JIMMA UNIVERSITY JIMMA INSTITUTE OF TECHNOLOGY

FACULTY OF COMPUTING AND INFORMATICS

MASTERS PROGRAM IN INFORMATION SCIENCE (IKM)

COFFEE ARABICA NUTRIENT DEFICIENCY DETECTION SYSTEM USING IMAGE PROCESSING TECHNIQUES

BY: FIREZER TENAYE MARU

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A RESEARCH SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR DEGREE OF MASTERS OF SCIENCE (MSc) IN INFORMATION SCIENCE (IKM)

BY: FIREZER TENAYE MARU

PRINCIPAL ADVISOR: Mr. CHALA DIRIBA (ASS. PROFESSOR)
CO-ADVISOR: Mr. MUKTAR BEDASO (MSc)

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As members of the board of examining of the MSc. research defense examination of the above title, we members of the board listed below have read, evaluated and examined this thesis.

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______________________	Chair Person	____________	_________
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Declaration

I declare that this thesis is my original work and it has not been presented for a degree in any other Universities. All the material sources used in this work are scientifically acknowledged.

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Firezer Tenaye Maru

November, 2021

This thesis has been submitted to the Information Management chair MSc in Information Science for examination with our approval as uuniversity aadvisors:

Principal Advisor: Chala Diriba (Assistant Professor) Signature………. Date ……...

Co-Advisor: Muktar Bedaso (MSc) Signature………....Date……….

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Abstract

This study mainly focused on the detection of Coffee Arabica nutrient deficiency by using image processing techniques. There are problems on Coffee productivity because of Coffee nutrition deficiency. Coffee nutrition deficiency techniques are very traditional and time taking which means the agronomists simply detect deficiencies by observing the leaves of the coffee and decide by guessing. The study employed experimental research design which involves dataset preparation, designing classification model and evaluation. Experimentation and image processing steps are followed with: image acquisition, image preprocessing (image filtering and attribute selection), image analysis (segmentation, feature extraction and classification), and image understanding for raw qualifying and image scaling. In addition, Python programming languages were used.. The researcher has 422 total nutritional deficient Coffee plant leaves image data set, from this data first the researcher split 20 percent for testing which is 84 images and 338 training image data, and further from the remaining training data, the researcher again split20 percent validation data which is 10 images.

The three pre-trained deep learning models were used to evaluate the experiments. The evaluation of the system indicated the performance of Mobile Net (0.9882), VGG16 Net (0.6471) and Inception_V3 (0.8095). Therefore, testing and training value of Mobile Net model was more accurate than the rest of two models. Finally, the prototype for detection of Coffee nutrient deficiency developed by using Mobile Net deep learning model. For the feature the researchers suggest performing deeper researchers for CNN and image processing with regards to coffee. Also, this research can be improved in terms of portability and innovative collaboration with another platform technology.

Keywords: Nutritional deficiencies, Coffee Arabica, Computer Vision, image processing.

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the study

Coffee is a beverage obtained from cherry or the fruit of coffee plant. Coffee is an edible commodity. It is widely used as a beverage but nowadays it is also used as input in some food processing industries. Coffee can be used as a flavoring to various pastries, ice-creams, chocolate. The coffee plant refers to several species of the genus coffee of the madder family, which is actually a tropical evergreen shrub (Teketay, 2016).

There are different types of coffee in the world. Among different types of coffee, the major economic species are coffee Arabica and coffee Robusta. Coffee Arabica accounts for 80% of the world coffee trade, and coffee Robusta accounts the remaining 19.5%, Coffee ***Liberica*** and ***Excelsa*** together supply less than 1% (Nation, 2018). From various coffee types, Ethiopia produces only coffee Arabica, which was originated in the country.

Coffee Arabica is a wild crop that grows in the forests of south-western parts of the country, which contain an important source of genetic resources for the world coffee industry. Coffee production in Ethiopia is a longstanding tradition which dates back to dozens of centuries. Ethiopia is where Coffee Arabica the Coffee plant originates. The plant is now grown in various parts of the world. Ethiopia itself accounts for around7-9% of the global Coffee market (Coffee Production and Marketing In Ethiopia). Coffee is important to the economy of Ethiopia around 27%of foreign income comes from Coffee, with an estimated 25 million of the population relying on some aspect ofCoffee production for their livelihood (Amamo, 2014).

Agriculture has always been an important component of the economy of many countries across the world. For instance, Agriculture is the main source of the Ethiopian economy. This means, Coffee production and marketing is the common occupation for Ethiopian farmers. This is due to that Ethiopia is the birthplace of Coffee and that the plant was discovered there earlier in the tenth century (Khanna & Solanki, 2014).

Ethiopian mountain peoples had been the first to recognize the red cherries of Coffee beans that have stimulating effect. Although they ate the red cherries directly, they did not drink it as a beverage initially. Then the mystic Sufi pilgrims of Islam spread Coffee throughout the Middle East. From the Middle East these Ethiopian Coffee beans spread to Europe and then throughout their colonial empire including Indonesia and American states.

Hence, a story of Coffee was beginnings in Ethiopia, and the country is the original home of Coffee plant. Nobody is sure, exactly how Coffee originally was discovered as a beverage plant. However, observing the natural settings, scholars believed that its cultivation and use began as early as the 9th century in Ethiopia.

Some authors claim that coffee was cultivated in Yemen earlier, around 575 AD; while, it originated in Ethiopia, from where it traveled to the Yemen about 600 years ago. Finally, it began its journey around the world from Arabia (Amamo, 2014). Accordingly, ahead of 1,000 years, a goatherd, in the southwestern highlands of Ethiopia, plucked a few red berries from some young green Coffee trees growing in the forest, tasted them to check if they have the flavor and make feel-good effect to the consumers at that time (Amamo, 2014).

A plant disease is any abnormal condition that alters the appearance or function of a plant. It is a physiological process that affects some or all plant functions. This could emerge because of various reasons: it could be due to deficiency of nutrients, drought/deficiency of water and/or due to pathologic microorganisms.

Among all, this paper focuses on the image processing of the plant disease caused by nutrient deficiency. Nutrient deficiency reduces amount and quality of harvested products. Nutrient deficiency is a gradual process or a change that occurs over time. It does not occur instantly like injury (Kinzer, 2011). Therefore, plants Nutrient deficiency usually takes the attention of several researchers, in order to prevent and mitigate the negative effect of diseases in crops. Several efforts have been focused on exploiting digital image processing techniques and supervised classification approaches for detecting plants diseases through the analysis of several parts such as roots, fruits, stems, and leaves (Mahlein, 2016).

The main purpose of such efforts is the reduction of the subjectivity arising from human experts in the manual detection and recommendation of coffee plant Nutrient deficiency. Specifically, in the last few years, there have been developed several research works focused on processing digital images of plants leaves for detecting Nutrient deficiency. In this way, some key samples are the use of neural networks for processing features of rice leaves, the use of feature-based rules for processing images with citrus's leaves, or the use of neural networks also for processing maize disease images. Thus, although most of the research is focused on popular crops such as maize, rice, or vegetables, there is a lack of works focused on a worldwide demanded crop like the Coffee tree especially Coffee Arabica in Ethiopia.

Coffee Nutrient deficiency can cause significant damage on Coffee production. The outbreak and spread of Coffee Nutrient deficiency in to Coffee production areas can reduce the Coffee yields. Hence, it would be essential to detect the types and characteristics features of the nutrient deficiency so that they can be under control that the production sustain successfully. Although such practices are processed traditionally/manually, it requires high cost and long period of time as well as much labor. On the other hand, the plants need the right combination of nutrients to live, grow and reproduce. Otherwise, malnutrition affects their proper growth, and they show symptoms of being unhealthy. Too little or too much of any nutrient can cause problems (Avelino, 2008). For instance, nutrient deficiency in Coffee plants affects its yield or production. Therefore, its early identification would be important to solve the problem based on descriptions in images of the Coffee tree leaves.

Image processing is a set of technologies, in which an image data analysis and processing algorithms as well as tools that are applied to improve the interpretation of data images. The process yields more useful information for determining values and providing decision. Image processing allows the extraction of useful information from different parameters, and increases the likelihood of determining the coffee Nutrient deficiency more accurately (caicedo, 2017).

Image processing is a rapidly growing area of computer science. Its growth has been fueled by technological advances in digital imaging, computer processors, and mass storage devices. Fields which traditionally used analog imaging are now switching to digital systems, for their flexibility and affordability. Digital image processing has an expanding area with applications in our daily life (Birhanu Turi, 2013).

Many image processing and analysis techniques have been developed to aid the interpretation of data images and to extract as much information as possible from the image that can help us in making decision on the quality of agricultural products. It uses various techniques such as: image acquisition, preprocessing, segmentation, feature extraction and classification to improve the quality of images and assists in understanding and interpreting detail of agricultural product images (Daskalakis, 2020).

