UNIVERSITY OF THESSALY

SCHOOL OF ENGINEERING

DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

DIPLOMA THESIS

Deep Learning and Drones in Precision Agriculture

Author:
George Iosifidis

Supervisor:
Dimitrios Katsaros, Associate Professor

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ΠΑΝΕΠΙΣΤΗΜΙΟ ΘΕΣΣΑΛΙΑΣ

ΠΟΛΥΤΕΧΝΙΚΗ ΣΧΟΛΗ

ΤΜΗΜΑ ΗΛΕΚΤΡΟΛΟΓΩΝ ΜΗΧΑΝΙΚΩΝ ΚΑΙ ΜΗΧΑΝΙΚΩΝ ΥΠΟΛΟΓΙΣΤΩΝ

Διπλωματική Εργασία

Βαθιά Μάθηση και Μη Επανδρωμένα Ιπτάμενα Οχήματα στην Γεωργία Ακριβείας

Γιώργος Ιωσηφίδης

Επιβλέπων: Δημήτριος Κατσαρός

Βόλος 2020

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ΥΠΕΥΘΥΝΗ ΔΗΛΩΣΗ ΠΕΡΙ ΑΚΑΔΗΜΑΪΚΗΣ ΔΕΟΝΤΟΛΟΓΙΑΣ ΚΑΙ ΠΝΕΥΜΑΤΙΚΩΝ ΔΙΚΑΙΩΜΑΤΩΝ

«Με πλήρη επίγνωση των συνεπειών του νόμου περί πνευματικών δικαιωμάτων, δηλώνω ρητά ότι η παρούσα διπλωματική εργασία, καθώς και τα ηλεκτρονικά αρχεία και πηγαίοι κώδικες που αναπτύχθηκαν ή τροποποιήθηκαν στα πλαίσια αυτής της εργασίας, αποτελεί αποκλειστικά προϊόν προσωπικής μου εργασίας, δεν προσβάλλει κάθε μορφής δικαιώματα διανοητικής ιδιοκτησίας, προσωπικότητας και προσωπικών δεδομένων τρίτων, δεν περιέχει έργα/εισφορές τρίτων για τα οποία απαιτείται άδεια των δημιουργών/δικαιούχων και δεν είναι προϊόν μερικής ή ολικής αντιγραφής, οι πηγές δε που χρησιμοποιήθηκαν περιορίζονται στις βιβλιογραφικές αναφορές και μόνον και πληρούν τους κανόνες της επιστημονικής παράθεσης. Τα σημεία όπου έχω χρησιμοποιήσει ιδέες, κείμενο, αρχεία ή/και πηγές άλλων συγγραφέων, αναφέρονται ευδιάκριτα στο κείμενο με την κατάλληλη παραπομπή και η σχετική αναφορά περιλαμβάνεται στο τμήμα των βιβλιογραφικών αναφορών με πλήρη περιγραφή. Αναλαμβάνω πλήρως, ατομικά και προσωπικά, όλες τις νομικές και διοικητικές συνέπειες που δύναται να προκύψουν στην περίπτωση κατά την οποία αποδειχθεί, διαχρονικά, ότι η εργασία αυτή ή τμήμα της δεν μου ανήκει διότι είναι προϊόν λογοκλοπής».

Ο/Η Δηλών/ούσα

(Υπογραφή)
Γιώργος Ιωσηφίδης
Ημερομηνία 10/2/2020

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Περίληψη

Σκοπός της παρούσας διπλωματικής εργασίας είναι η μελέτη και ανάλυση των εφαρμογών που μπορεί να έχουν οι αλγόριθμοι της τεχνητής νοημοσύνης και τα drones στην γεωργία. Αρχικά πραγματοποιήθηκε βιβλιογραφική διερεύνηση των αλγορίθμων Μηχανικής Μάθησης που χρησιμοποιούνται με την μεγαλύτερη συχνότητα στον συγκεκριμένο τομέα. Η θεωρητική παρουσίαση αφορά τους οκτώ αλγορίθμους με τις περισσότερες εφαρμογές, όπως προκύπτει από τα άρθρα που μελετήθηκαν.

Μετά την σύντομη παρουσίαση των αλγορίθμων, ακολουθεί η κατηγοριοποίηση των άρθρων σύμφωνα με τους τρεις βασικούς κλάδους της γεωργίας και τις επιμέρους υποκατηγορίες τους. Αρχικά παρουσιάζεται ο στόχος κάθε εργασίας και τα μοντέλα που χρησιμοποιήθηκαν για την επίτευξή του. Στη συνέχεια παρουσιάζονται τα αποτελέσματα των μοντέλων, τα κριτήρια αξιολόγησης των αλγορίθμων και η ακρίβεια που προκύπτει. Τέλος πραγματοποιείται στατιστική ανάλυση της συχνότητας χρήσης κάθε αλγορίθμου συγκριτικά με τους υπόλοιπους και βάσει των επιμέρους κλάδων.

Στη συνέχεια, πραγματοποιείται βιβλιογραφική διερεύνηση της χρήσης των drones στην γεωργία. Παρουσιάζονται οι βασικές εφαρμογές τους στους κλάδους της γεωργίας, τα προτερήματα της χρήσης τους και οι νέες προοπτικές που προσφέρουν. Στην ενότητα των drones, γίνεται επίσης μία σύντομη παρουσίαση των δημοφιλέστερων drones γεωργίας που είναι διαθέσιμα στην αγορά, μαζί με τα τεχνικά χαρακτηριστικά τους.

Τέλος παρουσιάζονται τρεις από τις πιο δημοφιλείς αρχιτεκτονικές νευρωνικών δικτύων στον τομέα της αναγνώρισης εικόνας και αφου εκπαιδευτούν στο ίδιο σύνολο αγροτικών δεδομένων παρατίθενται τα αντίστοιχα αποτελέσματά τους.

Abstract

The purpose of this diploma thesis is to study and analyze the applications that artificial intelligence algorithms and drone technology can have in agriculture. At first, a bibliographic search of the most frequently used Machine Learning algorithms was performed. The theoretical presentation regards the eight algorithms with the most applications based on the articles studied.

After briefly presenting the algorithms, the articles are categorized according to the three main branches of agriculture and their subcategories. Initially, the purpose of each task and the models used to achieve it are presented. Moreover, the results of the models, the performance criteria of the algorithms, and the resulting accuracy are presented as well. Finally, a statistical analysis of the frequency of appearance of each algorithm is performed relative to the rest and to the individual branches.

A bibliographical search of the use of drones in agriculture is carried out as well. Their main applications in the agricultural sector, their advantages as well as the new prospects they offer are presented. Also, in the drone section a brief introduction of the most popular farm drones available in the market is given, along with their technical features.

Finally, three of the most popular neural network architectures in the field of image recognition are presented, and after being trained in the same set of agricultural data their respective results are presented and compared.

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List of Abbreviations

Because of the large number of abbreviations used in the relative scientific works, **Tables 1–4** list the abbreviations that appear in this work, categorized to ML models, algorithms, statistical measures, and general abbreviations, respectively.

Table 1. Abbreviations for machine learning models.

Abbreviation	Model
ANNs	artificial neural networks
BM	bayesian models
DL	deep learning
DR	dimensionality reduction
DT	decision trees
EL	ensemble learning
IBM	instance based models
SVMs	support vector machines

Table 2. Abbreviations for machine learning algorithms.

Abbreviation	Algorithm
ANFIS	adaptive-neuro fuzzy inference systems
Bagging	bootstrap aggregating
BBN	bayesian belief network
BN	bayesian network
BPN	back-propagation network
CART	classification and regression trees
CHAID	chi-square automatic interaction detector
CNNs	convolutional neural networks
CP	counter propagation
DBM	deep boltzmann machine
DBN	deep belief network
DNN	deep neural networks
ELMs	extreme learning machines
EM	expectation maximisation
ENNs	ensemble neural networks
GNB	gaussian naive bayes
GRNN	generalized regression neural network
KNN	k-nearest neighbor
LDA	linear discriminant analysis

LS-SVM	least squares-support vector machine
LVQ	learning vector quantization
LWL	locally weighted learning
MARS	multivariate adaptive regression splines
MLP	multi-layer perceptron
MLR	multiple linear regression
MOG	mixture of gaussians
OLSR	ordinary least squares regression
PCA	principal component analysis
PLSR	partial least squares regression
RBFN	radial basis function networks
RF	random forest
SaE-ELM	self adaptive evolutionary-extreme learning machine
SKNs	supervised kohonen networks
SOMs	self-organising maps
SPA-SVM	successive projection algorithm-support vector machine
SVR	support vector regression

Table 3. Abbreviations for statistical measures for the validation of machine learning algorithms.

Abbreviation	Measure
APE	average prediction error
MABE	mean absolute bias error
MAE	mean absolute error
MAPE	mean absolute percentage error
MPE	mean percentage error
NS	nash-sutcliffe coefficient
R	radius
R^2	coefficient of determination
RMSE	root mean squared error
RMSEP	root mean square error of prediction
RPD	relative percentage difference
RRMSE	average relative root mean square error

Table 4. General Abbreviations.

Abbreviation	
AUS	aircraft unmanned system
Cd	cadmium
FBG	fiber bragg grating
HSV	hue saturation value color space

K	potassium
MC	moisture content
Mg	magnesium
ML	machine learning
NDVI	normalized difference vegetation index
NIR	near infrared
OC	organic carbon
Rb	rubidium
RGB	red green blue
TN	total nitrogen
UAV	unmanned aerial vehicle
VIS-NIR	visible-near infrared

Chapter 1

Introduction

1.1 Motivation

Agriculture has always been a crucial part of global economy. As human population continue expanding in a high rate, more pressure will be put on the agricultural system and the efficiency of its methods. Agriculture production systems have already benefited, throughout the history, from incorporating technological advantages primarily developed for other industries. The industrial age offered mechanization and synthesized fertilizers, while the technology age brought genetic engineering and automation to agriculture. Nowadays, the compelling need of increased production, as well as the reduction of consumed resources like water and fertilizers with respect to the environment, set the use of new techniques and methods as a first priority. The information age offers the opportunity for integrating the latest technological advances into precision agriculture (PA). For this reason it is of the utmost importance to understand how these new technologies work precisely, in order to integrate them optimally in agriculture and increase their effectiveness in the near future.

1.2 Introduction

Precision farming or agriculture, also termed as digital agriculture, has arisen as a new scientific field and is defined as an application of technologies and principles using information to manage spatial and temporal variability in order to increase the effectiveness of the resources and minimize environmental degradation. The data are

generated from a variety of different sensors. The sensors monitor the plants' state and their environment throughout the year, bringing the potential for a better understanding of the operational environment (an interaction of dynamic crop, soil, and weather conditions) and the operation itself (machinery data), leading to more accurate and faster decision making.

Machine and Deep Learning (ML/DL) has emerged along with big data technologies and high-performance computing to offer new ways of unravel and understand data intensive processes in agricultural operational environments. ML is defined, among other definitions, as the scientific field that gives machines the ability to learn without being strictly programmed.

The main focus of this thesis is to present a thorough review of ML/DL applications in agriculture. In addition, this work's aim extends to the examination of drone technology as a main source of agricultural data and monitoring option.

1.2 Thesis Structure

This thesis is divided in six chapters. The rest of this thesis is organised as follows:

Chapter 2 provides a brief overview of the machine learning models that are later used in the papers studied for ML agriculture applications in this work.

Chapter 3 presents a bibliographic investigation of the main categories of Precision Agriculture where ML models are applied. The models and techniques used are explained and their results are discussed and compared.

In Chapter 4, a comprehensive overview of UAV technology in agriculture provided. The benefits of this integration are presented along with the best agricultural UAVs available in the market to date.

Finally, Chapter 5 provides a brief presentation of three of the most known and state-of-the-art neural network architectures for image classification. AlexNet, GoogLetNet and ResNet are explained and then trained in an agricultural dataset consisted of plant diseases. The results are presented and compared.

Chapter 6 concludes this thesis by discussing the overall vision of this thesis about the future of agriculture and by presenting some directions for future work.

Chapter 2

Machine/Deep Learning Models Overview

2.1 Overview

Machine learning (ML) is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without using explicit instructions, relying on patterns and inference instead. Machine learning algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task. In most cases, an individual example is described by a set of attributes, also known as features or variables. A feature can be nominal (enumeration), binary (i.e., 0 or 1), ordinal (e.g., A+ or B−), or numeric (integer, real number, etc.). The performance of the ML model in a given task is measured by a performance metric which improves with experience over time. These metrics are statistical and mathematical models. **Figure 1.1** shows a typical ML procedure.

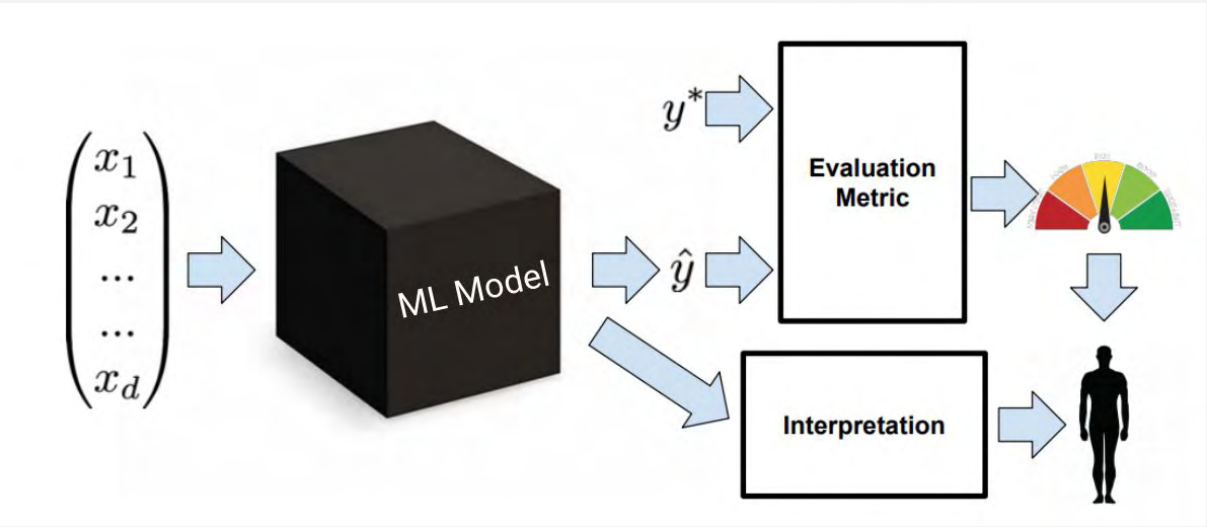

Figure 1. A typical ML procedure.

ML tasks are typically classified into different broad categories depending on the learning type (supervised, unsupervised and reinforced learning) and the learning model (classification, regression, clustering, and dimensionality reduction).

2.2 Machine Learning Tasks

While ML tasks are classified into several broad categories, two of them are considered the main ones: (i) supervised and (ii) unsupervised learning. In *supervised learning* the algorithm builds a mathematical model that maps inputs to outputs, from a set of data that contains both the inputs and the corresponding outputs. *Classification* and *regression* algorithms are typical examples of supervised learning. On the other hand, *unsupervised learning* algorithms try to construct a general input-output mapping rule from a set of unlabeled data. This type of learning is used to find structure/patterns in the data, like grouping or clustering of data points. Occasionally, algorithms develop mathematical models from incomplete training data, where a portion of the sample input doesn't have labels (*semi-supervised learning*) or are given feedback in the form of positive or negative reinforcement in a dynamic environment (*reinforced learning*). The latter are used in autonomous vehicles or in learning to play a game against a human opponent. **Figure 2** shows the three big learning categories and their respective models and tasks.

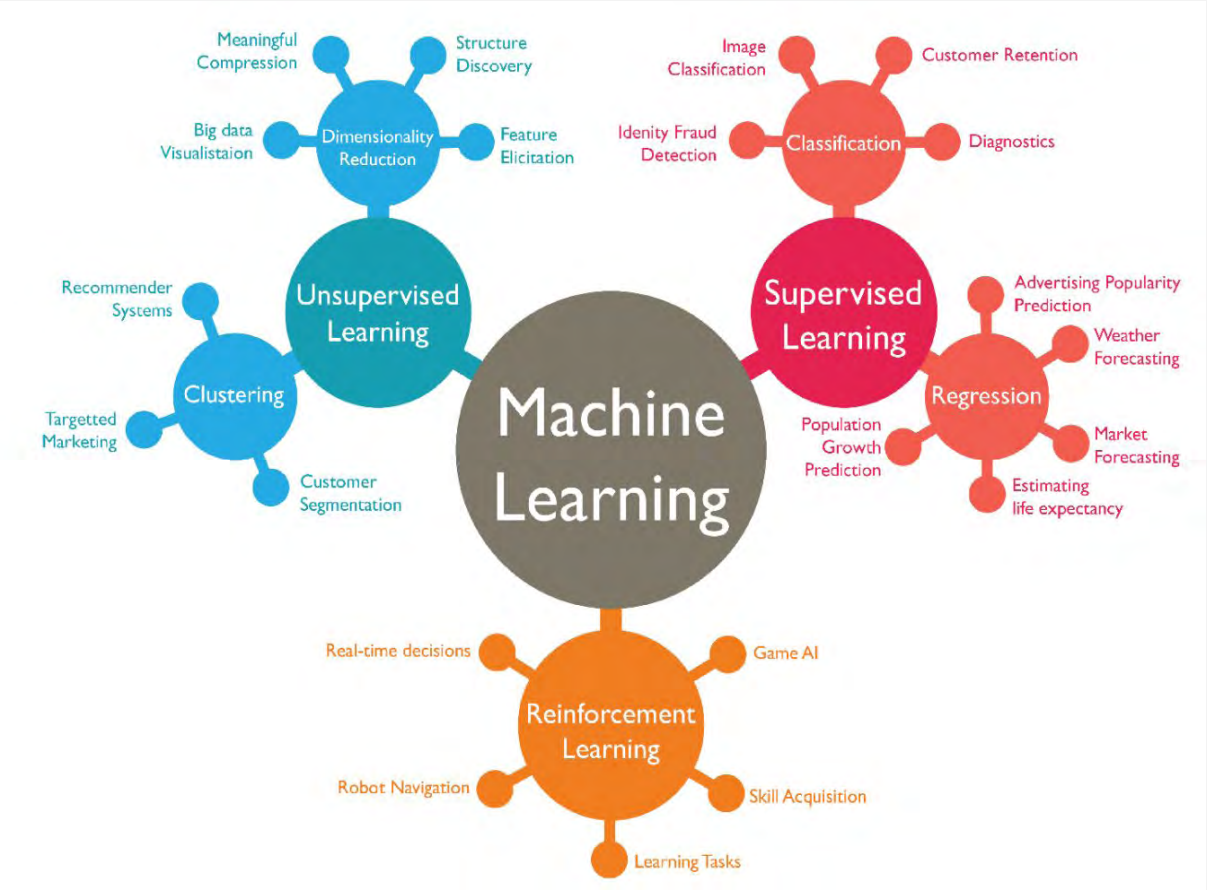

Figure 2. Types of ML tasks

2.3 Learning Analysis

Dimensionality reduction (DR) is the process of reducing the number of random variables by defining a set of principal variables. DR analysis is essential for both supervised and unsupervised algorithms and aims at providing a more solid, lower-dimensional representation of a dataset with focus on preserving as much information as possible from the original. Data analysis such as regression or classification can be done in the reduced space more accurately than in the original space. Some of the most commonly used DR algorithms for agricultural data analysis, according to the papers studied for this thesis, are the following: (i) principal component analysis (PCA), (ii) partial least squares regression, and (iii) linear discriminant analysis (LDA).

