https://www.researchgate.net/publication/339787521_Review_of_control_on_agricultural_robot_tractors

[27] A. Tzounis, N. Katsoulas, T. Bartzanas, and C. Kittas, “Internet of Things in agriculture, recent advances and future challenges,” Biosystems Engineering, vol. 164, pp. 31–48, Dec. 2017, doi: 10.1016/j.biosystemseng.2017.09.007.

[28] H. Klaina et al., “Analysis of low power wide area network wireless technologies in smart agriculture for large-scale farm monitoring and tractor communications,” Measurement, vol. 187, p. 110231, Jan. 2022, doi: 10.1016/j.measurement.2021.110231.

[29] D. Glaroudis, A. Iossifides, and P. Chatzimisios, “Survey, Comparison and Research Challenges of IoT Application Protocols for Smart Farming,” Computer Networks, p. 107037, Nov. 2019, doi: 10.1016/j.comnet.2019.107037.

[30] N. Islam, B. Ray, and F. Pasandideh, “IoT Based Smart Farming: Are the LPWAN Technologies Suitable for Remote Communication?,” IEEE Xplore, Aug. 01, 2020. https://ieeexplore.ieee.org/document/9192008 (accessed May 04, 2022).

[31] C. Maraveas, D. Piromalis, K. G. Arvanitis, T. Bartzanas, and D. Loukatos, “Applications of IoT for optimized greenhouse environment and resources management,” Computers and Electronics in Agriculture, vol. 198, p. 106993, Jul. 2022, doi: https://doi.org/10.1016/j.compag.2022.106993.

[32] N. Hashimoto, Y. Saito, M. Maki, and K. Homma, “Simulation of Reflectance and Vegetation Indices for Unmanned Aerial Vehicle (UAV) Monitoring of Paddy Fields,” Remote Sensing, vol. 11, no. 18, p. 2119, Jan. 2019, doi: 10.3390/rs11182119.

[33] A. M.-M. Stoiconi and A. Neda, “THE USE OF VEGETATION INDICES IN THE CONTEXT OF PRECISION AGRICULTURE,” vol. 6, pp. 141–148, 2018, Accessed: Jan. 31, 2023. [Online]. Available: https://journalofyoungscientist.usamv.ro/pdf/vol_VI_2018/art22.pdf

[34] A. Camacho, E. Vargas, and H. Arguello, “Hyperspectral and multispectral image fusion addressing spectral variability by an augmented linear mixing model,” International Journal of Remote Sensing, vol. 43, no. 5, pp. 1577–1608, Mar. 2022, doi: 10.1080/01431161.2022.2041762.

[35] U. Shafi et al., “A Multi-Modal Approach for Crop Health Mapping Using Low Altitude Remote Sensing, Internet of Things (IoT) and Machine Learning,” IEEE Access, vol. 8, pp. 112708–112724, 2020, doi: 10.1109/access.2020.3002948.

[36] A. Sharma, A. Jain, P. Gupta, and V. Chowdary, “Machine Learning Applications for Precision Agriculture: A Comprehensive Review,” IEEE Access, vol. 9, pp. 4843–4873, 2021, doi: 10.1109/access.2020.3048415.

[37] S. K. S. Durai and M. D. Shamili, “Smart farming using Machine Learning and Deep Learning techniques,” Decision Analytics Journal, p. 100041, Apr. 2022, doi: 10.1016/j.dajour.2022.100041.

[38] A. Kamilaris and F. X. Prenafeta-Boldú, “Deep learning in agriculture: A survey,” Computers and Electronics in Agriculture, vol. 147, pp. 70–90, Apr. 2018, doi: 10.1016/j.compag.2018.02.016.

[39] A. Mercer and J. Dyer, “A Southeastern United States Warm Season Precipitation Climatology Using Unsupervised Learning,” Climate, vol. 11, no. 1, p. 2, Dec. 2022, doi: 10.3390/cli11010002.

[40] M. Eady and B. Park, “An Unsupervised Prediction Model for Salmonella Detection with Hyperspectral Microscopy: A Multi-Year Validation,” Applied Sciences, vol. 11, no. 3, p. 895, Jan. 2021, doi: 10.3390/app11030895.