Image processing would be implemented through the science of Computer vision that develops the theoretical and algorithmic basis. Useful information can be automatically extracted and analyzed from an observed image using computation made by computers. Thus, the aim of this study is to design a prototype for coffee Nutrient deficiency detection by using digital image processing techniques by means of computer vision.

1.2. Statement of the problem

Coffee contributes the lion's-share of Ethiopian export earnings. It plays an important role in the economy of Ethiopia's rural population. The total area coverage of Coffee land in the country is 1.2 million hectares, of which 900,000 hectares of land is estimated to be productive (Authority, 2017). According to some studies, about 92-95% ofCoffee is produced by 4.7 million small scale farmers and 5-8% by large scale plantations (Tsegaye, 2017).

An annual Coffee production in Ethiopia is 500,000-700,000 tones and an average national productivity is 7 quintal per hectare which is far from average productivity of the world 25 quintal per hectare (Zewudie & Rahmeta, 2019). In Ethiopia, there are several attributed factors for the low level of average production and income of Coffee by the world standard. These include low availability of improved or hybrid seed, insufficient credit and distribution of input devices for Coffee growing farmers, low profitability, efficiency of fertilizer used, lack of complimentary improved practices and seed, lack of irrigation and water constraints.

Nutrition includes essential elements for the growth and development of a healthy Coffee bush. Nutrients are categorized into two: Macro and Micro nutrients. Macro-nutrients are further classified as Primary and Secondary nutrients. Nitrogen, Phosphorus and Potassium constitute the primary nutrients because of the large amounts required for the Coffee growth and development. The bush depends on the sufficient supply of the respective nutrients, and the yield would be limited by the nutrients which are in short supply. Balanced fertilization of all major and minor nutrients result in two important functions: namely production of good crops and also production of fresh cropping wood framework for the succeeding year (Dawid & Hailu, 2018).

Deficiency of nutrients is a common problem that causes reduction of Coffee productivity and low quality of the bushes. Coffee nutrition deficiency detection techniques are very traditional and time taking in Ethiopia these days. More than 90 percent of Coffee is produced by Ethiopian small scale farmers that have a minimal awareness to detect and prevent the Coffee nutrition deficiency. Consequently, the production, then the income from that may reduce time after time.

On the other hand, agronomists detect the nutrition deficiency by observing the Coffee leaves on the berries in the large scale productions. For instance, in Limmu Coffee Farm, they detect the problem and give some common fertilizer like Foliar NPK and NPS (Limmu Coffee farm, 2020). Which is in consistent and less accurate the other method is soil and leaves laboratory test which is very expensive, need foreign currency and more than a month to get expected result. Those practices are not effective to overcome the immerging problem at a time, these cause the Coffee expose to other disease, on the other hand those practices are not effective to overcome the immerging problem at a time, these cause expose to other disease.

In addition, quantity and quality of Coffee production is reduced for more than one production year. In Coffee plant, there are main nutrient deficiencies namely: Potassium, Boron, Calcium and Iron. Detection and recognition of Coffee plant nutrient deficiency is very important in order to cure and control the quality of the Coffee. The method of detecting these plant nutrient deficiencies or not is based on the knowledge of experts. Image processing approach is noninvasive technique which provides consistent, reasonably accurate, less time consuming and cost-effective solution for farmers to manage nutrition's.

Research questions

- What is the suitable image classification algorithm that helps to identify Potassium, Boron, Calcium and Iron nutrient deficiency?
- How to develop an automatic Coffee nutrient deficiency identification and recommendation system using image processing technique
- How is the performance of the proto type system to detect Coffee nutrient deficiency?

1.3. Objective of the study

1.3.1. General Objective

- The general objective of this study is to develop Coffee Arabica Nutrient deficiency detection and recommendation system by using image processing techniques.

1.3.2. Specific Objectives

This study is specifically intended to:

- Identify suitable classification algorithm that helps us to identify Potassium, Boron, Calcium, Iron deficiency.
- Develop an automatic Coffee nutrient deficiency identification system using image processing technique.
- Conduct performance of the prototype system, to test how much it will be detecting Coffee nutrient deficiency and give recommendation.

1.4. Scope and Limitation of the study

The study on Detection of Coffee Arabica Nutrient Deficiency by using Image Processing Technique was carried collecting images and interviewing professionals from Jimma town, Horizon Plantation, Limmu Coffee Farm and Jimma Agricultural Research Institute. The study specifically focuses on how to detect Coffee nutrient deficiency and recommend for the solution. The images were collected from Limmu Coffee Farm and Jimma Agricultural Research Institute. The study duration is from Jan, 2020 up to Jun, 2021G.C.

1.5. Significance of the study

The result of this study may have a great impact to handle any Coffee nutrition deficiency problems easily. This is by enhancing agricultural practices, improving accuracy and consistency of processes while reducing Agronomists manual monitoring. Often, it offers flexibility and effectively substitutes the agronomists' visual decision making. Many times, expert advice may not be affordable, majority times the availability of expert and their services may consume time. Image processing along with availability of communication network can change the situation of getting the expert advice well within time and at affordable cost since image processing was the effective tool for analysis of parameters.

The system hopefully detects Coffee nutrient deficiency which is very important in terms of informing types of Coffee deficiency, enable the agronomists to distinguish the measure to be taken, enabling to control the diseases ,increase the product and decrease unnecessary production cost, labor and time. In the long run, the project outcomes will modernize the agricultural process, improve the quality of production, increase foreign currency, develop the economic status of country, and increase the people per-capital income. Beyond the above-described benefits, the output of this research can be an input for other further studies to be done locally as well as globally, as per the recommendation made in this study.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Overview

The technological integration of a camera and a computer, which is called machine vision system, provides an alternative to the manual inspection of biological products. Human inspections of agricultural products using morphological and color features that correlate with quality are being supported by machine inspection systems in different industries with their acceptance in recent years (Sergio , Aleixos, & Moltó, 2011).

Any tasks of visual inspection such as defect detection, dimensional measurement, orientation detection, scaling, sorting and counting, could be conducted with such automated inspection techniques. Machine vision includes several advantages over the manual methods of inspection. Some of the advantages are capability of being compatible with other on-line processing tasks, taking dimensional measurements more accurately and consistently than a human being, and provision of measure of color and morphology of an item objectively than subjectively. More importantly, the absence of physical contact involved makes this method more needed and the possibility of damage during inspection to homogenous biological products is very low. Besides, computer vision system is non-destructive, in addition to its attractive feature; it can be used to create a permanent record of any measurement at any point in time (Tout, 2018)

2.2. The Coffee plant

Coffee is extracted from several species of shrub of the genus Coffee produce the berries The two main species commercially cultivated are Coffee canephor (predominantly a form known as 'Robusta') and Coffee Arabica (ICO, 2011). Coffee Arabica, the most highly regarded species, is native to the south western highlands of Ethiopia and the Boma Plateau in south eastern Sudan and possibly Mount Marsabit in northern Kenya (Davis, 2006). C. Robusta is native to western and central Sub-Saharan Africa, from Guinea to Uganda and southern Sudan (Maurin, 2007). Less popular species are Coffee liberica, Coffee stenophylla, Coffee mauritiana, and Coffee racemosa. All coffee plants are classified in the large family Rubiaceae. They is ever green shrubs or small trees that may grow 5 m (15 ft) tall when un pruned (Anthony, 2010).

2.3. The Leaves of the coffee plant

The leaves of the coffee are dark green and glossy (shine &smooth), usually10–15cm (4–6 in) longand6cm (2.4in) wide, simple, entire (smooth edges), and opposite. Petioles of opposite leaves fuseat base to form interpetiolar stipules, characteristic of Rubiaceae. The developmental stages of the leaves are categorized as buds and young leaves, mature leaves, and aged leaves. Young leaves are the most recently emerged, and they weighed approximately 25mg (fresh weight) and are approximately 20 mm long and 7 mm wide. Mature leaves comprised the fully expanded, second and third leave below the apex (weight approximately 1.2g); whereas aged leaves are dark green from near the base of the shoot and weighed approximately 1.3 g. (Ashihara, 1996).

The flowers are between branch and steam, and clusters of fragrant white flowers bloom simultaneously. Gynoecium consists of inferior ovary, also characteristic of Rubiaceae. Flowers followed by oval berries of about 1.5 cm (0.6 in). Green when immature, they ripen to yellow, then crimson, before turning black on drying. Each berry usually contains two seeds, but 5–10 % of the berries have only one these are called pea berries. Arabica berries ripen in six to eight months, while Robusta taken in e to eleven months (Tao Chen, 2020).

2.4. Essential minerals in coffee plant leaves

Nutrients are very essential for plant growth. In total, seventeen nutrients (or chemical elements) are known in relation to tree growth. These are divided in two groups: non-mineral and mineral. Non-mineral nutrients are: CO_2 (part of the air) and H_2O (water). Under normal conditions these are freely available and are absorbed by the tree through leaves and roots. Although water availability might be insufficient during dry spells. Fourteen mineral nutrients can be divided in three group’s source.