2.4 Learning Models

This section provides a comprehensive review of learning models in ML. The presentation of these models is limited to the ones that have been implemented in the reviewed works for this thesis.

2.4.1 Regression Analysis

Regression analysis which belongs to the supervised learning family of ML algorithms, is a set of statistical processes for estimating causal relationships between a dependent variable and one or more independent variables. Importantly, regressions by themselves only reveal relationships between a dependent variable and a collection of independent variables in a fixed dataset. Amongst the most common forms is linear regression, in which the goal is to find the line that most closely fits the data according to a specific mathematical criterion. Logistic as well as stepwise regression are also well known regression algorithms. This type of analysis is widely used for prediction and forecasting. [wikipedia, sensors]

2.4.2 Cluster Analysis

Cluster analysis or clustering is a typical application of unsupervised learning. The task of cluster analysis is to divide the population or data points into a number of groups such that data points of the same group are more similar to each other and dissimilar to the data points in other groups. It is basically a collection of objects on the basis of similarity and dissimilarity between them. Clustering itself is not one specific algorithm, but the general task to be solved. It can be achieved by various algorithms that differ significantly in their understanding of what constitutes a cluster and how to efficiently find them. Most known

clustering algorithms are the k-means technique, the hierarchical clustering and the expectation maximisation technique.

2.4.3 Bayesian Models

Bayesian models (BM) are a family of probabilistic graphical models in which the analysis is undertaken within the context of Bayesian inference. The probability expresses a degree of belief in a event. Bayesian statistical methods use Bayes' theorem to compute and update probabilities after obtaining new data. According to Bayes' theorem given two events A and B, the conditional probability of A given that B is true is expressed as follows:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}, \; where\; P(B) \neq 0$$

where P(B) is not zero. BM belong to the supervised learning category and are mainly used for solving classification and regression problems. Most prominent algorithms in the literature are Naive bayes, gaussian naive bayes, multinomial naive bayes, bayesian network, mixture of gaussians and bayesian belief network.

2.4.4 Instance Based Models

Instance based models (IBM) are memory-based models that learn by comparing new examples with instances in the training database. They are called instance-based because they construct hypotheses directly from the training instances themselves and generate classification or regression predictions using only specific instances. One advantage that instance-based learning has over other methods of machine learning is its ability to adapt its model to previously unseen data. Instance-based learners may simply store a new instance or throw an old instance away. The disadvantage of these models is that their

complexity grows with data. Examples of instance-based learning algorithms are the *k*-nearest neighbors algorithm, kernel machines, locally weighted learning and RBF networks.

2.4.5 Decision Trees

Decision trees (DT) are classification or regression models formulated in a tree-like architecture. A decision tree is a flowchart-like structure in which each internal node represents a "test" on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represent classification rules. Tree models where the target variable can take a discrete set of values are called classification trees. In these tree structures, leaves represent class labels and branches represent conjunctions of features that lead to those class labels. Decision trees where the target variable can take continuous values (typically real numbers) are called regression trees.

2.4.6 Artificial Neural Networks

Artificial Neural Networks (ANNs) is an information processing paradigm that is inspired by the way the biological nervous system such as animals' brain process information. An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it. In **Figure 3** the architecture of an artificial neuron (left) and a biological neuron (right) are presented.

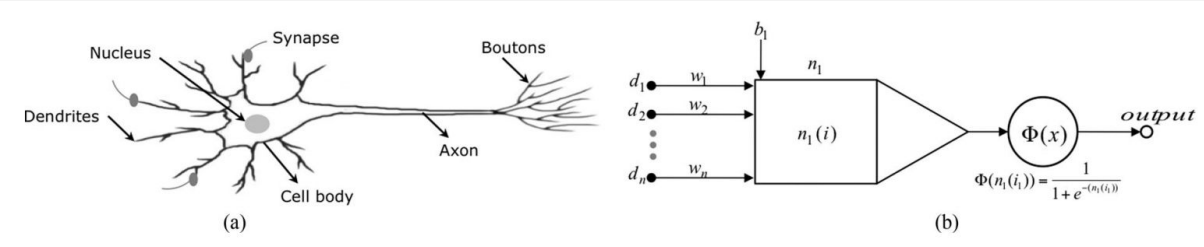

Figure 3. a) Biological neuron, (b) unit artificial neuron

The neurons are typically organized into multiple layers. Neurons of one layer connect only to neurons of the immediately preceding and immediately following layers. The layer that receives external data is the *input layer*. The layer that produces the ultimate result is called the *output layer*. In between them there can be zero or more hidden layers, a feature that distincts the two big categories of ANNs. "Traditional" ANNs consist of one hidden layer at most, while Deep ANNs use multiple layers to progressively extract higher level features from the raw input.

ANNs are supervised models that are typically used for regression and classification problems. Most commonly used learning algorithms in ANNs include the *radial basis function networks, perceptron algorithms* and *back-propagation*. Moreover plenty of ANN-based algorithms have arisen such as adaptive-neuro fuzzy inference systems, supervised Kohonen networks as well as Hopfield networks, multilayer perceptron, self-organising maps, extreme learning machines, generalized regression neural network, ensemble neural networks or ensemble averaging and self-adaptive evolutionary extreme learning machines.

Deep ANNs, widely known as Deep Learning (DL) or Deep Neural Networks (DNNs), are part of a broader family of machine learning methods based on artificial neural networks. They were introduced in 1943 when threshold logic was introduced to build a computer model closely resembling the biological pathways of humans. This field of research is still evolving; its evolution can be divided into two time periods-from 1943–2006 and from 2012–until now. Learning can be supervised, semi-supervised or unsupervised. DL models have dramatically improved the state-of-the-art in many different sectors and industries,

including agriculture. Deep learning architectures such as deep neural networks, deep belief networks, recurrent neural networks (RNNs) and convolutional neural networks (CNNs) constitute the most known DNNs with applications to numerous fields, where they have produced results comparable to and in some cases superior to human experts. **Figure 4,** shows the evolution of DL over the years.

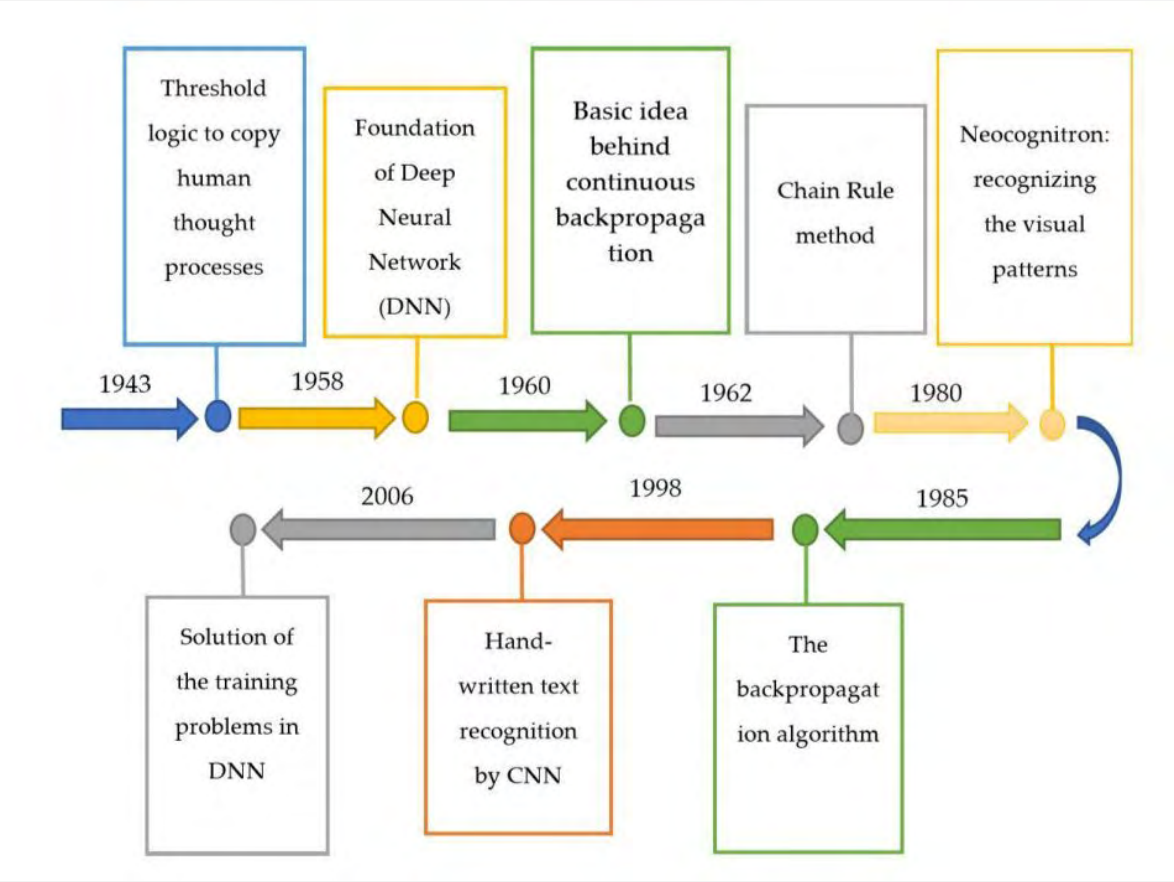

Figure 4. The evolution of deep learning from 1943-2006.

2.4.7 Support Vector Machines

Support Vector Machines (SVMs) are supervised learning models that analyze data used for classification, regression and in some cases clustering analysis. They were first introduced in the work of Vapnik (1995) [1] on the foundation of statistical learning theory. An SVM model is a representation of the examples as points in space, mapped so

that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on the side of the gap on which they fall. SVM is intrinsically a binary classifier. In addition to performing linear classification, it can efficiently perform a non-linear classification using the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

They can be used to solve various problems like text and hypertext categorization, classification of images, handwritten character recognition etc. Most used SVM algorithms include the support vector regression, least squares support vector machine, and successive projection algorithm-support vector machine.

2.4.8 Ensemble Learning

Ensemble learning (EL) and methods combine several trees base algorithms to construct better predictive performance than a single tree base algorithm. The main principle behind the ensemble model is that a group of weak learners come together to form a strong learner, thus increasing the accuracy of the model. When we try to predict the target variable using any machine learning technique, the main causes of difference in actual and predicted values are noise, variance, and bias. Ensemble helps to reduce these factors (except noise, which is irreducible error). Decision trees have been typically used as the base learner in EL models, for example, random forest, whereas a large number of boosting and bagging implementations have been also proposed, for example, boosting technique, adaboost and bootstrap aggregating or bagging algorithm.

Chapter 3

ML in Precision Agriculture Review

3.1 Review

The reviewed articles have been classified in three generic categories; namely, crop management, livestock management and field condition management. ML applications in crop management section were divided into sub-categories including yield prediction, disease detection, weed detection, crop quality, and species recognition. In the livestock section, ML applications were also divided in two sub-categories; animal welfare and livestock production. Field condition management consists of two sub-categories as well; water and soil management. Despite the fact that climate prediction is very important for agricultural production, it has not been taken into consideration in this thesis due to the fact that ML in climate forecasting is a complete area by itself. Finally, all articles used in this thesis regard works presented solely in journal papers which were published in the period from 2004 up to the present.

3.2 Crop Management

3.2.1 Yield Prediction

Achieving maximum crop yield at minimum cost with a healthy ecosystem is one of the main goals of agricultural production. Yield prediction, one of the most significant topics in precision agriculture, is of high importance for yield mapping, yield estimation, matching of crop supply with demand, and crop management to increase productivity.

Early detection and management of problems associated with crop yield restrictions can help increase yield and subsequent profit and estimating yield is important to numerous crop management and business decisions.

In recent years different ML techniques have been implemented to achieve accurate yield prediction for different crops as it is reported in Subhadra et al. (2016) recent work [2]. The most successful among them have been *Artificial Neural Networks* [3,4], *Support Vector Regression* [5], *M5-Prime Regression Trees* [6,7,8] and *k-nearest neighbour* [9].

Gonzalez-Sanchez et al. (2014) [10] presented a comparative study of ANN, SVR, M5-Prime, kNN and Multiple Linear Regression (MLR) ML techniques for crop yield prediction in ten crop datasets. Four accuracy metrics were used for the validation of these models; Root Mean Square Error (RMS), Root Relative Square Error (RRSE), Normalized Mean Absolute Error (MAE) and Correlation Factor (R). Results showed that M5-Prime achieved the lowest errors across the produced crop yield models. The results of that study ranked the techniques from the best to the worst, according to RMSE, RRSE, R, and MAE results, in the following order: M5-Prime, kNN, SVR, ANN and MLR.

In another study, Nari and Yang-Won (2016) [11] applied four ML techniques, SVM, Random Forest (RF), Extremely Randomized Trees (ERT) and Deep Learning (DL) to estimate corn yield in Iowa State. Comparisons of the validation statistics showed that DL provided more stable results by overcoming the overfitting problem.

A great example of ML applications in yield prediction include the work of Ramos et al. (2017) [12]. A SVM model that automatically counted coffee fruits on a branch was implemented. The method calculates the coffee fruits in three categories: harvestable, not harvestable, and fruits with disregarded maturation stage. In addition, the method estimated the weight and the maturation percentage of the coffee fruits. The core idea of this work was to provide information to coffee growers to optimise economic benefits and plan their agricultural work. The visibility percentage of harvestable ripe/overripe fruits varied from 82.54 to 87.83%, whereas in semi-ripe fruits it varied from 68.25 to 85.36%. On the other hand, in the not-harvestable category, the results varied from 76.91 to 81.39%.

Sengupta et al. (2014) [13] in their recent work, developed an early yield mapping system for the identification of immature green citrus in a citrus grove under outdoor conditions. The SVM implemented had an accuracy of 80.4%. As all other relative studies, the aim of the study was to provide growers with yield-specific information to assist them to optimise their grove in terms of profit and increased yield.

In addition, another comparative study that ML techniques were tested is Ali's et al. (2016) work, where the authors developed three models for the estimation of grassland biomass (kg dry matter/ha/day) based on ANNs and multitemporal remote sensing data ; a MLR, an ANN and a five layer Adaptive Neuro Fuzzy Inference Systems (ANFIS) model [14]. The evaluation criteria of the models' performance used by the authors were the RMSE and the coefficient of determination (R^2). The results generated by this work showed that the ANNs outperformed the MLR as expected and especially ANFIS gave the best estimation results ($R^2 = 0.85,\ RMSE = 11.07$).

Spectral vegetation indices (VIs) are mathematical combinations (often ratios) of mainly red, green and infrared spectral bands. They are designed to find functional relationships between crop characteristics and remote sensing observations [15]. Since the development of the Simple Ratio Index (SR) [16,17,18] and the Normalized Difference Vegetation Index (NDVI) [19,20,21] a large number of vegetation indices have been developed, such as the two-band Enhanced Vegetation Index (EVI2) and Normalized Difference Water Index (NDWI) to name a few. The availability of a large number of indices leads to the need to optimally choose and combine indices for maximally accurate crop yield estimation. Panda et al. (2010) implemented Back-propagation Neural Network (BPNN) modelling to test the efficiency of the following four spectral vegetation indices: NDVI, green vegetation index (GVI), soil adjusted vegetation index (SAVI) and perpendicular vegetation index (PVI) in corn crop yield prediction. The results showed that the corn yield was best predicted using BPNN models that used the means and standard deviations of PVI grid images [22].

Although spectral vegetation indices are widely used, they depend only on a small number (usually two) of the available image bands and the full spectrum information in hyperspectral data is not exploited. In their recent publication You et al. (2017) used Convolutional Neural Network (CNN) and Long-Short Term Memory (LSTM) to automatically discover relevant features from raw data [23]. Deep Gaussian Process was employed to integrate the spatio-temporal information from the data. They evaluated the proposed approach on the task of predicting county-level soybean production in the United States. The results of this study showed that the proposed approach outperformed competing techniques by a large margin.

Many other studies have been conducted on the application of ML techniques to crop yield estimation from remotely sensed and in-situ data. **Table 5** presents a review of the studies and provides a summary, methodology and discussion for each publication. This discussion is concentrated on some key technical aspects of the used ML techniques.

Table 5. Publications that use machine learning techniques for crop yield estimation with a focus on their technical aspects.