[41] S. Franceschini, C. Grelet, J. Leblois, N. Gengler, and H. Soyeurt, “Can unsupervised learning methods applied to milk recording big data provide new insights into dairy cow health?,” Journal of Dairy Science, vol. 105, no. 8, pp. 6760–6772, Aug. 2022, doi: 10.3168/jds.2022-21975.

[42] Symeonaki, Arvanitis, and Piromalis, “A Context-Aware Middleware Cloud Approach for Integrating Precision Farming Facilities into the IoT toward Agriculture 4.0,” Applied Sciences, vol. 10, no. 3, p. 813, Jan. 2020, doi: https://doi.org/10.3390/app10030813.

[43] “precision agriculture - Android Apps on Google Play,” play.google.com. https://play.google.com/store/search?q=precision+agriculture&c=apps (accessed Feb. 01, 2023).

[44] “Top 7 Most Innovative Agriculture Apps,” BinarApps, Aug. 31, 2021. https://binarapps.com/top-7-most-innovative-agriculture-apps/ (accessed Feb. 01, 2023).

[45] S. Fountas, and T. Gemtos, “Παγκόσμια Συστήματα Προσδιορισμού Θέσης (GPS),” In Γεωργία ακριβείας, Kallipos, Open Academic Editions, 2015 pp: 45-54. Accessed: Jan. 23, 2023 [Online]. Available: https://hdl.handle.net/11419/2670

[46] P. Pridal, “Precision Agriculture with MapTiler | MapTiler,” www.maptiler.com. https://www.maptiler.com/news/2016/04/precision-agriculture-with-maptiler/ (accessed Feb. 04, 2023).

[47] “DJI introduces company's first Agriculture Drone,” DJI Official, 27-Nov-2015. [Online]. Available: https://www.dji.com/newsroom/news/dji-introduces-company-s-first-agriculture-drone. (Accessed: 04-Feb-2023).

[48] “Farming,” ASI. https://asirobots.com/farming

[49] “The Climate Corp. and Veris Technologies Partner for Improved Soil Data,” Seed World, Aug. 19, 2016. https://seedworld.com/climate-corp-veris-technologies-partner-improved-soil-data/ (accessed Feb. 04, 2023).

[50] “AgMemo March 2020,” www.agric.wa.gov.au. https://www.agric.wa.gov.au/newsletters/agmemo/agmemo-march-2020?page=0%2C5 (accessed Feb. 04, 2023).

[51] P. Benedetti, D. Ienco, R. Gaetano, K. Ose, R. G. Pensa, and S. Dupuy, “$M^3\text{Fusion}$: A Deep Learning Architecture for Multiscale Multimodal Multitemporal Satellite Data Fusion,” IEEE Journal of Selected

Topics in Applied Earth Observations and Remote Sensing, vol. 11, no. 12, pp. 4939–4949, Dec. 2018, doi: 10.1109/jstars.2018.2876357.

[52] T. Lin, "labelImg: LabelImg is a graphical image annotation tool and label object bounding boxes in images," PyPI. https://pypi.org/project/labelImg/1.4.0/

[53] Google, "Google Colaboratory," Google.com, 2019. https://colab.research.google.com/

[54] "TensorFlow 2 Object Detection API tutorial — TensorFlow 2 Object Detection API tutorial documentation," tensorflow-object-detection-api-tutorial.readthedocs.io. https://tensorflow-object-detection-api-tutorial.readthedocs.io/en/latest/

[55] "Google Colaboratory," colab.research.google.com. https://colab.research.google.com/drive/19ycUy5qIZKCO8tKy37f4zkUiHzgKs05I?usp=sharing

[56] "TensorFlow 2 Detection Model Zoo," GitHub. https://github.com/tensorflow/models/blob/master/research/object_detection/g3doc/tf2_detection_zoo.md

[57] "Satellite Maps, Satellite Imagery, GIS Data | Satellite Imaging Corp," Satimagingcorp.com, 2017. https://www.satimagingcorp.com/

[58] L. Google and F. Chollet Google, "Efficient Graph-Friendly COCO Metric Computation for Train-Time Model Evaluation." Accessed: Mar. 16, 2023. [Online]. Available: https://arxiv.org/pdf/2207.12120.pdf

[cover page] "CORDIS | European Commission," Europa.eu, 2020. https://cordis.europa.eu/article/id/413531-unleashing-the-full-potential-of-smart-agriculture