Table: 1 Mineral nutrients of coffee plant

Primary nutrients	Secondary nutrients	Micronutrients	
Nitrogen(N)	Calcium(Ca)	Boron (B)	Manganese (Mn)
Phosphorus(P)	Magnesium(Mg)	Chloride(Cl) Copper(Cu)	Molybdenum(Mo) Nickel (Ni)
Potassium(K)	Sulfur (S)	Iron (Fe)	Zinc (Zn)

Source: (Manual for Arabica coffee, 2004)

Primary nutrients are called such because they are present in the tree in larger quantities. The secondary and micronutrients are present in much lower concentrations. Usually, the tree will show deficiencies of primary nutrients, although after the harvest Calcium and Magnesium deficiencies can be observed in coffee trees. In general the tree uses large amounts of primary nutrients and only smaller amounts of secondary-and micronutrients. Still the second and third Groups are just as important to the tree source.

2.5. Nutrient uptake of coffee tree

The nutrient uptake of coffee plat varies from organ to organ. Three elements (carbon, hydrogen and oxygen) makeup 94% of the plant tissues and are obtained from air and water. The other 13 elements are obtained from the soil and are divided in to two broad categories 'macro' and 'micro'. These terms do not refer to the importance of the elements; macro nutrients are required in greater amounts than micronutrients for normal plant growth (Feller, Kopriva, & Vassileva, 2018).

In humans minerals are also essential for health normal body functioning. Micro nutrients are vitamins and minerals needed but not synthesized by the body in small amounts for a wide range of functions and processes. Micro nutrients are essential for optimal human growth and development, and healthy maintenance of the body over life span. Micro nutrient deficiencies affect more than 2 billion people globally. Although less prevalent in higher-income populations, these deficiencies do occur in such groups, especially among premature infants, infants, children, and the elderly (Siekmann, 2003). Micro nutrients are needed to maintain strong bodies and mental sharpness, to fight against disease, and bear healthy children. Micro nutrient deficiencies can cause learning disabilities, mental retardation, decreased immunity, low work capacity, blindness, and premature death. They affect child survival, women's health, educational achievement, adult productivity, and overall resistance to illness. They may impair immune function; increase the risk of opportune is tic infections; and the severity of diseases (GibsonandFerguson, 1998).

Boron

Boron deficiency resulted in abnormal growth of young leaves and the apical bud. The youngest leaves were light green, smaller, curved, and mottled with small necrotic spots leaf tips also were necrotic. Failure of leaves to expand normally resulted in irregular margins. Symptoms were also present on youngest leaves of lateral branches. Older leaves were unaffected (Nagao, Kobayashi, & Yasuda, 1986).

Potassium

Potassium deficiency symptoms were localized in older leaves and first appeared as a chlorotic band (mineral deficiency symptom of coffee) along leaf margins. Later, dark brown necrotic spots developed along the leaf margins. Spots continued to enlarge until entire margins were necrotic, with the central portion of the blade remaining green. Young leaves were unaffected. Leaves of deficient plants contained 0.36-1.07 percent leaf potassium, compared with 2.62-3.86 percent for control plants. (Nagao, Kobayashi, & Yasuda, 1986)

Figure2.3.1.2. Potassium nutrient deficiency

Source: (Coffee Production and Utilization in Kenya, 2019)

Calcium

Poor mobility of calcium within plants was evidenced by development of deficiency symptoms in the youngest leaves. Young leaves turned bronze in color, particularly along the margins, while the area along the midrib stayed green; leaves did not expand normally and were cupped down ward. In advanced stages, emerging leaves were necrotic, and eventually the entire apical bud died back. Older leaves had some chlorosis, generally along the margins, or large necrotic patches on the blade. Poor root development was also observed in deficient plants. Leaf calcium was 0.36-0.55 percent in deficient plants and 0.94 1.16 percent in control plants (Nagao, Kobayashi, & Yasuda, 1986)

Calcium is the most abundant mineral element in the body. It small proportions regulates critical functions including nerve impulses, muscle contractions and the activities of enzymes and (more than 99%) is located in the bones, plays an important role for structure and strength of bones. The body of an adult man contains about 1.2 kg calcium, accounting for about 2% of body weight. The element is present in two body parts: bone and teeth. Sufficient calcium intake is essential for obtaining optimal peak bone mass in youth and for minimizing bone loss later in life (Gurr, 1999).

Figure2.3.1.3. Calcium nutrient deficiency

Source: (Coffee Production and Utilization in Kenya, 2019)

Iron

Iron is the fourth most abundant and one of the cheapest elements in the Earth's crust, but iron deficiency is still the most prevalent nutritional disorder in the world (Lind,2004).The main causative factors of iron deficiency are poor iron content of the diet, low bio availability of iron in the diet, or both. Food components such as phytate, tannins, and selected dietary fibers, which bind iron in the test in eallumen, which can impair iron absorption. Phytate has the greatest effect on iron status because many plant foods shave high phytate content that can severely impaired on absorption (Mendoza, 2001). The absorption of iron in food depends on iron status of the body; the presences of iron absorption inhibit or sand enhancers, and types of iron (haem and non-haem); vitamin A status of the body and the status of other micro-nutrients. Weaning foods made from cereals is often low in Iron content and contains significant quantities of iron absorption in hibitors, phytic acid and condensed tannins (Pynaert, 2006).Age, gender and physiological status determine iron requirements. Rapid growth of infants during the first year of life requires an adequate supply of iron for synthesis of blood, muscle, and other tissues.

Iron requirements are especially high in infants from the age of 6 months, in young children, and in pregnant and menstruating women. The increased iron requirement of infants and pregnant women is due to rapid growth and new tissue formation. Men striation and parasitic diseases cause excessive iron loss, and iron utilization is impaired during chronic infection (WHO, 2000, Domellof, 2002). Iron deficiency is one of the major nutritional problems in the developing world, affecting primarily women of child bearing age, infants, and children. Infants of age between 6 and 24 months are especially vulnerable to the development of iron deficiency. Iron deficiency ranges in severity from iron depletion, which causes no physiological impairment, to iron deficiency anemia.

Iron deficiency anemia (IDA) affects about 30% of the global population; 43% of the world's infants and children under the age of 4 years; and 20–38% of school children in West and North Africa. In sub-Saharan Africa, the prevalence of iron deficiency among pregnant women is estimated about 44%, and 42% to 53% pre-school African children suffer from anemia (WHO, 2000, Domellof, 2002, Iannoti, 2006, Zimmerman, 2004). Consequences of ID Aare: physical growth retardation, prenatal mortality, compromised mental development, lowered physical activity and labor productivity, and increased maternal morbidity. It can also affect mental and motor development. IDA impairs thyroid metabolism and reduces the efficacy of iodine prophylaxis in areas of endemic goiter (WHO, 2000, Domellof, 2002, Iannoti, 2006, Zimmerman, 2004). IDA in infancy is associated with significant loss of cognitive abilities, decreased physical activity, and reduced resistance to diseases. Iron deficiency in women of child bearing age increases hazards associated with complications of pregnancy, premature birth and low birth weight, and leads to new born with sub-optimally on reserves and it is responsible for a large share of maternal deaths. In school-age children, IDA may affects school performance ;in adulthood, it can cause fatigue and reduced work capacity(slinger land, 2006)

Figure2.3.1.4. Iron nutrient deficiency

Source: (Coffee Production and Utilization in Kenya, 2019)

2.6. Digital Image processing

An image is defined as a two-dimensional function, f (a, b), where and b are spatial or geographical coordinates. The amplitude of **(function)** at any pair of coordinates (a, b) is also called the intensity of the image at that point. When a, b, and the amplitude values of an image f are all finite, discrete quantities, the image is a digital image. In general, as noted by Gonzalez, a digital image is an array of numbers representing spatial distribution of a certain appearance parameters such as reflectivity of electromagnetic radiation, emissivity, temperature or some geophysical or topographical elevation. A digital image is composed of a finite number of elements, each of which having a particular location and value.

Digital image consists of discrete picture elements called pixels. Associated with each pixel is a number represented as DN (Digital Number) that show the average radiance of relatively small area within a scene, with DN values normally ranging of from 0 to 255 in 3 elements or 0 to 224-1 in single numbering. The size of this area effects the reproduction of details within the scene. As the pixel size is reduced more scene detail is preserved in digital representation. The field of digital image processing refers to processing digital images by means of a digital computer. Digital image processing involves efficient techniques of data acquisition and retrieval through sound image representation, display, pre-processing and segmentation approaches.

2.7. Digital Image processing for detecting of plant diseases

The analysis of the literature related to the use of digital image processing techniques for detecting plant diseases shows an important amount of research contributions in the last few years. According to Kumars, several authors have proposed methods supported by digital image processing for pathologies detection in almost all the parts of plants, such as: roots, fruits, stems, and leaves. Considering that the current paper focused on Coffee tree leaves (Ibid, 2019).