Paper	Summary	Methodology	Discussion
Pantazi et al. (2016) [24]	This paper developed and evaluated a yield prediction model for wheat. For the yield prediction the fusion vectors have been used as input for the three ANNs. The fusion vectors consist of the values of the eight soil parameters collected with the on-line soil sensor, the satellite imagery calculated NDVI values and historic yield data from the previous two years.	Self-Organizing Map Models (SOMs): • Counter-Propagation Artificial Neural Networks (CPANN) • XY-Fused Networks (XY-Fs) • Supervised Kohonen Networks (SKNs)	The presented approach incorporates the yield limiting factors in a multi-layer fusion model
Stas et al. (2016) [25]	The paper presented a comparison of two machine learning techniques (BRT and SVM) for prediction of winter wheat yield in Henan province of China. Three types of NDVI-related predictors have been used: Single NDVI, Incremental NDVI and Targeted NDVI. The results of comparison, which are based on a cross-validation error (RMSE), showed that BRT model consistently outperforms SVM	• Boosted Regression Trees (BRT) • Support Vector Machines (SVM)	When a limited number of training samples is available, ML techniques used in this paper are better able to cope with large set of predictors (compared to MLR)

Heremans et al. (2015) [26]	In this paper two regression tree methods (BRT and RF) were used in order to evaluate the accuracy of winter wheat yield, using NDVI data from the SPOT-VEGETATION sensor together with meteorological variables and fertilization levels, in the North China. The aim was not only to compare the performance of the methods but also to assess the potential for early-season predictions of winter wheat yield at the prefecture level (five prefectures were involved). The comparison of methods was based on cross-validation R2 and RMSE. The results showed that BRT outperforms RF for four out of the five prefectures.	• Boosted Regression Trees (BRT) • Random Forest (RF)	BRT is sensitive to noise, prone to overfitting and much slower than bagging. At the same time, boosting has been shown to be more accurate than bagging. RF can be used to improve the performance of bagging. In terms of accuracy, RFs are comparable to boosting but don't have the mentioned limitations. RF has much lower computational cost than boosting
Liang et al. (2015) [27]	The paper presented a non-destructive method - the hybrid inversion method, for estimation of leaf area index (LAI) values of crops. The method used different regression algorithms and allowed determining the relationships between optimal simulated VIs and simulated LAI values. To establish hybrid inversion model ANN and RFR have been used.The comparison of the used algorithms showed that RFR was a better method for modelling with the higher R2 and lower RMSE values for different datasets and various VIs.	• Curve fitting • Artificial Neural Network (ANN) • Random Forest Regression (RFR)	In contrast to full-spectrum approaches, using VIs to estimate LAI requires a reduction in the number of model input parameters and therefore may result in lower inversion accuracy. However, RFR can enable good performance with several or even a single parameter if that input parameter is highly correlated and representative.
Wu et al. (2015) [28]	This paper developed and compared two inversion models, using Statistical Regression model and BPNN model, to estimate the LAI of a temperate meadow steppe in China. The results of comparison showed that BPNN method (accuracy: 82.2%) outperforms Statistical Regression model (accuracy: 78.8%).	• Statistical Regression Model • BPNN	BPNN refers to a broad family of ANNs where the error is calculated at the output layer (using the observations) and is propagated back through the layers of the ANN. The optimisation process adjusts the weights in each layer by minimising the pre-defined loss function
Li et al. (2016) [29]	The paper aimed to produce accurate and timely predictions of grassland LAI for the meadow steppes of northern China, using different regression approaches and hybrid geostatistical methods. The comparison of predictions via hybrid geostatistical methods, followed by different regression models was presented. The results showed that the RF model provides the most accurate predictions among the regression models	• Partial Least Squares Regression (PLSR) • ANNs • RFs • Regression Kriging (RK) • Random Forests Residuals Kriging (RFRK)	RFs can provide better resistance to the over-fitting problem and to noise in the data compared with other regression methods. However, RF method ignores spatial autocorrelation information. RFRK is an extension of RF and is very similar to RK. It helps to include the spatial

			autocorrelation into the RF
Papag. et al. (2011) [30]	The main aim of the paper was to connect yield defining parameters with yield in cotton crop production in Central Greece. The simulation approach based on the soft computing technique of Fuzzy Cognitive Maps was investigated (FCM tool). The data from six subsequent years were used to estimate the average classification accuracy of the yield production, using the FCM tool. The results of estimation were compared with results of some ML techniques obtained from the same data. The results of comparison based on the overall accuracy of each method showed that the FCM technique performed better in most of the cases	• Fuzzy Cognitive Mapping (FCM) • ANNs • Decision Trees (DTs) • Bayesian Networks (BNs)	Fuzzy cognitive Map (FCM) represents a combination of neural networks and fuzzy logic, and can be used for information representation and decision making in complex processing environments. In particular, FCMs can be used to model and represent expert knowledge for cotton yield prediction and crop management
Kaul et al. (2005) [31]	The paper described the development of ANN models as an accurate technique for corn and soybean yield prediction in Maryland nutrient management planning. The results showed that ANN yield prediction is more accurate than the MLR-based yield model.	• Artificial Neural Network (ANN) - • Multiple Linear Regression (MLR)	ANN and MLR are among the techniques that can be used for agricultural modelling and prediction. The MLR is a simple methodology which is also easy to apply. ANN is a much more sophisticated technique
Morellos et al. (2016) [32]	To predict total nitrogen (TN), organic carbon (OC) and moisture content (MC) in fresh (wet and unprocessed) soil samples two multivariate and two machine learning methods have been compared. The results indicated that machine learning methods outperformed the multivariate methods for the prediction of all three soil properties.	Multivariate methods: • Principal Component Regression (PCR) • Partial Least Squares Regression (PLSR), Machine learning methods: • Least Squares Support Vector Machines (LS-SVM) • Cubist	The advantage of ML methods is that they are capable of tackling non-linear problems in the dataset. The ML techniques can be used in field spectroscopy for off-line and online prediction of the soil parameters studied in the fields (if the soil type and variability is similar to the one studied in this paper)
Wang et al. (2017) [33]	The paper investigated the modelling performances of four different chemometric techniques and three vegetation indices. Results showed that the best modelling and prediction accuracy were found in the model established by PLSR and spectra measured with a black background. A higher coefficient of determination between the leaf N concentration and fruit yield was found at 50 days after full bloom	Four techniques: • Principal Components Regression (PCR) • Partial Least Squares Regression (PLSR) • Stepwise Multiple Linear Regression (SMLR) • BPNN Three indices: • Difference Spectral	PCR, PLSR, and BPNN use all available wavelengths simultaneously, while SMLR selects useful wavelengths from the available spectrum and ignores the remaining wavebands. To improve the performance of the methods normalization can be used on the raw spectra collected

Index • Normalized Difference Spectral Index • Ratio Spectral Index	by the probe, and wavelengths with very large atmospheric influence can be removed.

3.2.2 Disease Detection

Disease detection along with yield prediction due to their importance in PA, are the sub-categories with the highest number of articles presented in this thesis. Among the most significant concerns in agriculture is pest and disease control in open-air (arable farming) and greenhouse conditions. The most widely used practice in pest and disease control is to uniformly spray pesticides over the cropping area. This practice in order to be effective, requires significant amounts of pesticides which results in a high financial and significant environmental cost. Environmental impacts can be residues in crop products, side effects on ground water contamination, impacts on local wildlife and eco-systems and so on. ML is used as a part of the general precision agriculture management, where agro-chemicals input is targeted in terms of time, place and affected plants.

Pantazi et al. (2017) [reference] in their recent work, presented a ANN-based model for the detection and discrimination of healthy *Silybum marianum* plants and those infected by smut fungus *Microbotyum silybum* during vegetative growth [34]. The ANN training was based on leaf images and they achieved a remarkable accuracy of 95.16%. In another study, published at the same year, Ebrahimi et al. (2017) developed a new method based on image processing procedure for the classification of parasites and the automatic detection of thrips in strawberry greenhouse environment, for real-time control [35]. The performance metric that was used to evaluate the model was MPE with a score of 2.25%. In [36], Chung et al. presented a method for detection and screening of *Bakanae* disease in rice seedlings. More specifically, the aim of the study was the accurate detection of pathogen *Fusarium fujikuroi* for two rice cultivars. The automated detection of infected

plants increased grain yield and was less time-consuming compared with naked eye examination.

One of the most economically significant crops worldwide is wheat. Many studies have been conducted regarding the detection and discrimination of diseased and healthy wheat crops recently. The papers presented in this paragraph are dedicated to this topic. Pantazi et al. (2017) developed a new system for the detection of nitrogen stressed, and yellow rust infected and healthy winter wheat canopies based on hierarchical self-organizing classifier and hyperspectral reflectance imaging data [37]. The study aimed at the accurate detection of these categories for a more effective usage of fungicides and fertilizers according to the plant's needs. In another study by Moshou et al. (2014), the development of a system was presented that automatically discriminated between water stressed Septoria tritici infected and healthy winter wheat canopies [38]. The approach used a least squares (LS)-SVM classifier with optical multisensor fusion. In another similar study [39], Moshou et al. (2004) developed an ANN and spectral reflectance features based model that was used to detect either yellow rust infected or healthy wheat. The accurate detection of either infected or healthy plants enables the precise targeting of pesticides in the field. Finally, Ferentinos (2018) presented a CNN-based method for the disease detection diagnosis based on simple leaves images with sufficient accuracy to classify between healthy and diseased leaves in various plants [42].

There is a vast amount of literature on the disease detection in field crops. **Table 6** summarizes some of the key studies.

Table 6. Summary of the key papers for the case of the disease detection sub-category.

Paper	Crop	Observed Features	Functionality	Methodology	Results
Pantazi et al. (2017) [34]	Silybum marianum	Images with leaf spectra using a handheld visible and NIR spectrometer	Detection and discrimination between healthy Silybum marianum plants and those that are infected by smut	ANN/ XY-Fusion	95.16% accuracy

			fungus Microbotyum silybum		
Ebrahimi et al. (2017) [35]	Strawberry	Region index: ratio of major diameter to minor diameter; and color indexes: hue, saturation, and intensify	Classification of parasites and automatic detection of thrips	SVM	MPE = 2.25%
Chung et al. (2016) [36]	Rice	Morphological and color traits from healthy and infected from Bakanae disease, rice seedlings, for cultivars Tainan 11 and Toyonishiki	Detection of Bakanae disease, Fusarium fujikuroi, in rice seedlings	SVM	87.9% accuracy
Pantazi et al. (2017) [37]	Wheat	Hyperspectral reflectance imaging data	Detection of nitrogen stressed, yellow rust infected and healthy winter wheat canopies	ANN/ XY-Fusion	Nitrogen stressed: 99.63% accuracy Yellow rust: 99.83% accuracy Healthy: 97.27% accuracy
Moshou et al. (2014) [38]	Wheat	Spectral reflectance and fluorescence features	Detection of water stressed, Septoria tritici infected, and healthy winter wheat canopies	SVM/ LS-SVM	Four scenarios: 1) Control treatment, healthy and well supplied with water: 100% accuracy 2) Inoculated treatment, with Septoria tritici and well supplied with water: 98.75% accuracy 3) Healthy treatment and deficient water supply: 100% accuracy 4) Inoculated treatment and deficient water supply: 98.7% accuracy
Moshou et al. [39] (2004)	Wheat	Spectral reflectance features	Detection of yellow rust infected and healthy winter wheat canopies	ANN/MLP	Yellow rust infected wheat: 99.4% accuracy Healthy: 98.9% accuracy
Moshou et al. (2005) [40]	Wheat	Data fusion of hyper-spectral reflection and multi-spectral fluorescence imaging	Detection of yellow rust infected and healthy winter wheat under field circumstances	ANN/SOM	Yellow rust infected wheat: 99.4% accuracy Healthy: 98.7% accuracy

Moshou et al. (2006) [41]	Wheat	Hyperspectral reflectance images	Identification and discrimination of yellow rust infected, nitrogen stressed, and healthy winter wheat in field conditions	ANN/SOM	Yellow rust infected wheat: 99.92% accuracy Nitrogen stressed: 100% accuracy Healthy: 99.39% accuracy
Ferentinos (2018) [42]	Generalized approach for various crops (25 in total)	Simple leaves images of healthy and diseased plants	Detection and diagnosis of plant diseases	DNN/CNN	99.53% accuracy

3.2.3 Weed Detection

Apart from diseases, weeds are the most important threats to crop production. The biggest problem in weeds fighting is that they are difficult to detect and discriminate from crops. Computer vision and ML algorithms in conjunction with sensors can improve detection accuracy and discrimination of weeds at low cost and with no environmental issues and side effects. In future, these technologies will drive robots that will destroy weeds, minimizing the need for herbicides. Two papers on ML applications for weed detection issues in agriculture have been studied and are presented in this section.

In the first study, Pantazi et al. (2017) developed a method based on counter propagation (CP)-ANN and multispectral images captured by unmanned aircraft systems (UAS) for the identification of Silybum marianum, a weed that is hard to eradicate and causes major loss on crop yield [43]. In the second study, Binch and Fox (2017) implemented a new method based on ML techniques and hyperspectral imaging, for crop and weed species recognition [44]. More specifically, they created an active learning system for the recognition of Maize (*Zea mayas*), as crop plant species and Ranunculus repens, Cirsium arvense, Sinapis arvensis, Stellaria media, Tarraxacum officinale, Poa annua, Polygonum persicaria, Urtica dioica, Oxalis europaea, and Medicago lupulina as weed species. The main goal was the accurate recognition and discrimination of these species for economic and environmental

purposes. **Table 7** provides a summary of the above papers along with their technical specifications and results.

Table 7. Crop Management: Weed detection table.

Paper	Observed Features	Functionality	Methodology	Results
Pantazi et al. (2017) [43]	Spectral bands of red, green, and NIR and texture layer	Detection and mapping of *Silybum marianum*	ANN/CP	98.87% accuracy
Binch and Fox (2017) [44]	Spectral features from hyperspectral imaging	Recognition and discrimination of *Zea mays* and weed species	ANN/one-class SOM and Clustering/one-class MOG	*Zea mays*: SOM = 100% accuracy MOG = 100% accuracy Weed species: SOM = 53–94% accuracy MOG = 31–98% accuracy

3.2.4 Crop Quality

The identification of features connected with the crop quality is another crop management field, in which ML techniques can play an important role. The accurate detection and classification of crop quality characteristics can increase product price and reduce waste. In comparison with the human experts, machines can make use of seemingly meaningless data and interconnections to reveal new qualities playing role in the overall quality of the crops and to detect them.

Zhang et al. (2017) [45] tried to face the problem of detection and classification of botanical and non-botanical foreign matter embedded inside cotton lint during harvesting. The aim of the study was quality improvement while the minimizing fiber damage. They developed a SVM model trained by hyperspectral images and the classification algorithm achieved more than 95% accuracy for the spectra and the images. In the second paper [46], the study regarded pears production and more specifically, a method was presented for the identification and differentiation of Korla fragrant pears into deciduous-calyx or

persistent-calyx categories. The approach applied ML methods with hyperspectral reflectance imaging. In the final study for this sub-category, Maione et al. (2016) presented a model for the prediction and classification of the geographical origin for rice samples [47]. The model was based on ML techniques applied on chemical components of samples. More specifically, the main goal was the classification of the geographical origin of rice, for two different climate regions in Brazil; Goias and Rio Grande do Sul. The results showed that Cd, Rb, Mg, and K are the four most relevant chemical components for the classification of samples. **Table 8** sums up the presented papers along with some key technical features.

Table 8. Crop Management: Crop quality table.

Paper	Crop	Observed Features	Functionality	Methodology	Results
Zhang et al. (2017) [45]	Cotton	Short wave infrared hyperspectral transmittance images depicting cotton along with botanical and non-botanical types of foreign matter	Detection and classification of common types of botanical and non-botanical foreign matter that are embedded inside the cotton lint	SVM	According to the optimal selected wavelengths, the classification accuracies are over 95% for the spectra and the images.
Hu et al. (2017) [46]	Pears	Hyperspectral reflectance imaging	Identification and differentiation of Korla fragrant pears into deciduous-calyx or persistent-calyx categories	SVM/SPA-SVM	Deciduous-calyx pears: 93.3% accuracy Persistent-calyx pears: 96.7% accuracy
Maione et al. (2016)[47]	Rice	Twenty (20) chemical components that were found in composition of rice samples with inductively coupled plasma mass spectrometry	Prediction and classification of geographical origin of a rice sample	EL/RF	93.83% accuracy

3.2.5 Species Recognition

The last sub-category of crop management section is the species selection and recognition. Species selection is a tedious process of searching for specific genes that determine the effectiveness of water and nutrients use, adaptation to climate change, disease resistance, as well as nutrients content or a better taste. Machine learning, in particular, deep learning algorithms, take decades of field data to analyze crops performance in various climates and new characteristics developed in the process. Based on this data they can build a probability model that would predict which genes will most likely contribute a beneficial trait to a plant. On the other side, species recognition aims to replace the traditional human approach for plant classification. Instead of comparing the color and shape of leaves, ML can provide more accurate and faster results analyzing the leaf vein morphology which carries more information about the leaf properties. A DL-based method for the identification and classification of three legume species, namely, white beans, red beans, and soybean, via leaf vein patterns has been presented in [48]. The technical features of this work are presented in **Table 9** below.

Table 9. Crop Management: Species Recognition table.

Paper	Crop	Observed Features	Functionality	Methodology	Results
Grinblat et al. (2016) [48]	Legume	Vein leaf images of white and red beans as well as and soybean	Identification and classification of three legume species: soybean, and white and red bean	DL/CNN	White bean: 90.2% accuracy Red bean: 98.3% accuracy Soybean: 98.8% accuracy for five CNN layers

3.3 Livestock Management

The livestock category consists of two sub-categories, namely, animal welfare and livestock production. Animal welfare focuses on the health and wellbeing of animals, with the main application of ML in monitoring animal behaviour for the early detection of diseases. Livestock Production on the other hand, deals with issues in the production system. ML provides accurate prediction and estimation of farming parameters in order to optimize the economic efficiency of livestock production systems, such as cattle and eggs production. For example, weight predicting systems can estimate the future weights 150 days prior to the slaughter day, allowing farmers to modify diets and conditions respectively.