This section presents a brief survey on the previous development focused on analyzing plant leaves for the disease identification. To begin with, first images of the two of the most important crop plants across the world: maize and rice were taken as reference, to obtain a synthetic and also diverse screenshot that summarizes the most important previous works (Kumars, 2019). Second, two emerging families of crops, such as citrus and vegetables, were considered. Finally, at last, they were considered the previous works focused on Coffee trees. For each case, it was consulted Google Scholar through key terms such as plant disease, image processing, leaves, together; with recent published survey on this area, to obtain the research works to be analyzed, and by them a in computational intelligence tool used at the proposal (Kumars, 2019).

According to Tzotsos, popular computational intelligence approaches such as neural networks, support vector machines (SVMs), and clustering, have been used to support the resolution of the nutritional deficiency of the indicated crops. In this way, most of the presented works characterize images in terms of their texture, color and/or shape. Such information was obtained for training the mentioned supervised/unsupervised approaches preferred neural network, SVMs, or clustering (Tzotsos, 2008). Specifically, the two more popular approaches are the neural networks (used for supporting maize, rice, citrus, and vegetables), and the feature-based rules (used for supporting maize, rice, and citrus). In the case of neural networks, some works such as Kaietal, Sanyal and Pateluse texture features as input for a multilayer perception architecture for diseases identification in maize and rice, respectively.

Similarly, Pydipati, identifies diseased and normal citrus leaves based on Mahalanobis minimum distance classifier, introducer by P.C. Mahalanobis in 1936, using the nearest neighbor principle, *as* well as a neural network classifier based on the back propagation algorithm and radial basis functions. On the other hand, the group identified as *feature-based rules* is composed by a diversity of proposals which oscillate from a direct association regarding some features of the processed images to more complex models that consider rough set theory (conventional set theory described by Zdzislaw I. Pawlak (1991) in terms of pair of sets which give the lower and the upper approximation of the original set) and production rules for knowledge representation (Vassallo & Garnique, 2017).

2.8. Image Acquisitions

Images are produced by many means: cameras, x-ray machines, electron microscopes, radar and ultrasound. They are used in the entertainment, medical, scientific and business industries; for security purposes; and by the military and government. The goal in each case is for a human or machine observer to extract useful information about a scene. Digital imaging provides the means to enhance features of interest while attenuating details that are irrelevant to a given application, and then extracts useful information about the scene from the enhanced image. Image Acquisition is to transform an optical image real world data into an array of numerical data which could be later manipulated on a computer, before any video or image processing can commence an image must be captured by camera and converted into a manageable entity (Eldridge, 2017)

2.9. Image Preprocessing

Image pre-processing is the term for operations on images at the lowest level of abstraction. These operations do not increase image information content but they decrease it if entropy is an information measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task (Team, 2020). Image pre processing is technique of making image ready for processing; it involves scaling, magnification, reduction and rotations of image to adjust for process. Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analogue image processing. It allows a much wider range of algorithms to be applied to the input data the aim of digital image processing is to improve the image data features by suppressing unwanted distortions and/or enhancement of some important image features so that our AI Computer Vision models can benefit from this improved data to work on (Sarfraz, 2020).

2.10. Deep learning

Deep learning techniques which implement deep neural networks became popular due to the increase of high-performance computing facility. Deep learning achieves higher power and flexibility due to its ability to process a large number of features when it deals with unstructured data. Deep learning algorithm passes the data through several layers; each layer is capable of extracting features progressively and passes it to the next layer. Initial layers extract low-level features, and succeeding layers combines features to form a complete representation (Mathew & Arul, 2021).

Method	Description	Merits	Demerits
Back propagation	Used in Optimization problem	For calculation of gradient	Sensitive to noisy data
Stochastic Gradient Descent	To find optimal minimum in optimization problems	Avoids trapping in local minimum	Longer convergence time, computationally expensive
Learning Rate Decay	Reduce learning rate gradually	Increases performance, Reduces training time	Computationally expensive
Dropout	Dropsout units/ connection during training	Avoids overfitting	Increases number of iterations required to converge
Max-Pooling	Applies a max filter	Reduces dimension and computational cost	Considers only the maximum element which may lead to unacceptable result in some cases
Batch Normalization	Batch-wise normalization of input to a layer	Reduces covariant shift, Increases stability of the network, Network trains faster, Allows higher learning rates	Computational overhead during training
Skip-gram	Used in word embedding algorithms	Can work on any raw text, Requires less memory	Softmax function is computationally expensive, Training Time is high
Transfer learning	Knowledge of first model is transferred to second problem	Enhances performance, Rapid progress in training of second problem	Works with similar problems only

Table3 Comparison of Deep learning Methods ((Deng & Yu, 2014))

2.11. Deep learning frameworks

A deep learning framework helps in modeling a network more rapidly without going into details of underlying algorithms. Each framework is built for different purposes differently. Some deep learning frameworks are discussed below and are summarized in table 4.

2.12. Tensor Flow

Tensor Flow, developed by Google brain, supports languages such as Python, C++ and R. It enables us to deploy our deep learning models in CPUs as well as GPUs **(Mathew & Arul, 2021)**

2.13. Keras

Keras is an API, written in Python and run-on top of Tensor Flow. It enables fast experimentation. It supports both CNNs and RNNs and runs on CPUs and GPUs. **(Mathew & Arul, 2021)**

Deep Learning Framework	Release Year	Language written in	CUDA supported	Pre-trained models
TensorFlow	2015	C++, Python	Yes	Yes
Keras	2015	Python	Yes	Yes
PyTorch	2016	Python, C	Yes	Yes
Caffe	2013	C++	Yes	Yes
Deeplearning4j	2014	C++, Java	Yes	Yes

Table4 comparison of Deep Learning Frameworks

2.14. Convolution Neural Network

Convolution Neural Networks (CNN) is used mainly for images. It assigns weights and biases to various objects in the image and differentiates one from the other. It requires less preprocessing related to other classification algorithms. CNN uses relevant filters to capture the spatial and temporal dependencies in an image (Mathew & Arul, 2021). The following figure illustrates the basic structure of a deep neural network which contains three parts as the input layer, multiple concatenated (interconnected) hidden layers, and the output layer. The input layer represents input raw data to the network in the case of this study the raw input data is the pixel value of the medicinal plant leaves image by changing this image pixels into single-dimensional arrays. The complicated hidden layer receives data from the input layer and computes convolution, ReLU, and max polling activity to create a unique feature map for individual leaf images. The output layer receives mapped (extracted)feature from the hidden layers and start classification depending on the target labels(true value). At the output layery1,y2 and y3 represent the value of the target label(classes) to be predicted. (Kiranyaz, Avci , Abdeljaber, & Ince, 2018)

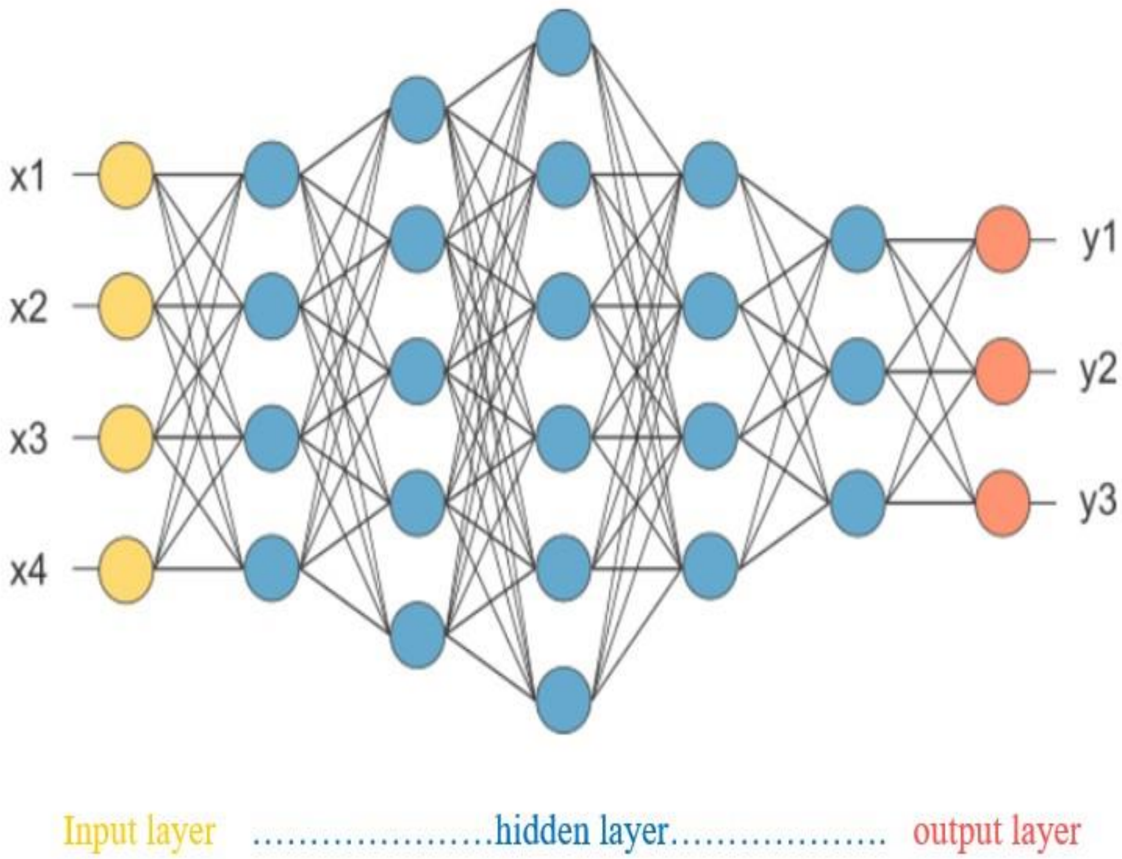


Figure6: Deep neural network (Kiranyaz, Avci , Abdeljaber, & Ince, 2018)

Here the following figure shows how convolution performed on CNN. This means that there is an input image of 5x5-pixel size and 1 kernel (filter) size of is 3x3 with stride size1. Stride means the number of pixel shift throughout image pixel size or to know by how many steps the kernel slide through image pixel in both vertical and horizontal directions. HS and VS stand for horizontal shift and vertical shift respectively. The image pixels multiply by the kernel pixel to detect the edge, sharpen blur, and perform other image processing tasks. Finally, the image filtered to 3x3 image pixel size. So, in CNN using convolution the researcher can extract feature map from the input image as shown. (Berhane, 2019)

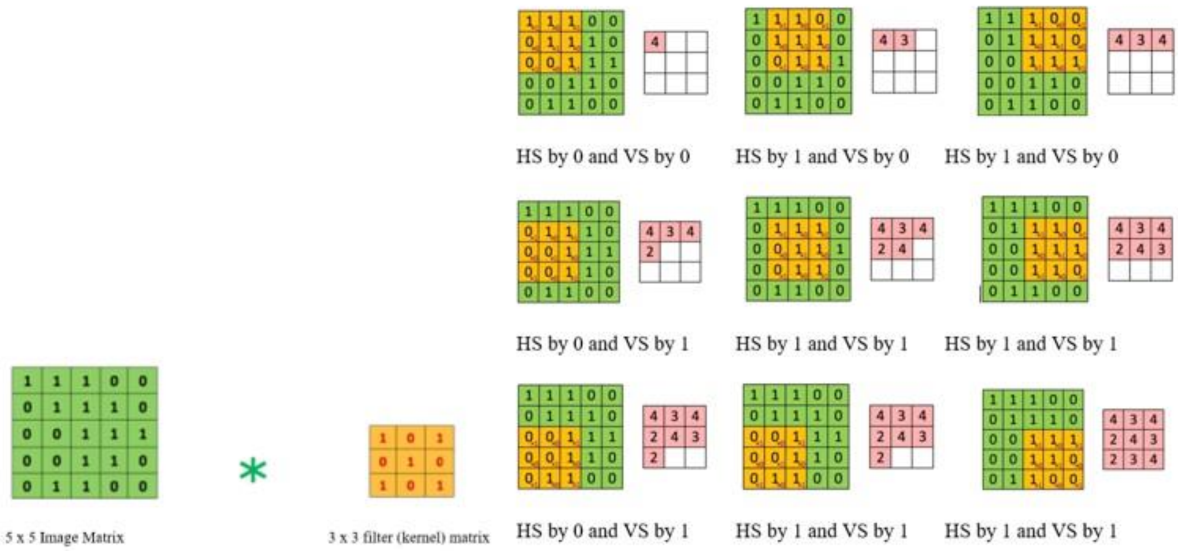


Figure7: Convolution processes

2.15. Max polling

In max-pooling a filter is predefined, and this filter is then applied across the no overlapping sub-regions of the input taking the max of the values contained in the window as the output. Dimensionality, as well as the computational cost to learn several parameters, can be reduced using max-pooling (Mathew & Arul, 2021) The purpose of max polling in deep learning is, reducing the size feature map produced by the convolution process to reduce computational complexity. By how much size it reduces the feature map is, depends on the window size of polling. If the size of a poll is 4 x4, features map size will reduce by this size and if the poll has 2 x2, the feature map reduces to this size. There is a variety of polling such as Max Polling, average Polling, and mean polling. From this type, in this study used Max polling to accelerate feature extraction from given input medicinal leaf image. With this technique, the researcher selects the highest pixel value from a region depending on its size. In other words, max-pooling takes the largest value from the window of the image currently covered by the kernel. (Brownlee, 2019)

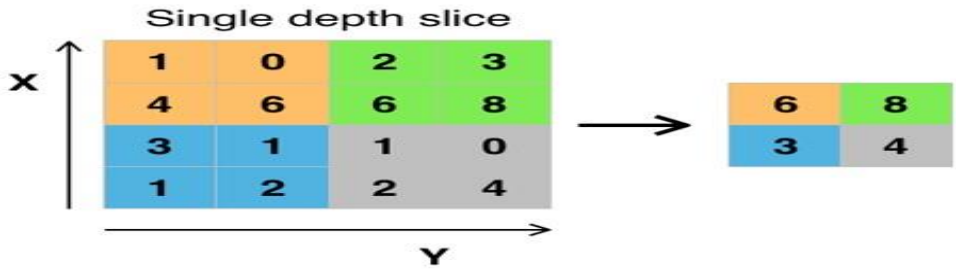


Figure 8: Max poling

2.16. Extract Features

When CNN go from the first layer to the last performs very complex tasks regarding feature extractions. As observed from the following figure CNN extracts features of leaves. At 1st, it detects simply identifiable patterns like horizontal and vertical lines present in leaves. At the 2nd layer, it gives more information than 1st layer like, it can detect different corners on leaves as a result it tries to identify the shape of leaves. At the 3rd layer, it further computes more complex feature map identification like extracting differently structured veins on the surface of leaves. At the 4th layer, it becomes more power full to exploit each tiny vein structure and while going to a very deep layer it can identify the ubiquitous structure. So, by going through this execution CNN can identify leaves unique feature for classification. (Zhang, Patras, & Haddadi, 2019)

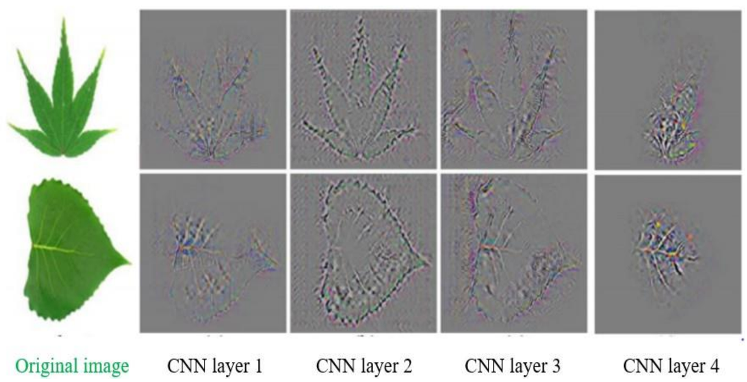


Figure 9: Feature extraction in internal layer of CNN

2.17. Activation Function

According to Nagilla, activation functions are functions used in neural networks to compute the weighted sum of input and biases, which is used to decide if a neuron can be fired or not. It manipulates the presented data through some gradient processing usually gradient descent and afterward produces an output for the neural network that contains the parameters in the data. (Nagilla, 2020) The position of an AF in a network structure depends on its function in the network thus: When the AF is placed after the hidden layers, it converts the learned linear mappings into non-linear forms for propagation and while in the output layer, it performs predictions (Ibid).

Some of these activation functions are ReLU, Tanh, Softmax, Sigmoid, and so on. Most of the time ReLU and Tanh are used in a base convolutional layer of the neural network and SoftMax and Sigmoid is utilized at the last layer of the network to make classification decision but the model by computing the numerical probability of a given class. In Softmax, each target label probability to be a winner is dependent on remaining probability values. On the other hand, in sigmoid the classes are identified using 0's and 1's binary classification (Chaudhary, 2020).

2.18. Rectified Leaner Unit (ReLU)

The rectified linear unit (ReLU) activation function was proposed by Nair and Hinton (2010), and ever since, has been the most widely used activation function for deep learning applications with state-of-the-art results to date. The ReLU is a faster learning AF, which has proved to be the most successful and widely used function. It offers better performance and generalization in deep learning compared to the Sigmoid and then activation functions. The ReLU represents a nearly linear function and therefore preserves the properties of linear models that made them easy to optimize, with gradient-descent methods (Enyinna, Ijomah, & Gachagan, 2020) The ReLU activation function performs a threshold operation to each input element where values less than zero are set to zero thus the ReLU.