3.3.1 Animal Welfare

Several studies have been conducted in the literature regarding the animal welfare sub-category. In the first paper, Dutta et al. (2015) developed a method for the classification of cattle behaviour based on ML models using data collected by collar sensors with magnetometers and three-axis accelerometers [49]. The aim of the study was the prediction of events such as the oestrus and the recognition of dietary changes on cattle. The performance metrics used for the model revealed that the k-NN classifier was the best overall performer in accuracy, specificity, sensitivity and F1 score. In the second paper, Pegorini et al. (2015) presented a system for the automatic identification and classification of chewing patterns in calves [50]. The system was based on ML applying data from chewing signals of dietary supplements, such as hay and ryegrass, combined with behaviour data, such as rumination and idleness. Data was collected by optical FBG sensors. In another similar study, Matthews et al. (2017) presented an automated monitoring system based on ML, for animal behavior tracking, including tracking of animal movements by depth video cameras, for monitoring various activities of the animal

(standing, moving, feeding, and drinking) [51]. **Table 10** summarizes the features of the above presented articles.

Table 10. Livestock Management: Animal Welfare table.

Paper	Animal Species	Observed Features	Functionality	Methodology	Results
Dutta et al. (2015) [49]	Cattle	Features like grazing, ruminating, resting, and walking, which were recorded using collar systems with three-axis accelerometer and magnetometer	Classification of cattle behaviour	EL/Bagging with tree learner	96% accuracy
Pegorini et al. (2015) [50]	Calf	Data: chewing signals from dietary supplement, Tifton hay, ryegrass, rumination, and idleness. Signals were collected from optical FBG sensors	Identification and classification of chewing patterns in calves	DT/C4.5	94% accuracy
Matthews et al. (2017) [51]	Pigs	3D motion data by using two depth cameras	Animal tracking and behavior annotation of the pigs to measure behavioral changes in pigs for welfare and health monitoring	BM: Gaussian Mixture Models (GMMs)	Animal tracking: mean multi-object tracking precision (MOTP) = 0.89 accuracy behavior annotation: standing: control $R^2 = 0.94$, treatment $R^2 = 0.97$ feeding: control $R^2 = 0.86$, treatment $R^2 = 0.49$

3.3.2 Livestock Production

In this sub-category, five papers will be presented, three with cattle production, one for hens' egg production and one DL-based model for pig face recognition. In the first paper studied, Craninx et al. (2008) developed a method for the prediction of the rumen fermentation pattern from milk fatty acids [52]. The main aim of the study was to achieve

the most accurate prediction, which play a significant role for the evaluation of diets for milk production. In addition, this work revealed that milk fatty acids have ideal features to predict the molar proportions of volatile fatty acids in the rumen. In the next study regarding the hen production, Morales et al. (2016) presented a SVM-based method for the early detection and warning of problems in the commercial production of eggs [53]. A SVM model was used in [54] as well, aimed at the accurate estimation of bovine weight trajectories over time. The accurate estimation of cattle weights is very important for breeders. Another similar study was [55], in which Alonso et al. (2013) tried to develop a function for the prediction of carcass weight for beef cattle of the Asturiana de los Valles breed, based on SVR models and zoometric measurements features. The results show that the presented method can predict carcass weights 150 days prior to the slaughter day. Finally, Hansen et al. (2018) presented a method based on convolutional neural networks (CNNs) applied in digital images for pig face recognition [56]. The main aim of the research was the identification of animals without the need for radio frequency identification (RFID) tags, which involve a distressing activity for the animal, are limited in their range and are a time-consuming method. **Table 11** summarizes the features of the above presented works.

Table 11. Livestock Management: Livestock Production table.

Paper	Animal Species	Observed Features	Functionality	Methodology	Results
Craninx et al. (2008) [52]	Cattle	Milk fatty acids	Prediction of rumen fermentation pattern from milk fatty acids	ANN/BPN	Acetate: RMSE = 2.65% Propionate: RMSE = 7.67% Butyrate: RMSE = 7.61%
Morales et al. (2016) [53]	Hens	Six (6) features, which were created from mathematical models related to farm's egg production line and collected over a period of seven (7) years.	Early detection and warning of problems in production curves of commercial hens eggs	SVM	98% accuracy

Alonso et al. (2015) [54]	Bovine	Geometrical relationships of the trajectories of weights along the time	Estimation of cattle weight trajectories for future evolution with only one or a few weights.	SVM	Angus bulls from Indiana Beef Evaluation Program: weights 1, MAPE = 3.9 + −3.0% Bulls from Association of Breeder of Asturiana de los Valles: weights 1, MAPE = 5.3 + −4.4% Cow from Wokalup Selection Experiment in Western Australia: weights 1, MAPE = 9.3 + −6.7%
Alonso et al. (2013) [55]	Cattle	Zoometric measurements of the animals 2 to 222 days before the slaughter	Prediction of carcass weight for beef cattle 150 days before the slaughter day	SVM/SVR	Average MAPE = 4.27%
Hansen et al. (2018) [56]	Pigs	1553 color images with pigs faces	Pigs face recognition	DNNs: Convolutional Neural Networks (CNNs)	96.7% Accuracy

3.4 Field Condition Management

Field condition management is divided in two sub-categories; namely, water and soil management.

Water management in agriculture impacts hydrological, climatological, and agronomical balance. So far, the most developed ML-based applications are connected with estimation of daily, weekly, or monthly evapotranspiration allowing for a more effective use of irrigation systems and prediction of daily dew point temperature, which helps identify expected weather phenomena and estimate evapotranspiration and evaporation.

On the other hand, soil, as specialists involved in agriculture claim, is a heterogeneous natural resource, with complex processes and vague mechanisms. Its temperature alone can

give insights into the climate change effects on the regional yield. It is a significant meteorological parameter controlling the interactive processes between ground and atmosphere. In addition, soil moisture has an important role for crop yield variability. Machine learning algorithms study evaporation processes, soil moisture and temperature to understand the dynamics of ecosystems and the impingement in agriculture.

3.4.1 Water Management

This section consists of four studies that were mostly developed for the estimation of daily, weekly, or monthly evapotranspiration. In 2017, Mehdizadeh et al. developed a computational method for the estimation of monthly mean evapotranspiration for arid and semi-arid regions [57]. It used monthly mean climatic data of 44 meteorological stations for the period 1951–2010. In another study for water management, Feng et al. (2017) presented two scenarios for the estimation of the daily evapotranspiration from temperature data collected from six meteorological stations of a region during the long period (i.e., 1961–2014) [58]. The third paper [59] presented also aims at the weekly estimation of evapotranspiration for two meteorological weather stations. For this cause, an ELM neural network was developed fed with temperature data. The purpose was the accurate estimation of weekly evapotranspiration in arid regions of India based on limited data scenario for crop water management. Finally, Mohammadi et al. (2015) in their published work for the prediction of daily dew point temperature, presented a model based on DL and more specifically they implemented an ANN and a ELM network [60]. The weather data used for the training of the neural networks were collected from two different weather stations. **Table 12** summarizes the presented papers for the water management sub-category.

Table 12. Field Condition: Water management

Paper	Property	Observed Features	Functionality	Methodology	Results
Mehdizadeh et al. (2017) [57]	Evapotranspiration	Data such as maximum, minimum, and mean temperature;	Estimation of monthly mean reference evapotranspiration arid and semi-arid	Regression/MARS	MAE = 0.05 RMSE = 0.07 R = 0.9999

		relative humidity; solar radiation; and wind speed	regions		
Feng et al. (2017) [58]	Evapotranspiration	Temperature data: maximum and minimum temperature, air temperature at 2 m height, mean relative humidity, wind speed at 10 m height, and sunshine duration	Estimation of daily evapotranspiration for two scenarios (six regional meteorological stations). Scenario A: Models trained and tested from local data of each Station (2). Scenario B: Models trained from pooled data from all stations	(i) Scenario ANN/ELM (ii) Scenario ANN/GRNN	(i) Scenario A: RRMSE = 0.198 MAE=0.267m d^{-1} NS = 0.891 (ii) Scenario B: RRMSE = 0.194 MAE=0.263m d^{-1} NS = 0.895
Patil et al. (2016) [59]	Evapotranspiration	Locally maximum and minimum air temperature, extraterrestrial radiation, and extrinsic evapotranspiration	Estimation of weekly evapotranspiration based on data from two meteorological weather stations	ANN/ELM	Station A: RMSE = 0.43 mm d^{-1} Station B: RMSE = 0.33 mm d^{-1}
Mohammadi et al. (2015) [60]	Daily dew point temperature	Weather data such as average air temperature, relative humidity, atmospheric pressure, vapor pressure, and horizontal global solar radiation	Prediction of daily dew point temperature	ANN/ELM	Region case A: MABE=0.3240◦C RMSE=0.5662 ◦C R = 0.9933 Region case B: MABE=0.5203 ◦C RMSE=0.6709 ◦C R = 0.9877

3.4.2 Soil Management

The final category of this review concerns ML application on prediction-identification of agricultural soil properties, such as the estimation of soil drying, condition, temperature, and moisture content. The first study [61] aimed at the provision of remote agricultural management decisions. For this purpose, Coopersmith et al. (2014) presented a method for the evaluation of soil drying for agricultural planning, which accurately evaluated the soil drying, with evapotranspiration and precipitation data, in a region located in Urbana, IL of the United States. In the second study, Nahvi et al. (2016) developed a new method based

on DL for the accurate estimation of soil temperature for agricultural management [62]. The implemented model was a self adaptive evolutionary-extreme learning machine (SaE-ELM) model trained by daily weather data, for the estimation of daily soil temperature at six different depths of 5, 10, 20, 30, 50, and 100 cm in two different in climate conditions regions of Iran; Bandar Abbas and Kerman. In another similar study, Johann et al. (2016) presented a novel method for the estimation of soil moisture, based on ANN models using data from force sensors on a no-till chisel opener [63]. **Table 13** provides additional information for the presented papers along with their respective results.

Table 13. Field condition management: Soil management.

Paper	Property	Observed Features	Functionality	Methodology	Results
Coopersmith et al. (2014) [61]	Soil condition	140 soil samples from top soil layer of an arable field	Prediction of soil OC, MC, and TN	SVM/ LS-SVM and Regression/ Cubist	OC: RMSEP = 0.062% & RPD = 2.20 (LS-SVM) MC: RMSEP = 0.457% & RPD = 2.24 (LS-SVM) TN: RMSEP = 0.071% & RPD = 1.96 (Cubist)
Nahvi et al. (2016) [62]	Soil temperature	Daily weather data: maximum, minimum, and average air temperature; global solar radiation; and atmospheric pressure. Data were collected for the period of 1996–2005 for Bandar Abbas and for the period of 1998–2004 for Kerman	Estimation of soil temperature for six (6) different depths 5, 10, 20, 30, 50, and 100 cm, in two different in climate conditions Iranian regions; Bandar Abbas and Kerman	ANN/ SaE-ELM	Bandar Abbas station: MABE = 0.8046 to 1.5338 ◦C RMSE = 1.0958 to 1.9029 ◦C R = 0.9084 to 0.9893 Kerman station: MABE = 1.5415 to 2.3422 ◦C RMSE = 2.0017 to 2.9018 ◦C R = 0.8736 to 0.9831 depending on the depth
Johann et al. (2016) [63]	Soil moisture	Dataset of forces acting on a chisel and speed	Estimation of soil moisture	ANN/MLP and RBF	MLP: RMSE = 1.27% R^2 = 0.79 APE = 3.77% RBF: RMSE = 1.30% R^2 = 0.80 APE = 3.75%

As nitrogen (N) plays a significant role in the process of photosynthesis, it is important for crop health and development. At the same time, environmental factors and cost require a prudent application of N. Because of these factors the problem of optimal N management has attracted the attention of numerous researchers. One of the approaches to optimal N management in PA is to use management zones, that is, identify subfield regions with homogeneous characteristics that require similar treatment. The most widely used methods for delineation of site-specific management zones are the fuzzy C-means and k-means algorithms (Schuster et al., 2011; Vrindts et al., 2005) [references]. These are popular clustering methods used extensively for unsupervised learning and identification of structure in datasets. However, determining subfield areas is a difficult task because of the complex correlations and spatial variability of soil properties and nutrient concentrations, which are responsible for variations in crop yield within the field. The rest of the papers presented in this section regard ML methods and techniques for the N management.

Yao et al. (2015) [64] applied different linear (CR, VI, SMLR and PLSR) and nonlinear (ANN and SVM) regression methods in order to determine which method, input variable and model could estimate the Leaf Nitrogen Concentration (LNC) in winter wheat with higher accuracy, more robustness, less time and lower complexity. A comparative assessment of those six methods was conducted using the following six metrics: coefficients of determination for the calibration ($R^2{}_C$) and validation ($R^2{}_V$) sets, the root mean square errors of prediction (RMSEP) for the calibration and validation sets, the ratio of prediction to deviation (RPD), the computational efficiency (CE) and the complexity level (CL). The results of the comparison showed that the SVM method was more robust in coping with potential confounding factors for most varieties, ecological site and growth stage. However, the VI method utilising the Soil-Adjusted Vegetation Index (1200 and 705 bands) was most accurate for the estimation of the LNC in wheat.

Three methods (PLS, ANN, LS-SVM) have been used to estimate the N status non-destructively in rice using canopy spectral reflectance with visible and near-infrared

reflectance spectroscopy [65]. The comparative analysis showed that the LS-SVM outperformed the other methods and it was concluded that LS-SVM is a promising alternative for the regression analysis to quantify N status in rice.

There are many other studies dedicated to precision N management, not only ML but also other techniques such as kriging, multivariate methods and inverse distance weighting. For the purpose of this thesis only ML-based models will be presented. **Table 14** presents some of those key studies and provides a summary, methodology and discussion for each publication.

Table 14. Publications that use machine learning and other techniques for precision nitrogen management.

Paper	Summary	Methodology	Discussion
Morellos et al. (2016) [66]	To predict total nitrogen (TN), organic carbon (OC) and moisture content (MC) in fresh (wet and unprocessed) soil samples two multivariate and two machine learning methods have been compared. The results indicated that machine learning methods outperformed the multivariate methods for the prediction of all three soil properties.	Multivariate methods: ● Principal Component Regression (PCR) ● Partial Least Squares Regression (PLSR) Machine learning methods: ● Least Squares Support Vector Machines (LSSVM) ● Cubist	The advantage of ML methods is that they are capable of tackling non-linear problems in the dataset. The ML techniques can be used in field spectroscopy for off-line and online prediction of the soil parameters studied in the fields (if the soil type and variability is similar to the one studied in this paper)
Castaldi et al. (2016) [67]	The paper proposed data fusion process in order to improve the choice of satellite bands for grain N uptake prediction. The results showed that the best spectral regions vary over the growing season of the wheat crop	Combination of: ● Stepwise Regression with Backward Selection ● Stepwise Variance Inflation Factors (VIFs) analysis ● Linear Mixed Effect Model (LMEM)	LMEM can be a very efficient technique to estimate the spatial variability of the soil and crop variables accurately across the field with limited data, thus saving time and reducing the costs
Wang et al. (2017) [68]	The paper investigated the modelling performances of four different chemometric techniques and three vegetation indices. Results showed that the best modelling and prediction accuracy were found in the model established by PLSR and	Four techniques:. ● Principal Components Regression (PCR) ● Partial Least Squares Regression (PLSR)	PCR, PLSR, and BPNN use all available wavelengths simultaneously, while SMLR selects useful wavelengths from the available spectrum and

	spectra measured with a black background. A higher coefficient of determination between the leaf N concentration and fruit yield was found at 50 days after full bloom.	• Stepwise Multiple Linear Regression (SMLR) • BPNN Three indices: • Difference Spectral Index • Normalized Difference Spectral Index • Ratio Spectral Index	ignores the remaining wavebands. To improve the performance of the methods normalization can be used on the raw spectra collected by the probe, and wavelengths with very large atmospheric influence can be removed.
Guo et al. (2015) [69]	The paper compared two different approaches (SLR and RFRK) to predict and map the spatial distribution of soil organic matter for the rubber plantation. Results showed that RFRK outperforms SLR, by providing lower prediction errors (ME, MAE, and RMSE) and higher R2	• Stepwise Linear Regression (SLR) • RFRK • Generalized Additive Mixed Model (GAMM) • Classification And Regression Tree (CART)	RFRK model required no assumptions about the relationships between the target variable and the predictor variables. Those relationships could be nonlinear and hierarchical. This can be revealed by using GAMM and CART.
Dai et al. (2014) [70]	The paper presented ANN-kriging methodology in order to predict accurate Soil Organic Matter (SOM) content maps. A comparison of proposed method with the other interpolation methods was performed to assess the prediction accuracy. The results indicated that ANN-kriging provides the lower RMSE.	• ANN-kriging • ANN • Inverse Distance Weighting (IDW)	It is suggested that the proposed ANN-kriging methodology can be used to improve the accuracy of SOM content mapping at large scale.

3.5 Results and Discussion

The number of articles included in this review was 54 in total. Among the articles, eight of them are related to applications of ML in livestock management, fourteen articles are related to applications of ML in field condition management, while the largest number of them (i.e., 32 articles) are related to applications of ML in crop management. **Figure 5** presents the distribution of the articles according to to the defined sub-categories.