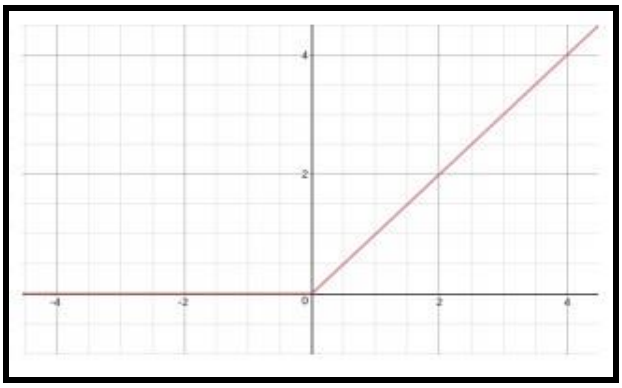


Figure 10: Rectified linear unit

2.19. Sigmoid

The Sigmoid AF (activation function) is sometimes referred to as the logistic function or squashing function in some literature. The Sigmoid is a non-linear AF used mostly in feed – forward neural networks. It is a bounded differentiable real function, defined for real input values, with positive derivatives range between 0 and 1 everywhere and some degree of smoothness. The sigmoid function appears in the output layers of the DL (deep learning) architectures, and they are used for predicting probability-based output and has been applied successfully in binary and multi-label classification problems, modeling logistic regression tasks as well as other neural network domains. (Yonaba, Anctil, & Fortin, 2010)

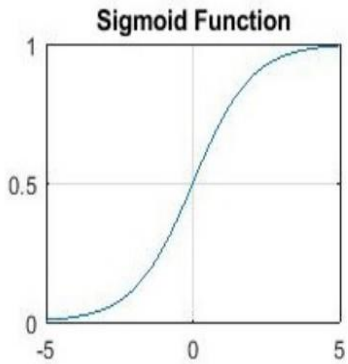


Figure 11: Sigmoid

2.20. Optimizers

Optimizers are the algorithm that is applied in machine learning or deep learning neural network adjust the weight parameters of each neuron to get small values of loss while performing training of the model (Soydaner, 2020). Some of these algorithms include Adam, Adamax, Adagrad, Adadelta, RMSprop, SGD and etc.

2.21. Adam

This Optimizer is designed to combine the advantages of two recently popular methods called AdaGrad which works well with sparse gradients, and RMSProp (Tieleman and Hinton, 2012), which works well in on-line and non-stationary settings. The method is also appropriate for non-stationary objectives and problems with very noisy and/or sparse gradients. Empirical results demonstrate that Adam works well in practice and compares favorably to other stochastic optimization methods. This optimizer is computationally efficient, has little memory requirements, invariant to the diagonal rescaling of the gradients, and is well suited for problems that are large in terms of data and/or parameters. (Lee, Ha, Zokhirova, & Hyeonjoon Moon, 2017)

2.22. AdaGrad

AdaGrad is the most straightforward improvement to SGD. AdaGrad adjusts the learning rate dynamically based on the historical gradient in some previous iterations. One main benefit of AdaGrad is that it eliminates the need to tune the learning rate manually when compare to SGD. (Shiliang Sun, Cao, Zhu, & Zhao, 2019)

2.23. RMSprop

The idea is to consider not accumulating all historical gradients, but focusing only on the gradients in a window over a period, and using the exponential moving average to calculate the second-order cumulative momentum. This optimizer developed to resolve the radically diminishing learning rates of AdaGrad. (Kingma & Lei Ba, 2017)

2.24. Learning rate

The learning rate is an important parameter in the training process. If the learning rate is high the modifications in the weights are bigger, that is, bigger steps are taken. A high learning rate makes the model converges faster on an optimal set of weights. (Kingma & Lei Ba, 2017)

2.25. Batch Normalization

Proposed to reduce internal covariate shift, and in doing so dramatically accelerates the training of deep neural nets. It accomplishes this via a normalization step that fixes the means and variances of layer inputs. Batch Normalization also has a beneficial effect on the gradient flow through the network, by reducing the dependence of gradients on the scale of the parameters or of their initial values. This allows us to use much higher learning rates without the risk of divergence. Furthermore, batch normalization regularizes the model and reduces the need for Dropout. Batch Normalization Applied to a state-of-the-art image classification model, Batch Normalization achieves the same accuracy with 14 times fewer training steps and beats the original model by a significant margin. (Shallue, Lee, Antognini, Sohl-Dickstein, & Frostig, 2019)

2.24.1. Batch size

The batch size means the number of training examples used in one iteration. For each batch, the gradients will be computed and updates will be made to the weights of the network accordingly. Normally the training continues until validation performance clearly deteriorates.

2.24.2. Dropout

It is one type of convolutional neural network layer in deep learning to overcome the problem of over fitting while training a deep neural network. It is implemented by making some layer of a neural network inactive. Dynamically removing certain connections existing between the nodes randomly. Dropout means that some units (hidden and visible) in the neural network are dropped out temporarily, that is, are removed from the network. The dropped-out units do not take part in the forward pass and back propagation. This makes the neural network sample a different architecture every time an input is presented.

2.25. Image histogram

A colored image is a set of pixels of different colors. Pixels are so small that the researcher don't distinguish them with our necked eye, as shown in the following figure, they concatenated together producing a complete image. So, the researcher cannot understand about intensity distribution of each color pixel of the image to judge brightness, contrast, and other image evaluation parameters. This study used an image histogram to analyze the intensity distribution of each RGB channel pixel inside the image. Using this histogram, an intuition about contrast, brightness, the intensity distribution of that image can be cleared. Image information on histogram i s shown by plotting color channels in both separate and group plotting. Using this histogram, how much the image dark and bright described by observing the graph horizontally and how much the color channel intensity is distributed in the body of the image by observing vertically. Generally, a histogram used to show the dataset includes a variety of images regarding pixel intensity and a light contrast. (Agu, 2018)

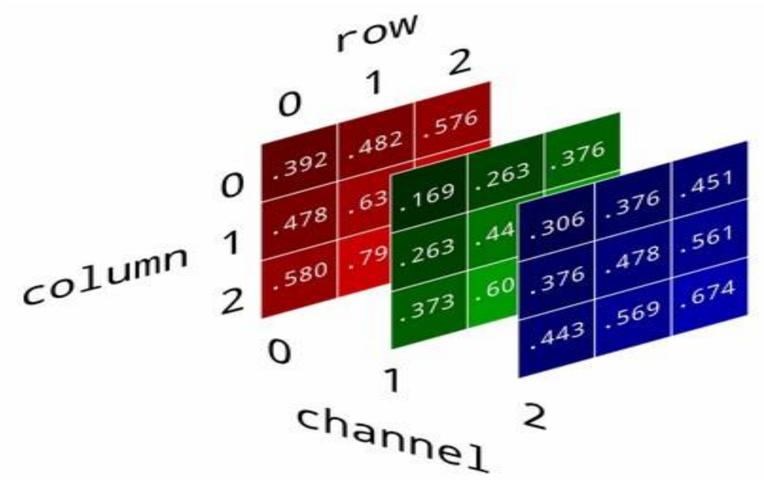


Figure 12: Pixel distribution of RGB image

2.26. Application of Image Processing on Agriculture

Image processing has been proved to be effective tool for analysis in various fields and applications. Agriculture sector where the parameters like canopy, yield, quality of product were the important measures from the farmers' point of view. Many times, expert advice may not be affordable, majority times the availability of expert and their services may consume time. Image processing along with availability of communication network can change the situation of getting the expert advice well within time and at affordable cost since image processing was the effective tool for analysis of parameters. The analysis of the parameters has proved to be accurate and less time consuming as compared to traditional methods. Application of image processing can improve decision making for vegetation measurement, irrigation, and fruit sorting. (Anup Vibhute, 2018).

2.27. Related Works

Mekuria, Neuhoff and K¨opke, (2004), in their work The Status of Coffee Production and the Potential for Organic Conversion in Ethiopia, indicate that collapse of world Coffee prices is contributing to a socio-economic decline affecting an estimate of 125 million people world-wide. Accordingly, the fall in Ethiopian farmers and the government revenues amounted to 42 percent within a year. In the country some of the major Coffee growing regions were visited and intensive discussions on Coffee production and marketing with farmers, advisors, traders and researchers were held on. The conclusion was drawn that Ethiopia has the potentials to produce certified organic high-quality Coffee due to favorable growing conditions and the high diversity of genetic resources in Coffee Arabica. Currently, certified organic Coffee production accounts for only an estimate of 0.1 percent of the total national production. Coffee farmers convert to organic production in expectation of higher revenues. Conversion to organic Coffee production may, however, result in a significant decrease of crop productivity. Multi-disciplinary research activities on sustainable organic Coffee production systems are expected to boost production and promote high quality Coffee. Various agronomic and socio-economic research programmers are highly needed. A key focal point is efficient nutrient management by composting Coffee husks/pulps, and green maturing by mixed planting of suitable legumes. Moreover, a systematic screening of cultivars with respect to potential use in organic Coffee production is recommended. Aspects of taste and quality of Coffee deserve special attention as well. Fair Trade organic Coffee impacts on rural development in Ethiopia by providing options to stabilize the market for organic growers. Furthermore, the consumer is provided with a range of new products. That could help alleviate the Coffee crises and improve social and environmental stability.

Image Analysis for Ethiopian Coffee Plant Diseases Identification (Abrham, Mengistu, Gebeyehu and Dagnachew 2016). In this research paper, the authors have evaluated four types of classifiers (ANN, KNN, Na¨ıve and combination of RBF and SOM) together with five different segmentation techniques for Ethiopian Coffee plant dis- eases identification. In their Experimental simulation, the combination of RBF and SOM with a combined segmentation technique has a better performance and also the combination of K-means and Gaussian distribution has a better performance. But the problem is the training time of the combination of RBF and SOM; it takes longer time in training. In addition to this, the authors recommend for further research and improvements on identification of Ethiopian Coffee diseases by exploring more segmentation techniques and more features on stem parts of Coffee plant.

Automatic estimation of live Coffee leaf infection based on image processing techniques by Eric and Oubong. In this paper, the authors proposed an automatic infected leaf detection algorithm that combines three processes: Image contrast enhancement, Image background removal, and estimation of detected infection. After adjusting the contrast by getting the value of gamma automatically, the system processes the original leaf image to keep the real leaf (foreground) by using the back- ground removal method which is based on luminance and color. The background free image is then processed in YUV color model on V channel, to maximize the detection of the leaf damage using the Fuzzy C-means Clustering. The estimation of the severity of infected leaf was fast and quantitatively maximized all leaf damages compared to other methods and the necked eye process used by the farmers. It can help farmers to be sure which quantity of pesticides or fungicides their field’s Coffee requires. The proposed method was compared with some current researches, and it is obvious that it can over perform them either in background removal or in infection detection, even the method is fast and avoids the defoliation done by all other methods surveyed. In the future, the authors recommend algorithm in real-time.

2.28. Research gap and solution

Most researchers used the older methods of image processing techniques for image detection mechanisms like image preprocessing, segmentation and feature extraction separately while in case of this study the deep learning methods perform it the back. But this approach leads to less accuracy, take longer time to detect and classify and it takes a lot of time to segment and feature extraction. Therefore, to solve this problem the researcher uses Deep Learning technique. Deep learning achieves higher power and flexibility due to its ability to process a large number of features when it deals with unstructured data. Which means the models and framework are per-trained. These approaches take input image as an RGB format and at the back many tasks done which mean preprocessing, segmentation and feature extraction without user interaction and then it automatically segments and extracts features then it gives the classified images or the classified results.

CHAPTER THREE

3. Methodology

3.1. Research design

This study was used experimental research design. Experimental research design is a systematic research study in which the researcher manipulated and controlled testing to understand causal process. In conducting experimental research design there are three major procedures followed, such as dataset preparation, model building/implementation, and prototype development and testing. To facilitate experimental research in the image domain, the researcher applied image processing steps, such as image acquisition, image preprocessing, segmentation, feature extraction, classification and evaluation.

3.2. Data source and sampling techniques

In this study purposive sampling technique was used to select the domain experts for the purpose of acquiring knowledge. The selection criterion of domain experts for the study was conducted based on the professions, educational qualification, years of experience on grading practice. Hence, the researcher selected a total of four/4 domain experts purposively for interview from Jimma Agricultural research Institute and Horizon Plantation staff.

In addition, the researcher obtained the samples of certified coffee leaves from Jimma Agricultural Research Institute and Horizon Plantation. The researcher recorded necessary attributes and statistical data regarding the various samples from the tagged coffee leaf packages in to the system`s database, processed by the experts during the manual detecting activities. Totally, the researcher employed samples of four hundred and twenty two (422) images of coffee leaves in the process. Hence, the procedures followed during dataset preparation in the study were discussed below.

3.3. Dataset preparation

This section includes the following five investigation procedures of the study. They are image: acquisition, preprocessing, segmentation, feature extraction and classification. The details are discussed below.

3.4. Image acquisition

The data acquisition technique in this research is crucial concern to generate clear, unbiased and simplified digital coffee leaf sample database for further analysis and processing. For acquiring images of Coffee plant canon EOS 600d camera was used. When images were taken, the camera was fixed on a stand which reduces the movement of hand and capturing uniform images of Coffee plant. It has used three varieties of distance 110mm, 130mm and 155mm form the Coffee leaf. Finally get better image on the distance of 130mm from the Coffee leaf. To obtain uniform lightning or balanced illumination 100W lamp were used. Whenever capture images of Coffee turn on the power of lamp so as to get minimal noises of Coffee plant leaf image. The images captured using a digital camera are transferred into a computer, displayed on a screen and stored on the hard disk in PNG format as digital color images.

Image analysis starts with image acquisition which involves all aspects that have to be addressed in order to obtain images of the objects of interest. The selection of radiation sources and sensors such as cameras has to be considered very carefully. The geometry of the viewing situation, the relative positioning of sources and camera with respect to the objects of interest, usually also has a major impact on the contrast between these objects and their background.

When acquiring images from the environment, experts can use different resolution pixels. Images can be acquired at 1200 x 1200, 1456 x 1544, 696x514 and others. But experts such as Rafael Gonzalez (2020) used1240x800 and 600x600 resolution when taking images from the environments for better resolution and less memory requirement. So, the researcher used 1240 x 800 resolutions to collect image’s dataset. . All the captured images were in PNG file format. PNG image file format is selected because of its lossless behavior for preserving image data. The Coffee tree leaves used in this research were recollected in Coffee plantations located at Jimma and Limmu Coffee farms. Such leaves were photographed in a controlled environment.

Afterwards, the nutritional deficiencies were identified by agricultural experts from Jimma agriculture research center and Limmu Coffee farm.

Deficiency Type	No. of Image
Boron	80
Iron	111
Calcium	110
Potassium	121
Total	422

Table5: Number of Coffee leaves image used

3.5. Image preprocessing

The capturing and quality of brightness has impact on digitizing activities using computer vision systems as with the human eye. The performance of the brightness system greatly influences the quality of an image and plays an important role in the overall efficiency and accuracy of the system, underlining the need for manipulation of the illumination system specifications like type, angle and the use of constant light. So, it needs to digitize the system with uniform lightning or balanced illumination.

Image processing is started from rendering of images on computer screen and storing images on hard disks or other media for further processing. Image preprocessing techniques; image filtering, image quality enhancement, normalization and Binarization were employed in this study to improve the quality of acquired images which deep learning support. They were used for the purpose of reducing noises from the acquired image data. Then, mean and median was used for the coffee leaves image filtering purpose. Smoothing quality enhancer techniques was also employed for enhancing the quality of images for better understanding. Images were normalized and converted in black-white space for further processing and analysis. Dynamic range expansion in the image is usually to bring the image into a range that is more familiar or normal to the senses.

3.6. Image classification

Image classification is a fundamental problem in pattern recognition. Pattern recognition is the study of how machines can observe the environment, learn to distinguish patterns of interest, make sound and reasonable decisions about the categories of the patterns. Patterns are any entity or object such as coffee leaf images.

The image classification model has three main components. They are representation of image features, learning and testing process for semantic categories using these representations and the classifier. Classifier is a program that takes input feature vectors and assigns it to one of a set of designated classes. Python is used for developing model by using the above three classifiers. In order to classify the obtained samples based on the features extracted by the descriptors, the researcher used the Mobile-Net, VGG16 and InceptionV3 pre-trained model to classify the four nutritional deficiencies Boron, Iron, Potassium and Calcium.

3.7. Mobile-Net

MobileNet is a streamlined architecture that uses depth wise separable convolutions to construct lightweight deep convolutional neural networks and provides an efficient model for mobile and embedded vision applications. The structure of Mobile-Net is based on depth wise separable filters, as shown in Figure 14.