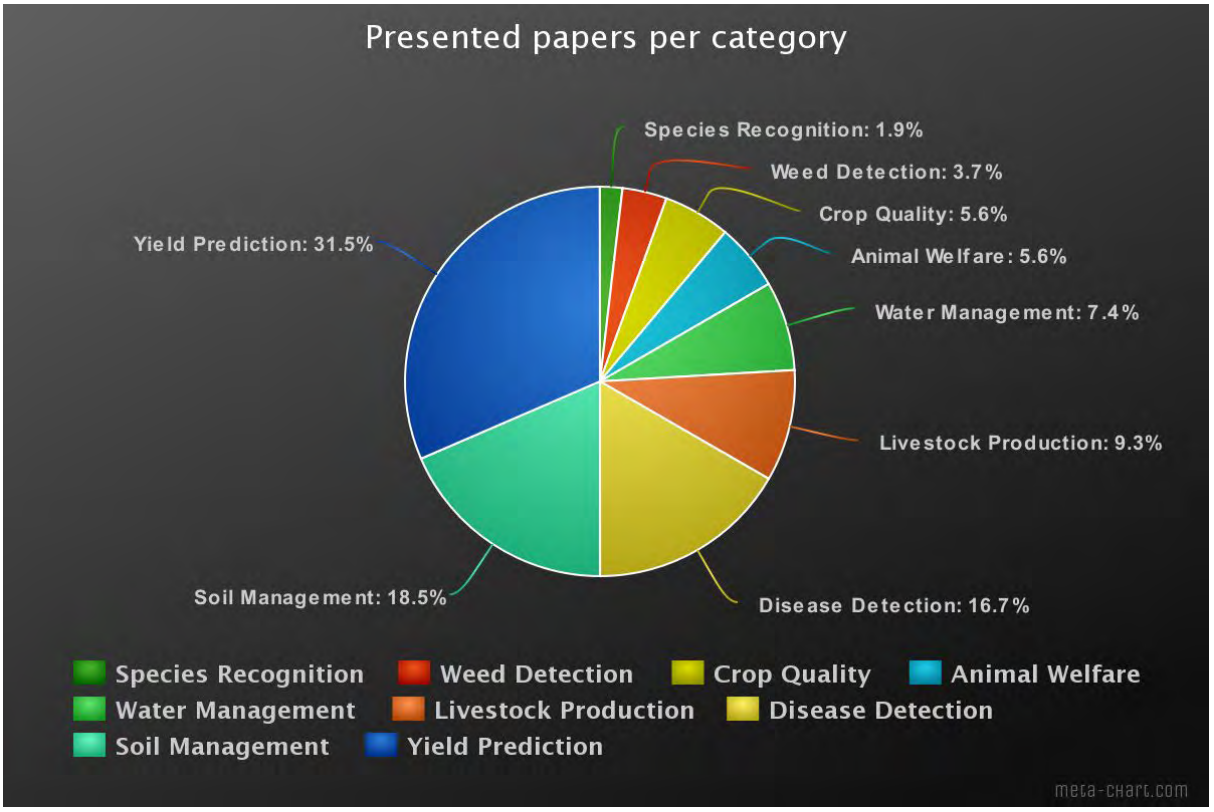

Figure 5. Pie chart presenting the papers according to the application domains.

From the analysis of these articles, it was found that eight general categories of ML models have been implemented in total. More specifically, six ML models were implemented in the approaches on crop management, where the most popular models were ANNs and DNNs (with most frequent crop at hand— wheat). In livestock management category, four ML models were implemented, with most popular models being SVMs (most frequent livestock type at hand—cattle). For water management in particular evapotranspiration estimation, two ML models were implemented and the most frequently implemented were ANNs. Finally, in the soil management category, five ML models were implemented, with the most popular once again being the ANNs and DNNs model. In **Figure 6**, the eight ML models with their total rates are presented.

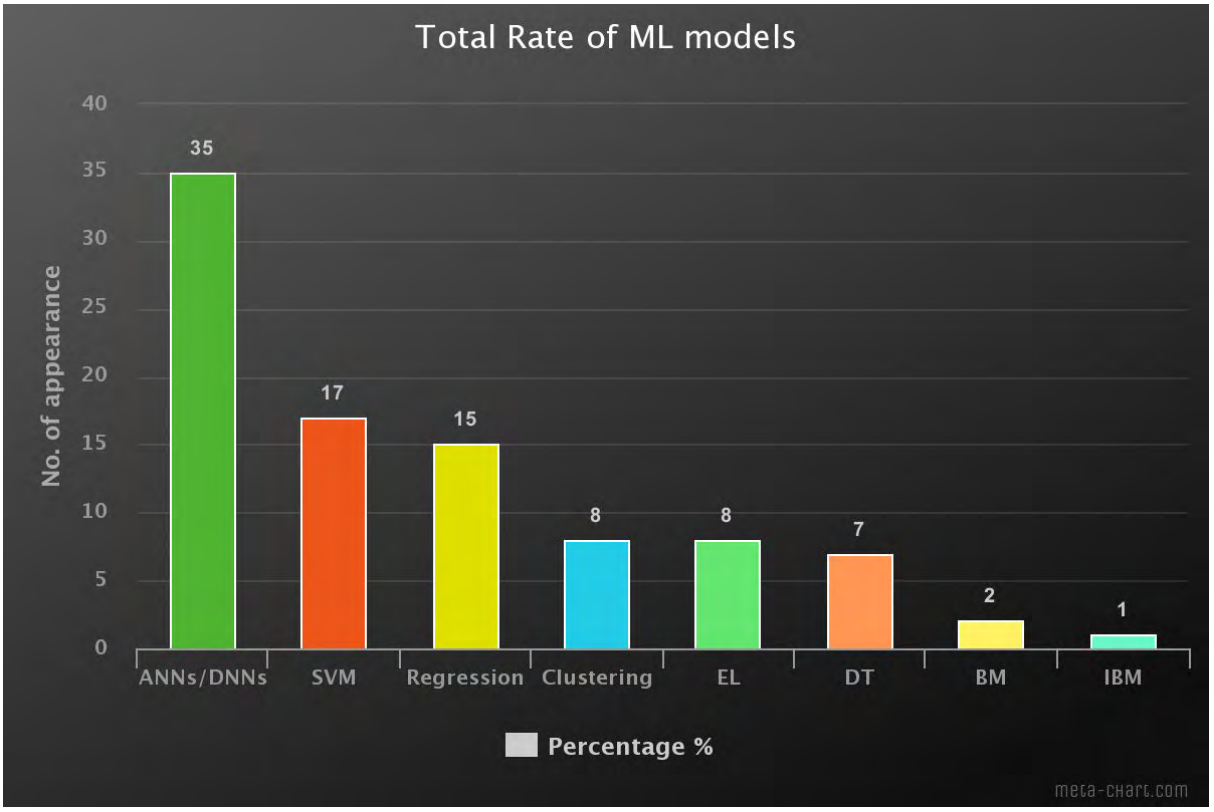

Figure 6. Presentation of machine learning (ML) models with their total rate.

From the above figure, it is shown that ML models have been applied in multiple applications for crop management (~60%); mostly yield prediction (31.5%) and disease detection (16.7%). This trend in the applications distribution reflects the data intense applications within crop and high use of images (spectral, hyperspectral, NIR, etc.). Data analysis, as a mature scientific field, provides the ground for the development of numerous applications related to crop management because, in most cases, ML-based predictions can be extracted without the need for fusion of data from other resources. In contrast, when data recordings are involved, occasionally at the level of big data, the implementations of ML are less in number, mainly because of the increased efforts required for the data analysis task and not for the ML models per se. It is also evident from the analysis that most of the studies used ANN and SVM ML models. More specifically, ANNs were used mostly for implementations in crop, water, and soil management, while SVMs were used mostly for livestock management.

By applying machine learning to sensor data, farm management systems are evolving into real artificial intelligence systems, providing richer recommendations and insights for the subsequent decisions and actions with the ultimate scope of production improvement. For this scope, in the future, it is expected that the usage of ML models will be even more widespread, allowing for the possibility of integrated and applicable tools. At the moment, all of the approaches regard individual approaches and solutions and are not adequately connected with the decision-making process, as seen in other application domains. This integration of automated data recording, data analysis, ML implementation, and decision-making or support will provide practical tools that come in line with the so-called knowledge-based agriculture for increasing production levels and bio-products quality.

Chapter 4

Agricultural Drones Overview

4.1 Introduction

As the global population has recently surpassed 7.5 billion, the trend for population growth is becoming an increasingly important and tangible problem. Because of this fact, humanity is called upon to manage its resources more intelligently in order to increase the production of agricultural products to meet its needs. An important role in the management of these resources is the proper use of the soil, the quality and the speed of production. A new and very promising proposal is the use of special drones in agriculture. **Figure 7** presents the rate of population growth per year.

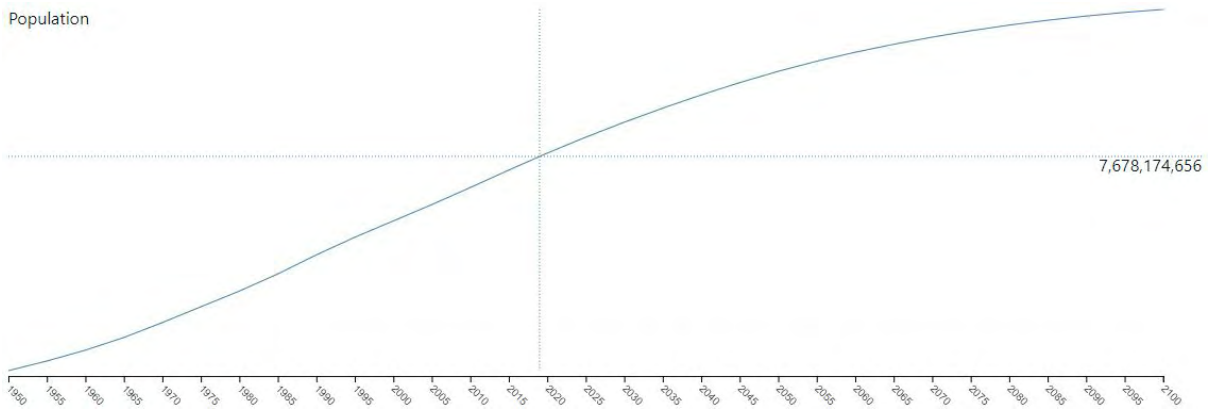

Figure 7. Population Growth graph.

Thanks to their high accuracy, efficiency and versatility, drones offer the potential to overcome many obstacles over traditional conventional agronomy machines. They can improve the industry with high precision measurements, real-time data collection and more efficient crop management with decisions based on the above data processing.

4.2 History of Drones

Drones, also known as Unmanned Aerial Vehicles (UAVs), are regarded as pilotless aircraft systems used in diverse applications such as Industrial Monitoring, Photography, battlefield surveillance, air ambulance, package delivery and many more. There are two basic categories of UAVs based on their architecture: 1) fixed-wing airplanes and 2) rotary motor helicopters. Drones operated by single-operated pilot, are considered to be short-range flying objects, in contrast to drones that navigate autonomously and fly at high altitudes and higher speeds. In **Figure 8** a drone of each type is presented.

Figure 8. Two types of unmanned aerial vehicles: Rotary copter (left) and fixed-wing airplane (right).

In recent years there has been significant development in the area of drones with improvements for all possible types. With GPS integration, drones have been able to navigate longer distances from their pilot's field of view, unlike the original RF planes. Moreover with the help of Wi-Fi in the form of First Person View (FPV), they can support HD cameras such as GoPro, DJI, Parrot et al. and broadcast real-time flight video, on a smartphone or tablet. Drones now have unique advantages due to their ease of use, being able to accurately track inaccessible areas, detect illegal activities, observe forest areas to prevent fires and monitor large tracts of land for their optimal exploitation. Currently, 85% of drone technology is mainly used for military purposes and only 15% by civilians for a variety of activities. But it is estimated that the market for drones in the coming years will

grow dramatically and will reach $200 billion by 2020, with a large proportion coming from agricultural activities.

4.3 Drone Technology in Precision Agriculture

The systematic use of drones in agriculture will revolutionize the field, which has remained stationary for many years. It will provide a range of solutions to the daily problems of farmers and various benefits which are presented in the rest of this chapter.

1. *Farm Analysis*: Drones as reliable high-tech machinery can be used by farmers to check the status of their farm at the beginning of the sowing season. Drones produce 3-D maps for soil analysis and help farmers optimize the tillage process. In addition, soil and field analysis via drones produce data useful for irrigation and nitrogen management of the field for optimal crop development.

2. *Time Saving*: It is not easy for farmers who manage large tracts of land to maintain a complete picture of their farms at all times. The solutions available for gaseous monitoring of the farm to date, have been either satellite photos or airplanes. The limitations resulting from the latter are, first, the low resolution of the satellite photos and secondly the time intervals between possible airplanes over land. The 15-cm resolution of UAV's cameras is about 40 times higher than that of the best commercial satellite images, taking into account that satellites and planes are above the clouds and therefore their data is often affected by possible bad weather. Satellite data is also available for a week or two, as it depends on the satellite's flight path. Drones can easily handle this task, enabling farmers to regularly monitor land and monitor their status at short intervals.

3. *Higher productivity*: The precision application of pesticides, water and use of fertilizers accurately monitored by drone will in turn increase the yield and overall quality can be taken care off.

4. *GIS Mapping Integration*: GIS Mapping is a useful tool that offers the ability to visualize raw data in map format. The purpose of this process is to reveal correlations between the data, which may not be visible from their original unstructured form. GIS Mapping has already proven its value and utility in the field of agriculture in terms of resource management, performance enhancement, start-up and business management as well as many other areas. Combined with the use of drones, it will help farmers better delineate the area where drones will fly and the accuracy of flight patterns.

5. *Imaging of Crop Health Status*: With drones, crop health imaging can be done using Infrared, NVDI and multispectral sensors making the farmers better track the health of crop, transpiration rates and sunlight absorption rates etc.
    a. *Normalized Difference Vegetation Index (NDVI)*: The concept of NDVI is based on the evaluation of the amount of incident light absorbed and reflected at different wavelengths. It has been used in the development of many ratios, known as markers, which are sensitive to different environmental and physiological conditions. NDVI uses measurements from only two types of sensors: optical and infrared. The mathematical formula of NDVI is the ratio of the near-infrared light (NIR) to the visible light (sum of light) for their sum, as shown below:

    $$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)},$$

    NDVI, simply put, is a calculation of vegetation biomass and/or crop health. Mathematically comparing Red and NIR light signals can help differentiate plants from non-plants (soil, water) and healthy plants from sick plants. This feature allows farmers to monitor crop health, transpiration rates and sunlight absorption in greater detail and efficiency. As shown in **Figure 9**, a stressed leaf and a healthy leaf reflect nearly the same amount of blue, green, red light, but a healthy leaf reflects more NIR near-infrared light.

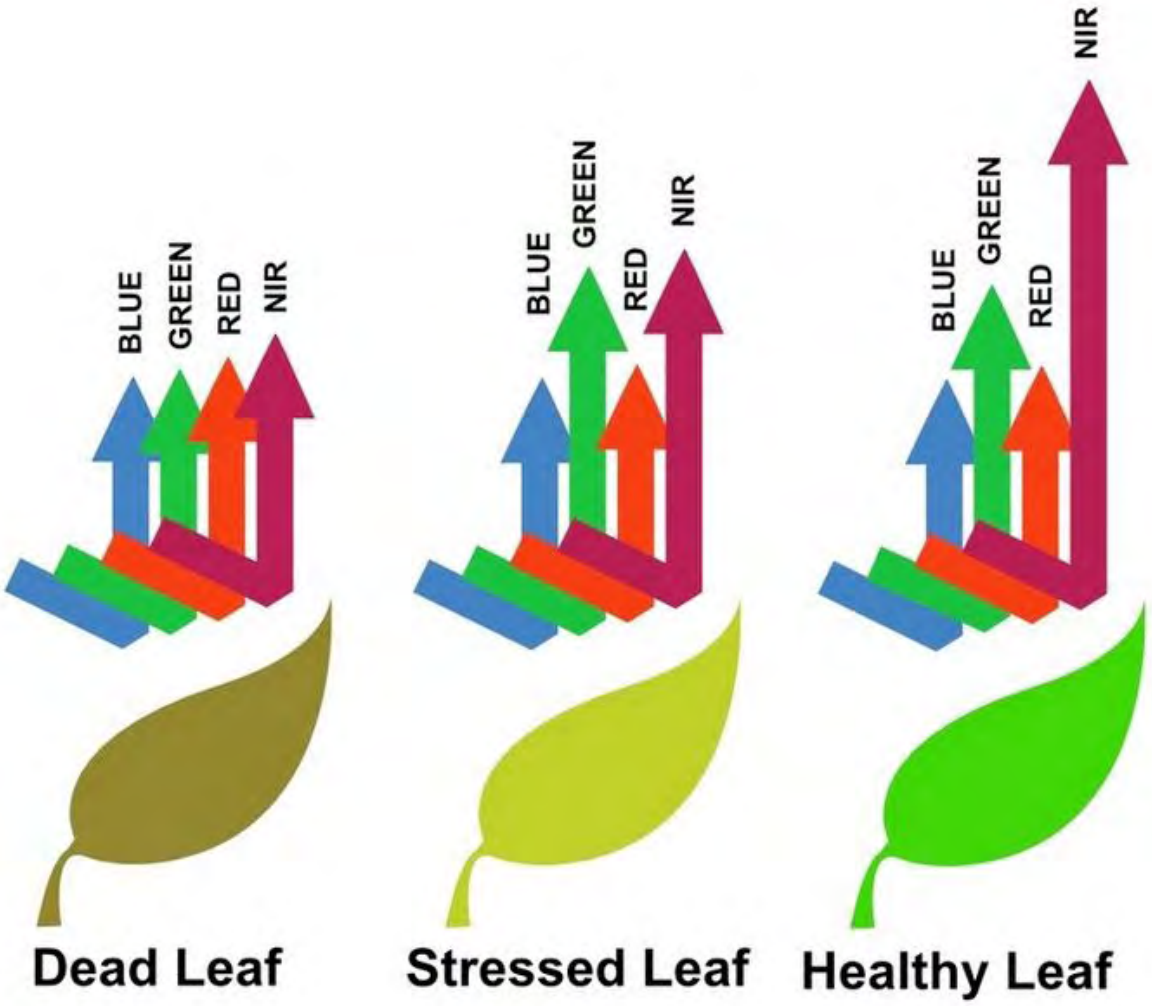

Figure 9. Comparison of leaf's health status based on light reflection.

4.3 Professional Agricultural Drones

This section will present the Agricultural Drones currently available in the market along with their technical features.

4.3.1 Honeycomb AgDrone System

Honeycomb Company's AgDrone system is considered one of the most sophisticated agricultural drones, with the ability to cover 600-800 acres per flight hour, flying at 400 feet (122m). The wings of the drone are composed of Kevlar Fiber composite, same material being used in Bulletproof jackets making the drone rugged for all conditions and in turn making it durable, versatile and powerful for agriculture.

Figure 10. Honeycomb AgDrone

Table 15. Technical Specifications of Honeycomb AgDrone.
[Src: http://www.honeycombcorp.com/agdrone-system]

Parameters	Values
Drone type	Fixed Wing
Material	Kevlar Exoskeleton
Wingspan and Battery	49in; 8000 mAh LiPo

Coverage	858 Acres
Trigger Method	Automatic Dual Camera Electrical Signal
Flight Specifications	Cruise Speed: 46 km/hr Max Speed: 82 km/hr

4.3.2 DJI Matrice 100

The DJI Matrice 100 is the best Quadcopter Drone for agriculture, with dual battery support that increases flight time by approximately 40 minutes. Some of the features that stand out are GPS, Flight Controller, DJI Flightbridge -which is regarded as an Advance Flight Navigation System that allows complex tasks to be assigned to drones- and of course ease of use under any environmental conditions.

Figure 11. DJI Matrice 100 Quadcopter Drone

Table 16. Technical Specifications of DJI Matrice 100 Quadcopter Drone.
[Src: http://www.dji.com/matrice100]

Parameters	Values
Drone type	Fixed Wing with Intelligent Flight Battery
Battery	5700 mAh LiPo 6S
Video Output	USB, HDMI-Mini
Flight Specifications	Max Speed: 5m/s (Ascent) Max Speed: 4m/s (Descent)
Operating Temperature	-10°c to 40 °C

4.3.3 DJI T600 Inspire 1

The DJI T600 Inspire 1 belongs to the Quadcopters category as well. It is a very powerful machine made of carbon fiber, known mainly for its very fast charging battery. It delivers features like 4K Video Capture, individual flight, camera control and easy navigational capabilities.

Figure 12. DJI T600

Table 17. Technical Specifications of DJI T600 Drone.

[Src: http://www.dji.com/inspire-1]

Parameters	Values
Material	Carbon Fiber
Interface Type	Detachable
Battery	4500 mAh LiPo 6s
Camera Features	Image: 4000x3000 ISO Range: 100-3200 (Video) 100-1600 (Photo) Modes (Photography): Single, Burst, Auto Exposure, Time-Lapse Modes (Video): UHD, FHD, HD File Formats: JPEG, DNG, MP4, MOV Memory Card: 64GB (Max)
Flight Operations	Max Speed: 5 m/s (Ascent) Max Speed: 4 m/s (Descent)
Flight Time	18 min / 40 Min with Additional Battery

4.3.4 *Agras MG-1-DJI*

The Agras MG-1-DJI is the ultimate Octocopter Drone designed to help farmers spray large areas of farmland with pesticides, insecticides and fertilizers. The unique feature of this drone is the ability to carry up to 10Kg of liquid loads, covering areas of 4000-6000 square meters in about 10 minutes, making it 70 times faster than manual spraying. The MG-1 has a fully sealed body and consists of an efficient, integrated, centrifugal cooling

system that keeps air flowing to each part of the Drone during flight time. It is equipped with 4 nozzles for precise spraying of fertilizers in the field and is fully equipped with three types of Flight Mode: Smart, Manual Plus Mode and Manual Mode depending on field specifications. The MG-1 has a Y-type folding structure without the use of any additional tools.

Figure 13. Agras MG-1-DJI

Table 18. Technical Specification of Agras MG-1-DJI.
[Src: https://www.dji.com/mg-1]

Parameters	Values
Material	High Performance Engineered Plastics
Liquid Tank	10 Kg (Payload), 10 L (Volume)
Nozzle	4
Battery	MG-12000
Flight Parameters	Max Take Off Weight: 24.5 Kg Max Operating Speed: 8 m/s Max Flying Speed: 22 m/s Operating Temperature: 0 to 40 °C

4.3.5 *EBEE SQ- SenseFly*

EBEE SQ is a high performance agriculture drone specifically designed to monitor crops from planting to harvest to assist farmers in better crop yield. This drone is fully integrated, highly precise and features a multi-spectrum sensor capable of capturing data in four invisible zones along with RGB images in just a single flight. The drone provides more coverage than other quadcopter drones and has automatic 3D flight planning. It is fully compatible with Pix4dmapper AG mapping software for the creation of NDVI maps for crop fields and identify problem areas during flight.

Figure 14. EBEE SQ-SenseFly

Table 19. Technical Specifications of EBEE SQ-Sense Fly.
[Src: https://www.sensefly.com/drones/ebee-sq.html]

Parameters	Values
Drone Type	Detachable Wings with Low-Noise, Brushless and Electric Motor
Flight Operations	Max Flight Time: 55 Minutes Linear Landing with ~ 5m Flight Planning Software: eMotion Ag

Sensors	4 Spectral Sensors, GPS, IMU, Magnetometer, SD Card
Camera	4-1.2 MP Spectral Camera 1fps 16MP RGB Camera

4.3.6 *Lancaster 5 Precision Hawk*

Figure 15. Lancaster 5 Precision Hawk

Lancaster 5 Precision Hawk is among one of the Autonomous Agricultural Drones especially designed for environmental monitoring and has the ability to optimize the flight plan for data collection in the most sophisticated way. By integrating smart flight controls, the drone adjusts accordingly to payloads and unpredictable environmental conditions to return the best possible flight data. It consists of Plug and Play sensors to deliver more data to the user as per the user application specifications. In addition, it has built-in sensors for controlling humidity, temperature, pressure as well as incident light. Finally, since the drone supports open source technology, it gives researchers wide prospects to contribute their own sensor code.

Table 20. Technical Specifications of Lancaster 5 Precision Hawk.

[Src: http://www.precisionhawk.com/lancaster]

Parameters	Values
CPU	720 MHz Dual Core Linux CPU
Interfaces	Analog, Digital, Wi-Fi, Ethernet, USB
Wing	Fixed Wing with Single Electric Motor
Battery	7000 mAhr
Flight Parameters	Altitude: 2500 m
Operating Temperature	40 °C

4.3.7 *SOLO AGCO Edition*

The SOLO AGCO Edition is regarded as to date the most optimal solution via drone for better farm management. The drone is fully autonomous in flight and provides better high resolution aerial maps to assist farmers in monitoring field conditions effectively. It uses intuitive mission planning and high-resolution cloud-based mapping software to increase flight efficiency. SOLO AGCO Edition uses Agribotix imaging and analysis software for precision agriculture.

Figure 16. SOLO AGCO Edition

Table 21. Technical Specifications of SOLO AGCO Edition.
[Src: https://www.pages05.net/agco/SOLO_UAV/contact]

Parameters	**Values**
Flight Controller	PIXHAWK 2
Material	Self-Tightening Glass-Fortified Nylon Props
CPU	1 GHz Onboard Computer
Video	Full HD Streaming to Mobile Device
Flight Parameters	Max Speed: 55 mph Flight Time: 25 Minutes Auto Take Off and Landing
Camera	2 Cameras- GoPro 4 Hero4 Silver for RGB NIR GoPro
Others	Field Health Mapping (NDVI) Management Zone Mapping

4.4 Applications in Agriculture

Many countries whose economy is heavily reliant on the agricultural sector are turning to the use of new technologies such as drones and the data processing algorithms that accompany them. Some typical examples are:

4.4.1 Brazil

Brazilian farmers through their partnership with SimActive Inc., a global leader in photogrammetry (precision aerial photography based digital mapping) and precision agriculture service provider Portal Produtos Agropecuarios Ltda (Portal), adopted the new technology of drones in agriculture, with the results being extremely profitable.

Portal undertakes projects of aerial mapping of agricultural areas in northern Brazil, providing high-level technical and agronomic assistance to farmers in the area. This helps a lot in making crop management decisions on a daily basis. The drone data are sent to be processed by SimActive's Correlator3D in order to extract and visualize all the information included. This data analysis not only leads to better optimization of efficiency and reduction of costs in the agricultural season but also to timely forecast of potential disasters.

The rate of inference is also worth mentioning, since once a farm abnormality is detected from the samples of the plants collected, the process of collecting drone data and completing their processing by Correlator3D, to accurately identify the cause of the problem, usually only lasts 24 hours.

4.4.2 Cape Town in South Africa

Cape Town-based data analytics firm Aerobotics uses sophisticated Machine Learning algorithms in high definition aerial photography to track and review crop development progress across regions around the world. Its cloud-based application, Aeroview, is capable of analyzing individual plants and collecting data on their health, height, volume and other characteristics.

Jean Kuiper, owner of Rosenhof Organic Farm near Cape Town, says her decision to work with Aerobotics to adopt drones in his business has led to a 30% reduction in the use of chemicals to reduce pests and insects in its crops. This results not only in improving the health of the plants, as chemicals greatly impede the plants, but also in preventing the transmission of these substances to animals that naturally feed on them. "By observing the food chain, we can deduce that the effort to improve human health starts with soil health and the less chemicals we use, the less toxic we make it," Kuiper says.

4.4.3 Japan

Another example of a different use of drones is found in Japan, where many farmers use them for the simpler need to spray fertilizers and pesticides on their crops. Young people's lack of interest in farming and their refuge in the larger cities deprive older farmers of the opportunity to maintain their crops and continue to do all the work manually. The solution of drones offers great flexibility as well as speed in these processes. For many, drones are an investment that will not only keep their business afloat but make it much more efficient and profitable.

These new technologies are difficult to be readily adopted by single, especially older farmers who are not used to big changes and risks in their profession. However as the benefits of drone technology will become more and more known from its practical

application in crops, more countries will promote its use and people will eventually embrace it.

Chapter 5

Tomato Leaf Disease Detection

5.1 Overview

In this chapter, a brief presentation of some of the state-of-the-art DL models for image classification will be presented, along with the implementation of three DNNs for the detection of plant diseases in PlantVillage dataset [71]. More specifically, the two most widely known and influential CNN architectures, namely AlexNet [72] and GoogLeNet [73], along with the cutting edge ResNet's [74] architecture will be explained, trained and compared to each other, based on the work of Zhang et al. (2018) [78].

Many state-of-the-art DL models/architectures evolved after the introduction of the first modern CNN, AlexNet, at 2012 , for image detection, segmentation, and classification. **Figure 17** showcases the evolution of DL models from 2012 to present, while **Figure 18** displays the citations that CNN-related papers have received for plant disease detection and classification since then.

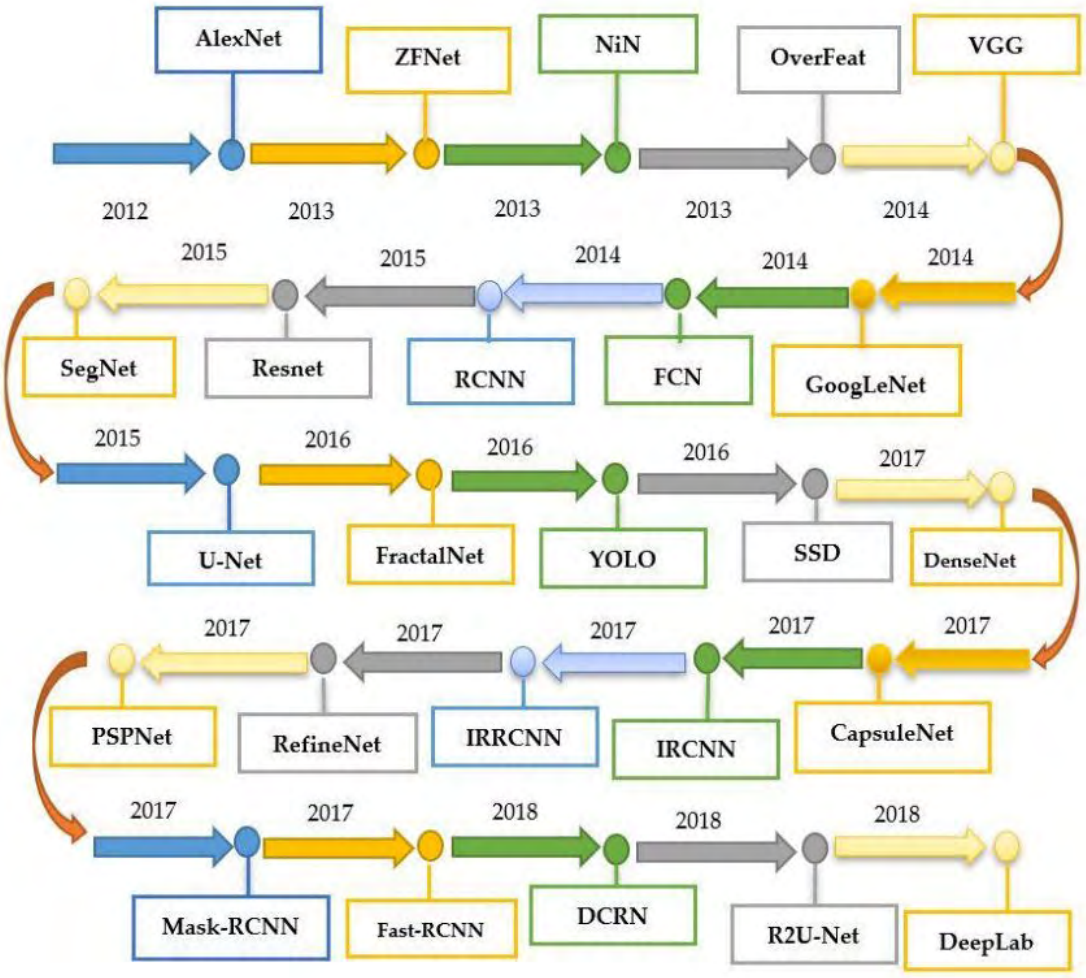

Figure 17. Summary of the evolution of various deep learning models from 2012 until now.

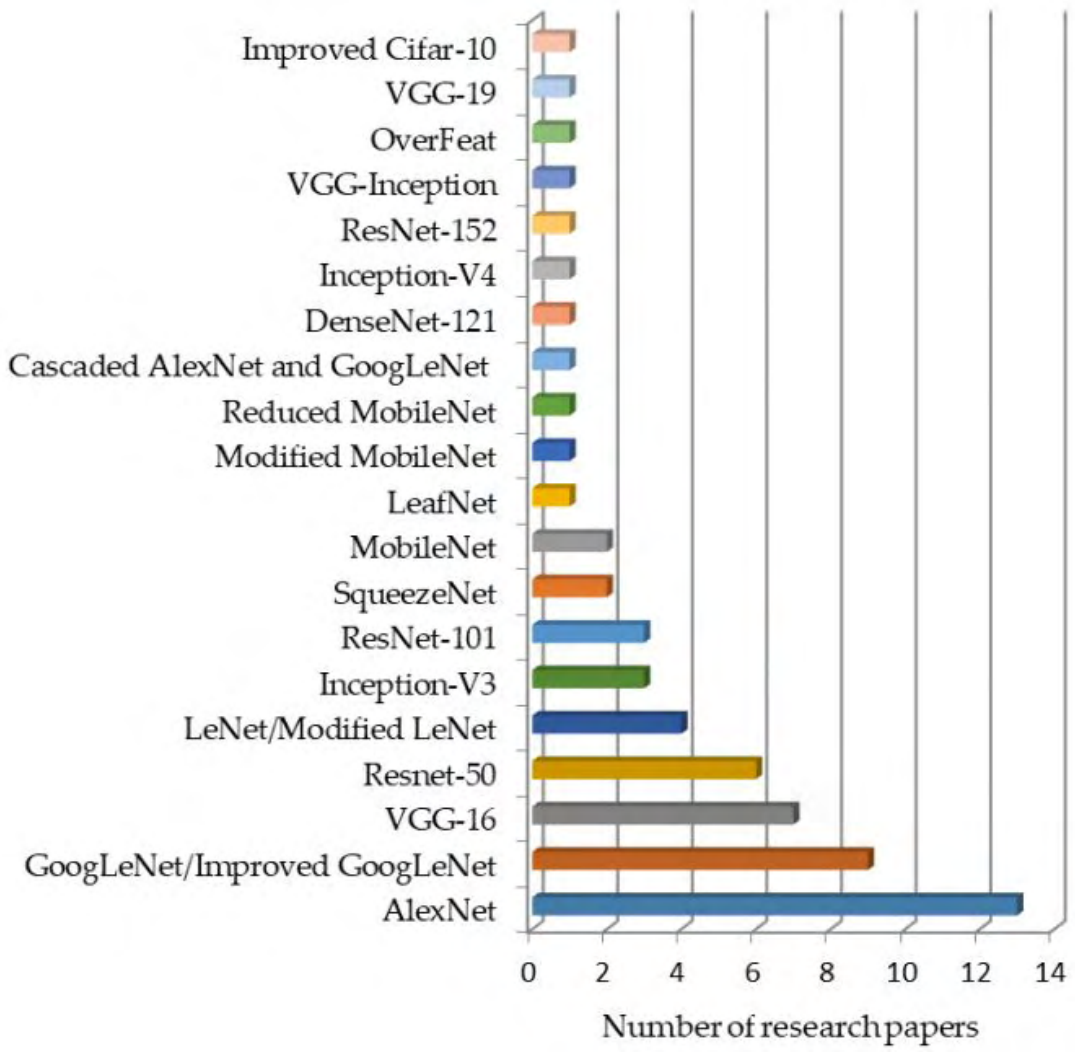

Figure 18. Deep learning models cited in plant disease detection works.

5.2 PlantVillage Dataset

PlantVillage is a widely used dataset for model testing and comparison, as it contains approximately 54,000 images of 14 different crops having 26 plant diseases, made openly available through the project of D. Hughes and M. Salathe (2015) [75]. .

Figure 19 shows an image example of every crop-disease pair used in PlantVillage. The images are listed as: (1) Apple Scab, Venturia inaequalis (2) Apple Black Rot, Botryosphaeria obtusa (3) Apple Cedar Rust, Gymnosporangium juniperi-virginianae (4)

Apple healthy (5) Blueberry healthy (6) Cherry healthy (7) Cherry Powdery Mildew, Podoshaera clandestine (8) Corn Gray Leaf Spot, Cercospora zeae-maydis (9) Corn Common Rust, Puccinia sorghi (10) Corn healthy (11) Corn Northern Leaf Blight, Exserohilum turcicum (12) Grape Black Rot, Guignardia bidwellii, (13) Grape Black Measles (Esca), Phaeomoniella aleophilum, Phaeomoniella chlamydospora (14) Grape Healthy (15) Grape Leaf Blight, Pseudocercospora vitis (16) Orange Huanglongbing (Citrus Greening), Candidatus Liberibacter spp. (17) Peach Bacterial Spot, Xanthomonas campestris (18) Peach healthy (19) Bell Pepper Bacterial Spot, Xanthomonas campestris (20) Bell Pepper healthy (21) Potato Early Blight, Alternaria solani (22) Potato healthy (23) Potato Late Blight, Phytophthora infestans (24) Raspberry healthy (25) Soybean healthy (26) Squash Powdery Mildew, Erysiphe cichoracearum (27) Strawberry Healthy (28) Strawberry Leaf Scorch, Diplocarpon earlianum (29) Tomato Bacterial Spot, Xanthomonas campestris pv. vesicatoria (30) Tomato Early Blight, Alternaria solani (31) Tomato Late Blight, Phytophthora infestans (32) Tomato Leaf Mold, Passalora fulva (33) Tomato Septoria Leaf Spot, Septoria lycopersici (34) Tomato Two Spotted Spider Mite, Tetranychus urticae (35) Tomato Target Spot, Corynespora cassiicola (36) Tomato Mosaic Virus (37) Tomato Yellow Leaf Curl Virus (38) Tomato healthy.

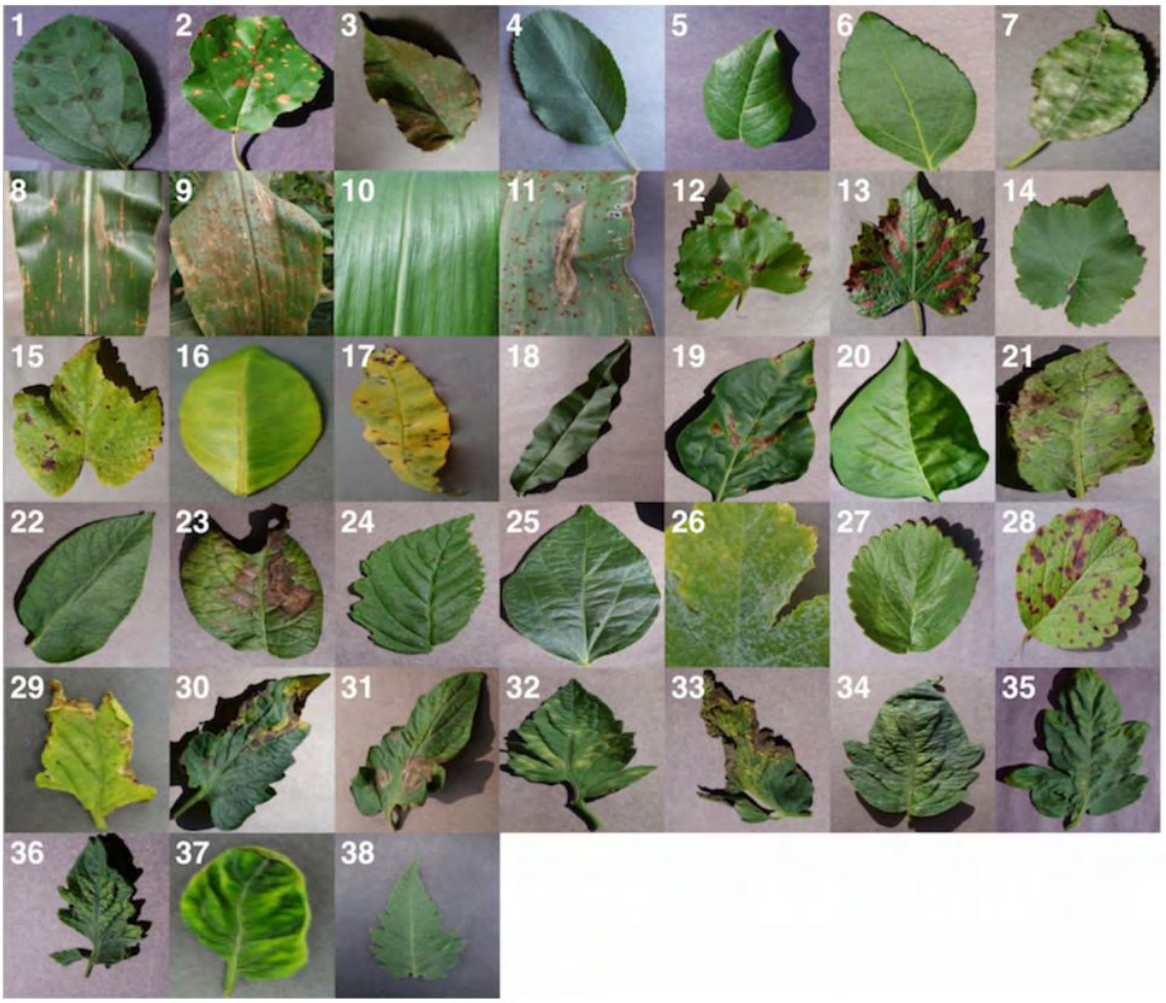

Figure 19. Example of leaf images from the PlantVillage dataset, representing every crop-disease pair used.

However, for the purpose of this chapter, only a part of the dataset will be used, containing 8 different diseases along with health, for tomato crop. The total number of available images in the cropped dataset is 5550. The respective sub-categories of tomato diseases are presented below:

1. Mosaic virus
2. Yellow leaf curl virus
3. Corynespora leaf spot
4. Healthy
5. Early blight
6. Late blight

7. Leaf mold
8. Septoria leaf spot
9. Two spotted spider mite

The dataset was split in a 80/20% train/test samples set and then the *Data Augmentation* procedure was conducted in order to reduce the problem of overfitting. At first, every image was flipped from left to right, from top to bottom and diagonally. Also the authors adjusted the brightness of image, setting the max delta to 0.4, and the contrast of image, setting the ratio from 0.2 to 1.5. The hue of image was also adjusted, setting the max delta to 0.5, along with the saturation, by setting the ratio from 0.2 to 1.5. Finally, they rotated the image by 90◦ and 270◦, respectively.

5.3 Model Presentation

As mentioned in the beginning of this chapter, three deep learning models will be presented by the names of AlexNet, GoogLeNet and ResNet. Among those architectures, AlexNet is considered to be a breakthrough in the field of DL as it won the ImageNet challenge for object recognition known as ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in the year 2012. Soon after, several architectures were introduced to overcome the loopholes observed previously.

5.3.1 AlexNet

At the ILSVRC (ImageNet Large-Scale Visual Recognition Challenge) 2012 challenge, AlexNet outperformed other methods on image classification. After the success of AlexNet, CNNs started to spread exponentially in the computer vision community. It's worthwhile mentioning that AlexNet used some of the now standard techniques in deep learning, such as ReLU units and dropout though they were first introduced by other papers. The most important features and hyperparameters of AlexNet are described below.

Highlights of AlexNet:

- *First use of Rectified Linear Units (ReLU):* By using ReLU function instead of tanh or sigmoid, the authors addressed the problem of the vanishing gradient when the backward input is larger and achieved 8 times faster training for the same error rate.
- *Used Norm Layers*
- *Multiple GPUs:* AlexNet allows for multi-GPU training by putting half of the model's neurons on one GPU and the other half on another GPU. Not only does this mean that a bigger model can be trained, but it also cuts down on the training time.
- *Dropout 0.5:* This technique consists of "turning off" neurons with a predetermined probability (e.g. 50%). This means that every iteration uses a different sample of the model's parameters, which forces each neuron to have more robust features that can be used with other random neurons. However, dropout also increases the training time needed for the model's convergence.
- *Batch size 128*
- *SGD Momentum 0.9*
- *Learning rate 0.01, reduced by 10 manually when val accuracy plateaus*
- *L2 weight decay 5e-4*
- *7 CNN ensemble: 18.2% → 15.4%*
- *Fixed input size of 256x256*
- *60 million Parameters*

Although ReLUs have the desirable property that they do not require input normalization to prevent them from saturating, the authors still applied normalization after applying the ReLU nonlinearity in certain layers.

$$b^i_{x,y} = a^i_{x,y}/(k + a \sum_{j=max(0,i-n/2}^{min(N-1,i+n/2)} (a^j_{x,y})^2)^\beta$$

They found that response normalization reduces the top-1 and top-5 error rates by 1.4% and 1.2%, respectively. Also, dropout was added in the first two fully-connected layers. Without dropout, the network exhibits substantial overfitting while dropout roughly doubles the number of iterations required to converge. Finally, they used overlapping pooling to reduce dimensions. They found that with s = 2 and z = 3, the scheme reduces the top-1 and top-5 error rates by 0.4% and 0.3%, respectively, as compared with the non-overlapping scheme with s = 2 and z = 2, which produces output of equivalent dimensions. They also observed that during training the models with overlapping pooling were more difficult to overfit.

The architecture of AlexNet consists of eight layers; five convolutional layers and three fully-connected layers. More specifically as described in the relative paper, the first convolutional layer filters the 224×224×3 input image with 96 kernels of size 11×11×3 with a stride of 4 pixels. The second convolutional layer takes as input the (response-normalized and pooled) output of the first convolutional layer and filters it with 256 kernels of size 5 × 5 × 48. The third, fourth, and fifth convolutional layers are connected to one another without any intervening pooling or normalization layers. The third convolutional layer has 384 kernels of size 3 × 3 × 256 connected to the (normalized, pooled) outputs of the second convolutional layer. The fourth convolutional layer has 384 kernels of size 3 × 3 × 192 , and the fifth convolutional layer has 256 kernels of size 3 × 3 × 192. The fully-connected layers have 4096 neurons each [72]. **Figure 20** illustrates the overall architecture of AlexNet.

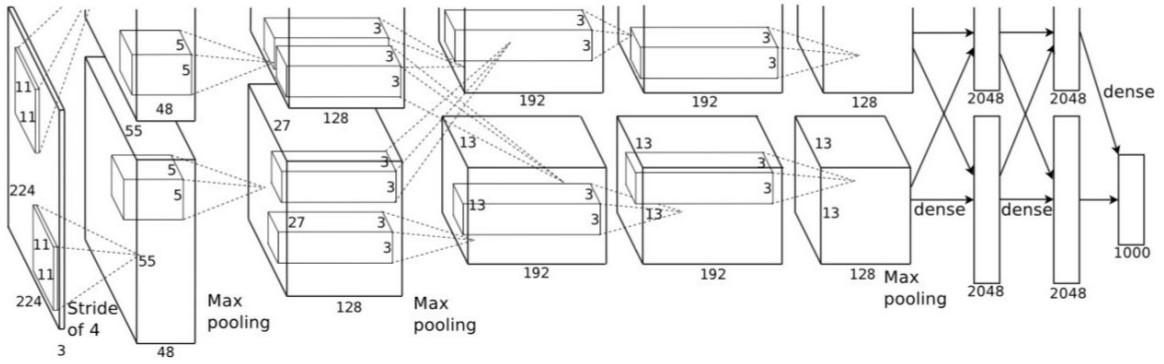

Figure 20. AlexNet architecture.

5.3.2 GoogLeNet

GoogLeNet, also known as Inception v1 (as there are v2, v3, v4 later on), is the winner of the ILSVRC 2014, which has significant improvement over ZFNet (The winner in 2013) and AlexNet, and has relatively lower error rate compared with the VGGNet (1st runner-up in 2014). As implied by its name, this network was built from Google. Also, the name GoogLeNet contains the word "LeNet" for paying tribute to Prof. Yan LeCun's LeNet [76]. The original paper has been cited over 19,000 times in relative works and has been one of the most influential papers regarding the evolution of CNNs. The architecture presented in this section regards the first version of the network.

This network architecture is quite different from AlexNet. It contains 1×1 Convolution at the middle of the network. Also, global average pooling is used at the end of the network instead of using fully connected layers. These two techniques were first introduced in another paper, called "Network In Network" (NIN) [77]. Another technique, called inception module, is to have different sizes/types of convolutions for the same input and stacking all the outputs. The most stand out features of GoogLeNet are listed below.

Highlights of GoogLeNet:

- *1x1 Convolution*
- *Inception Module/Layer*: It is mentioned by the authors that the name was inspired by the NIN paper and a famous internet meme coming from the movie "Inception" saying "We need to go deeper".
- *Global Average Pooling:* Improved the top-1 accuracy by about 0.6%.
- *Auxiliary Classifiers for Training:* Can be used for combating gradient vanishing problem, also providing regularization according to the authors.
- *22 layers*
- *7 million parameters*

More specifically, the 1×1 convolution introduced by NIN, is used with ReLU. Although, originally, NIN uses it for introducing more non-linearity to increase the representational power of the network, in GoogLeNet, 1×1 convolution is used as a dimension reduction module to reduce the computation. By reducing the computation bottleneck, depth and width can be increased. This particular technique when used before another more complex convolution (e.g. 5x5), appeared to decrease the number of operations needed by a fraction of 10. This is exceptionally important in reducing model size, can help reducing the overfitting problem and as a result, it helped GoogLeNet perform way better than AlexNet, with only 7M instead of the latter's 60M parameters. It is also the reason why the inception module was efficient, as it can be built without increasing the number of operations largely compared to the one without 1x1 convolution.

The idea of the inception layer is to cover a bigger area, but also keep a fine resolution for small information on the images. So the idea is to convolve in parallel different sizes from the most accurate detailing (1x1) to a bigger one (5x5). The naive version of this layer does not include 1x1 convolution, whereas the inception layer used in GoogLeNet, did. **Figure 20** below presents the two inception layers.

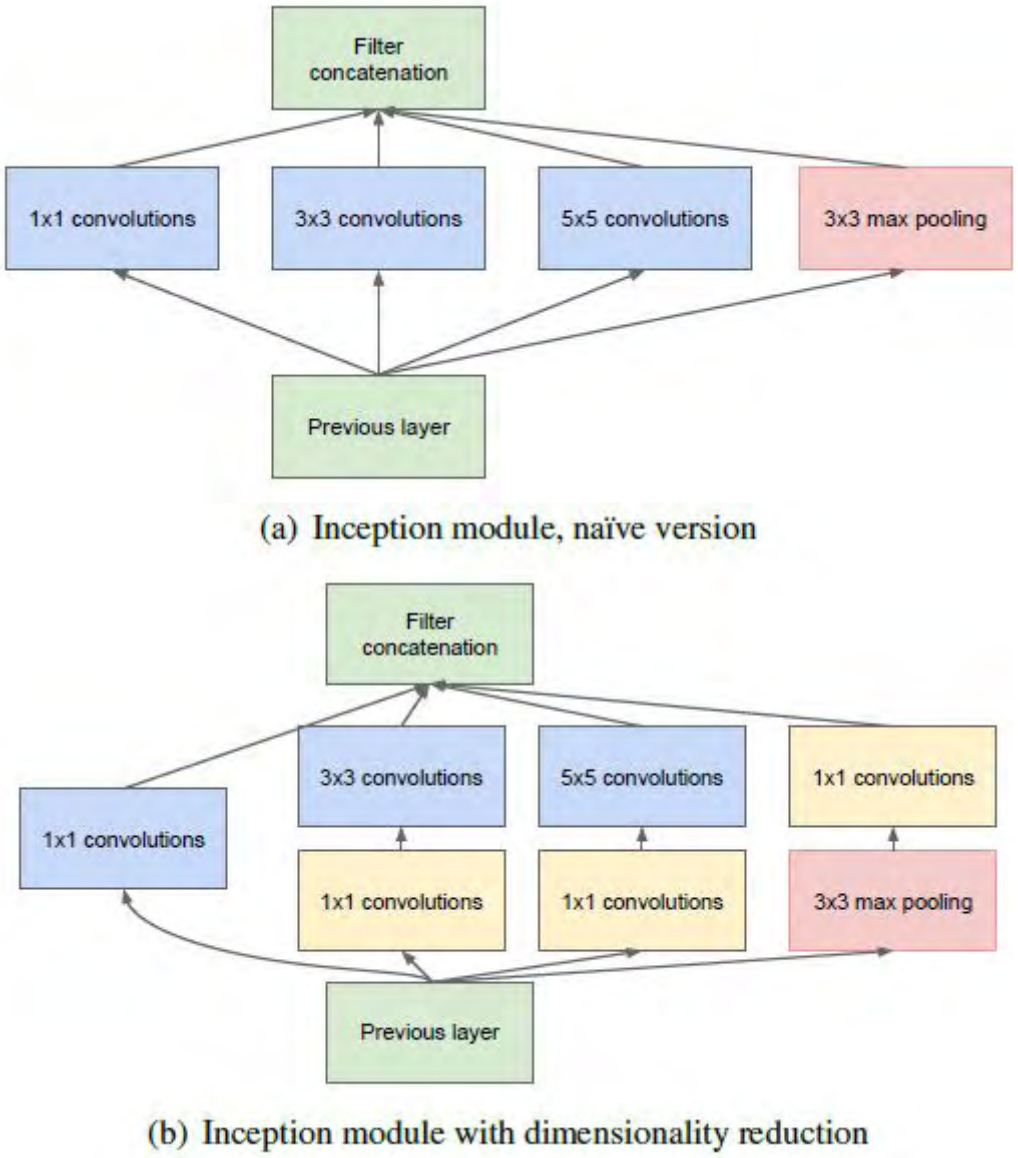

Figure 21. (a) Naive inception module, (b) inception module with 1x1 convolution technique.

As shown in **Figure 21**, 1×1 conv, 3×3 conv, 5×5 conv, and 3×3 max pooling are done altogether for the previous input, and stack together again at output. When an image is coming in, different sizes of convolutions as well as max pooling are tried. Then different kinds of features are extracted. Finally, all feature maps at different paths are concatenated together as the input of the next module.

GoogLeNet has 9 such inception modules stacked linearly. It is 22 layers deep (27, including the pooling layers). It uses global average pooling at the end of the last inception module. **Figure 22**, presents the overall architecture of GoogLeNet.

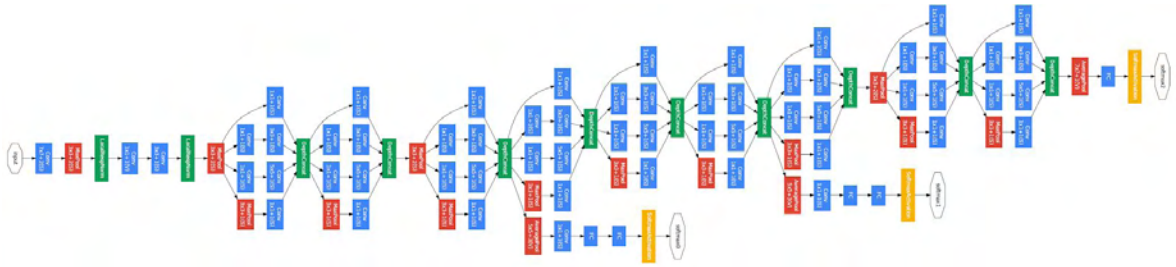

Figure 22. GoogLeNet architecture.

5.3.3 ResNet

After the victory of AlexNet at the LSVRC2012 classification contest, deep Residual Network (ResNet) was arguably the most groundbreaking work in the computer vision/deep learning community in the last few years. ResNet makes it possible to train up to hundreds or even thousands of layers and still achieves compelling performance.

Much of the success of DNNs has been accredited to additional layers. The intuition behind their function is that these layers progressively learn more complex features. The first layer learns edges, the second layer learns shapes, the third layer learns objects, the fourth layer learns eyes, and so on. However, increasing the network's depth does not work by simply stacking layers together. Deep networks are more challenging to train because of the notorious vanishing gradient problem — as the gradient is back-propagated to earlier layers, repeated multiplication may make the gradient infinitively small. As a result, when the network goes deeper, its performance gets saturated or even starts degrading rapidly. **Figure 23** presents the training and test error percentage per iteration for a basic 20-layer and a 56-layer network on CIFAR-10 [74].

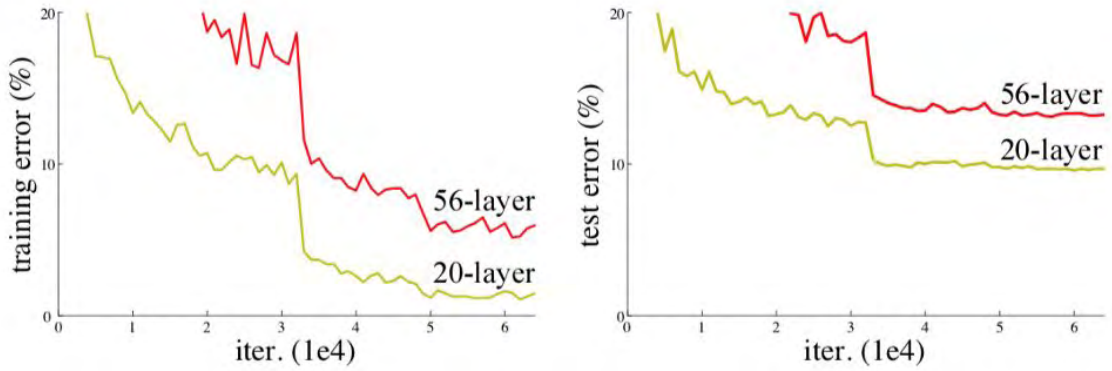

Figure 23. DNN performance as network goes deeper.

The problem of training very deep networks has been alleviated with the introduction of a new neural network layer — **The Residual Block. Figure 24** presents this new block.

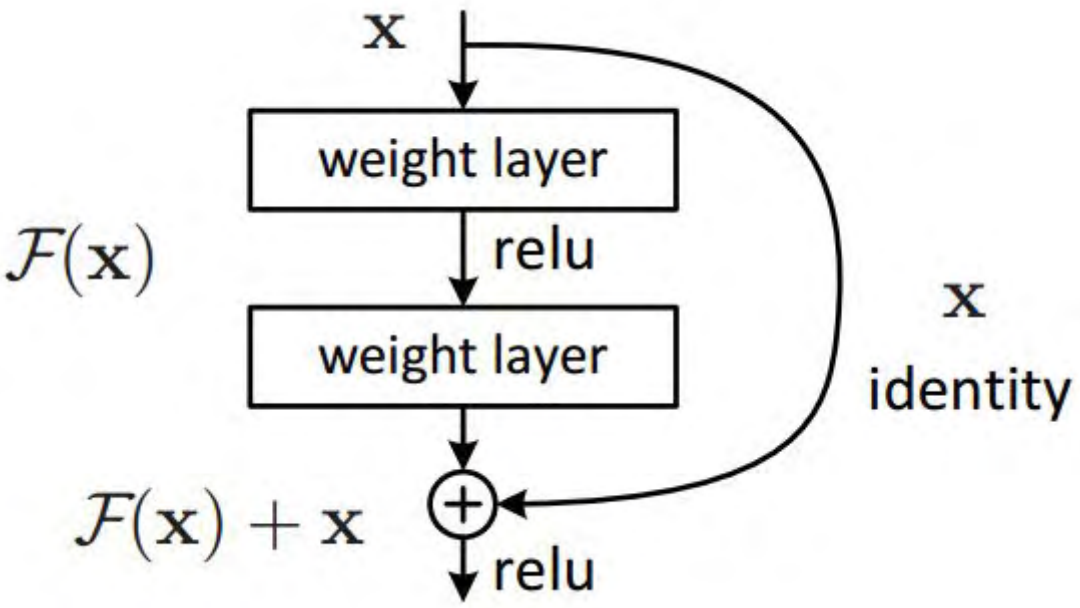

Figure 24. Residual learning: a building block.

The most important part of this new block is the "Skip connection", identity mapping feature. This identity mapping does not consist of any parameters and is just there to add the output from the previous layer to the layer ahead. However, occasionally x and F(x) will not have the same dimension, as a convolution operation typically shrinks the spatial

resolution of an image (unless the appropriate padding and stride is added). The identity mapping is multiplied by a linear projection W to expand the channels of shortcut to match the residual. This allows for the input x and F(x) to be combined as input to the next layer.

$$y = F(x, \{W_i\}) + W_s x.$$

The W_s term can be implemented with 1x1 convolutions and this introduces additional parameters to the model.

The Skip Connections between layers add the outputs from previous layers to the outputs of stacked layers. This results in the ability to train much deeper networks than what was previously possible. The authors of the ResNet architecture tested their network with 100 and 1,000 layers on the CIFAR-10 dataset. They also tested this architecture on the ImageNet dataset with 152 layers. An ensemble of deep residual networks achieved a 3.57% error rate on ImageNet which achieved 1st place in the ILSVRC 2015 classification competition. **Figure 25** illustrates the design of a 34-layer residual network. The dotted skip connections in the figure below, represent multiplying the identity mapping by the Ws linear projection term discussed earlier, to align the dimensions of the inputs.

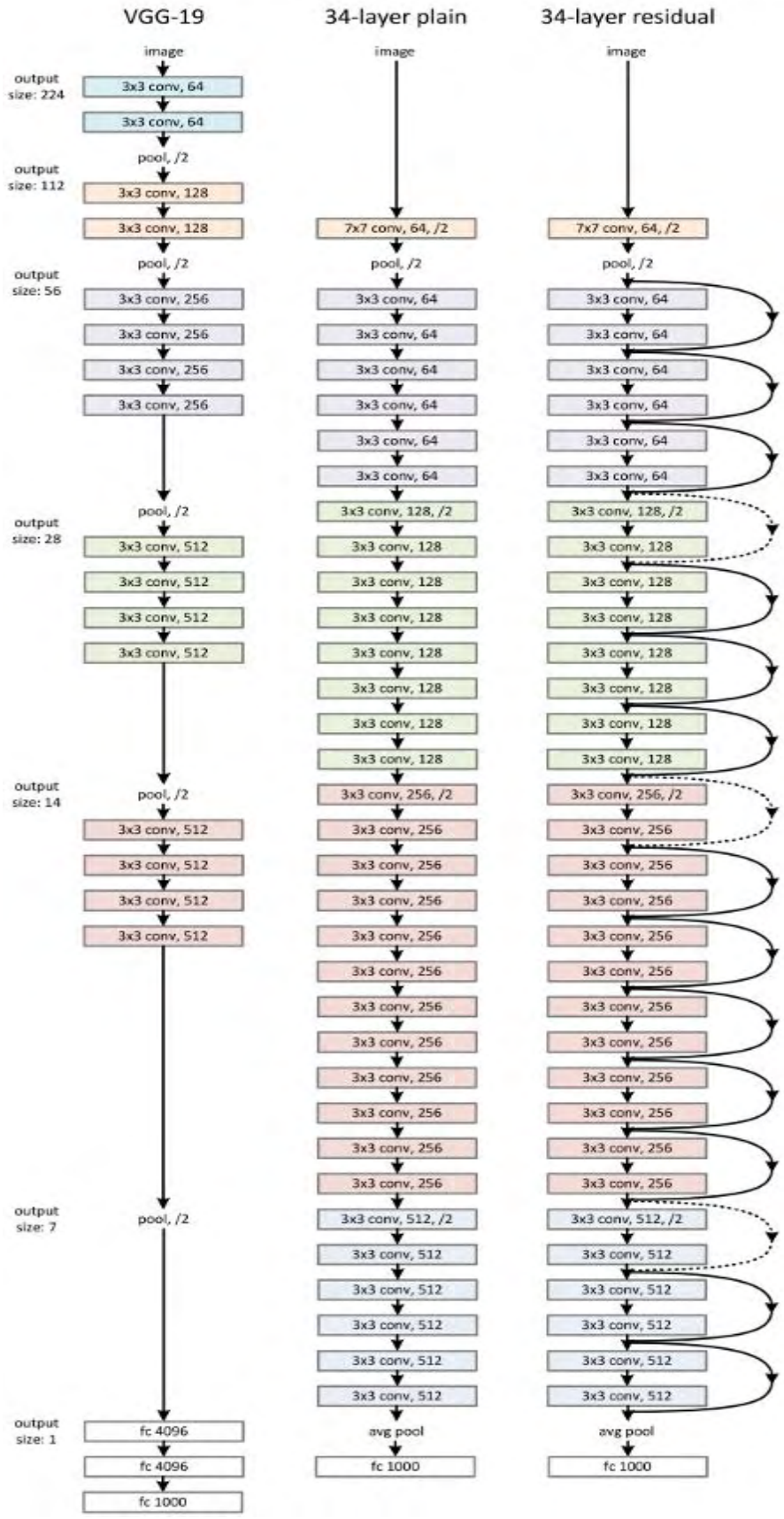

Figure 25. A 34-layer ResNet architecture.

5.4 Model Training and Results

In the relative work [78], the authors picked overall accuracy as the evaluation metric in every experiment on tomato leaf disease detection. Overall accuracy is the percentage of samples that are correctly classified as described by the equation below:

$$accuracy = \frac{true\ positive + true\ negative}{positive + negative},$$

where "true positive" is the number of instances that are positive and correctly classified as positive, "true negative" is the number of instances that are negative and classified as negative, and the denominator represents the total number of samples. The training time was also included as an additional performance metric of the network structure experiment.

The three specific architectures used in the experiment was AlexNet of ILSVRC 2012, GoogLeNet of ILSVRC 2014 and a ResNet of 50 layers instead of the 101 or the 152-layer ResNet due to less computing resources and training time, which also has great performance. **Figure 26, 27, 28** present the respective architectures.

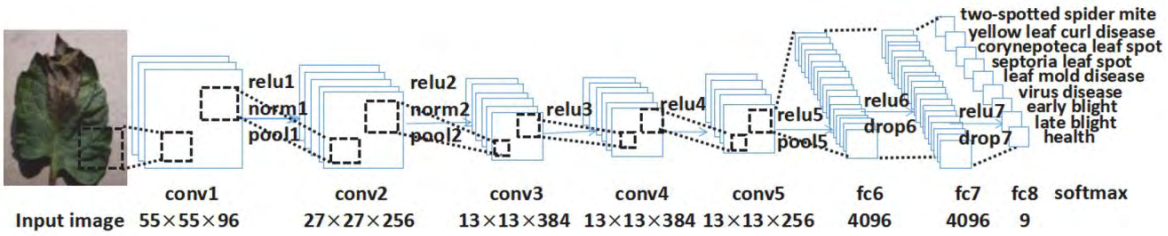

Figure 26. AlexNet's architecture in this work.

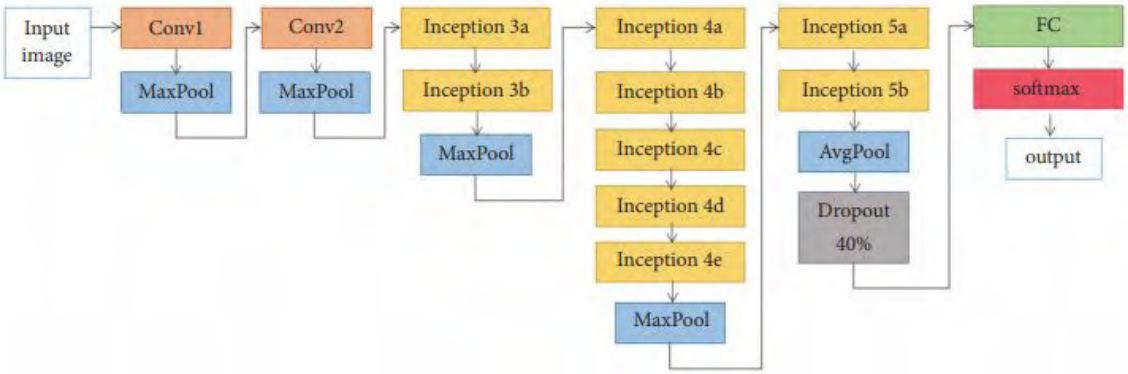

Figure 27. GoogLeNet's architecture.

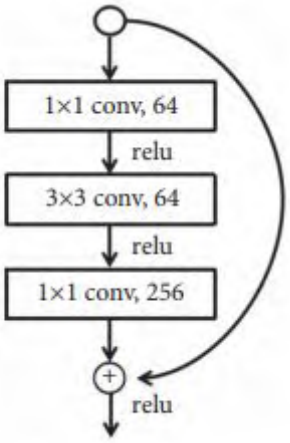

Figure 28. ResNet bottleneck residual building block.

Two optimization methods, SGD and Adam, were used and compared. The basic hyperparameters of the networks were set as shown below:

Hyperparameters:

- Batch size = 32
- Learning rate: 0.001, dropped by a factor of 0.5 every 2 epochs.
- Epochs = 5
- No. of iterations = 6240
- SGD

    - Momentum = 0.9
- Adam
    - Gradient decay rate $\beta_1 = 0.9$
    - Squared gradient decay rate $\beta_2 = 0.999$
    - Denominator offset $\varepsilon = 10^{-8}$

The accuracy of each of the models are displayed in **Table 22**.

Table 22. Models recognition accuracy.

Model	Accuracy
AlexNet (SGD)	95.83%
AlexNet (Adam)	13.86%
GoogLeNet (SGD)	95.66%
GoogLeNet (Adam)	94.06%
ResNet (SGD)	**96.51%**
ResNet (Adam)	94.39%

As shown in the table above, ResNet with SGD optimization method provides the best test accuracy (96.51%) in identifying tomato leaf diseases and it is superior to the others, as expected. AlexNet and GoogLeNet perform in a similar way. Adam optimization method proved inferior to the SGD in this experiment, though it is a method widely used in DL and usually performs quite better.

Chapter 6

Conclusion

6.1 Conclusion

In this thesis, a survey of machine learning-based research efforts applied in the agricultural domain was performed. 78 relevant papers were studied, examining the particular area and problem they focus on, the technical details of the models and techniques employed, sources of data used and overall performance according to the performance metrics employed by each paper. Additionally, there was a comparative analysis of most used models regarding each field of agriculture and as a total. The goal was to examine previous works and get a general idea about which are the best models for each agricultural task. Along with this effort, a brief presentation of the best professional agricultural drones was provided, as a part of the overall vision of this thesis for the future of agriculture. Drones are very flexible machines that can collect large amount of crop/field data with ease, whenever needed and provide that data for analysis by ML/DL models. Science is leaning towards artificial intelligence more and more over the last decade and provided that these models will be integrated in drones efficiently, this combination can lead to groundbreaking progress in the field of traditional agriculture.

6.2 Future Work

UAVs in precision agriculture is still in early stage and is a scope for further development in both the technology and the agriculture applications. A complete system of agricultural drones collecting the data and delivering them to a ML center for processing is the next

step of this thesis' vision. Undoubtedly, a lot of testing has to be executed before the integration of these two technologies is optimal. However, the benefits especially in the field of data collection, are so many and with high importance in quick decision making, which is the ultimate goal, that will eventually convince investors and governments to fund similar projects.

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