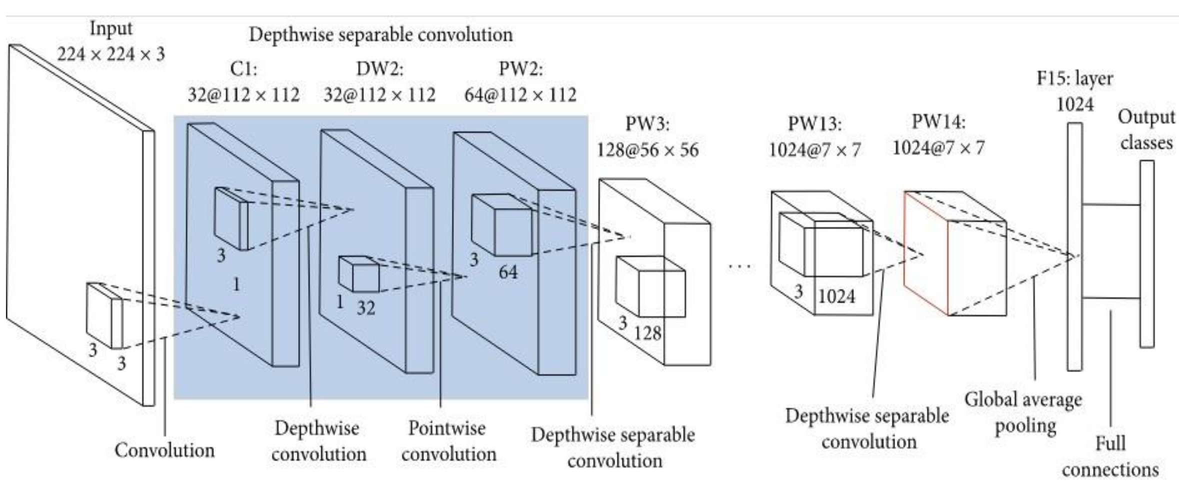
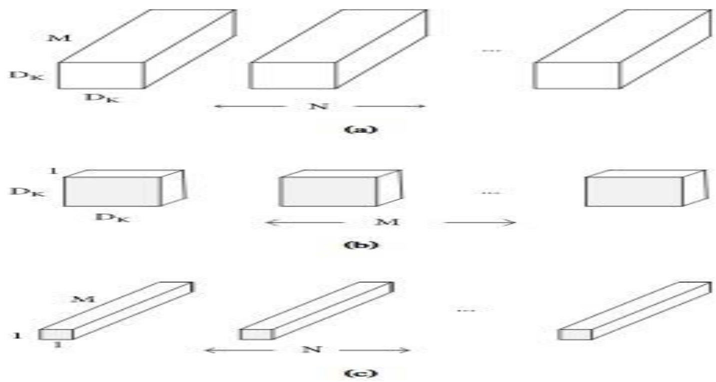


Figure 14: Architecture of MobileNet

Depth wise separable convolution filters are composed of depth wise convolution filters and point convolution filters. The depth wise convolution filter performs a single convolution on each input channel, and the point convolution filter combines the output of depth wise convolution linearly with convolutions, as shown in Figure 15.



(a) Standard convolutional filters, (b) depth wise convolutional filters, and (c) point convolutional filters.

Figure 15: Standard convolutional filters and depth wise separable filters.

3.8. VGG16

VGG16 is a convolution neural net (CNN) architecture which was used to win image competition in 2014. It is considered to be one of the excellent vision model architecture till date. Most unique thing about VGG16 is that instead of having a large number of hyper-parameter they focused on having convolution layers of 3x3 filters with a stride 1 and always used same padding and maxpool layer of 2x2 filter of stride 2. It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture. In the end it has 2 FC(fully connected layers) followed by a softmax for output. The 16 in VGG16 refers to it has 16 layers that have weights.

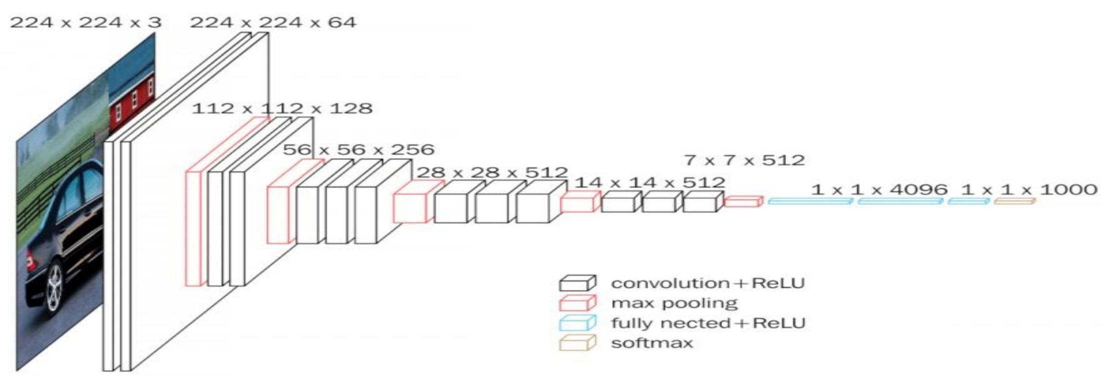


Figure 16: Architecture of VGG16

The input to cov1 layer is of fixed size 1240 x 800 RGB image. The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field: 303 which is the smallest size to capture the notion of left/right, up/down, center. In one of the configurations, it also utilizes 101 convolution filters, which can be seen as a linear transformation of the input channels followed by non-linearity. The convolution stride is fixed to 1 pixel; the spatial padding of conv. Layer input is such that the spatial resolution is preserved after convolution, therefore the padding is 1-pixel for 303 conv. Layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. A layer is not all the conv. layers are followed by max-pooling. Max-pooling is performed over a 202 pixel window, with stride 2. Three Fully-Connected (FC) layers follow a stack of convolutional layers which has a different depth in different architectures. The first two have 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels that mean one for each class. The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks. All hidden layers are equipped with the rectification (ReLU) non-linearity. It is also noted that none of the networks except for one contain Local Response Normalization (LRN), such normalization does not improve the performance on the ILSVRC dataset, but leads to increased memory consumption and computation time. This algorithm is used.

3.9. Inception-V3

Inception-v3 is convolutional neural network architecture from the Inception family that makes several improvements including using Label Smoothing, factorized 7 x 7 convolutions, and the use of an auxiliary classifier to propagate label information lower down the network along with the use of batch normalization for layers in the side head. For the purpose of this study it is experimented.

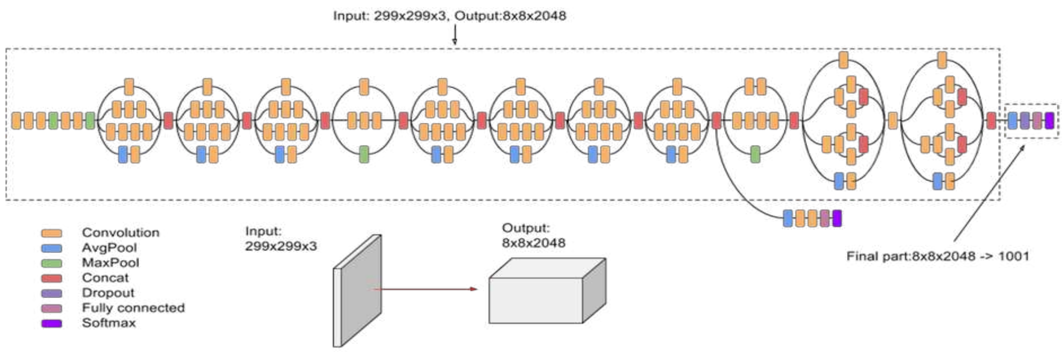


Figure 17: Architecture of Inception-V3

3.10. Implementation tools

All sample coffee leaf images were acquired using CANON color digital camera model LCD screen, Carl Zeiss VarioTessar lens with wide-angle lens of 30mm, optical zoom 4x, full HD 1080. The camera is mounted over the illumination chamber on a stand which provides easy vertical movement. Since deep learning needs high performance computing server for training, thus, due to that the researcher did not get such kind of resources and used limited online computing services such as Google co-laboratory research.

Google Co-lab is a project from Google Research, a free, Jupyter notebook based environment that allows us to create Jupyter (programming) notebooks to write and execute Python programs. Python based third-party tools and machine learning frameworks such as **tensorflow, Keras, OpenCV**, and others in a web browser. A programming notebook is a type of shell or kernel in the form of a word processor, where we can write and execute code. The data required for processing in Google Colab can be mounted into Google Drive or imported from any source on the internet. Project Jupyter is an open-source software organization that develops and supports Jupyter notebooks for interactive computing.

Colaboratory, or “Colab” for short, is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis and education. More technically, Colab is a hosted Jupyter notebook service that requires no setup to use, while providing free access to computing resources including GPUs. One of the main functionalities of Google Colab is that it allows anyone to share live code, mathematical equations, data visualizations, data processing (cleaning and transformation), numerical simulations, machine learning models, and many other projects with others.

Google Colab has unique and critical features one of the most important A Jupyter notebook environment that require no setup to use. It is the most top tools especially for data scientists, because no need of install manually most of the package and libraries, jut import them directly by calling them. But currently there is no machine in hand which can fulfill the above hardware requirements. So, the researcher uses Google-Colab to meet this requirement and train the designed model using CNN classifier and to convert the prototype into mobile app the researcher used android programming language.

3.11. Architecture / Framework of the model

Regarding the necessity of identifying nutritional deficiencies in images of Coffee leaves using a computational approach, here it is proposed the development of a framework that is based on the usual architecture employed in approaches focused on images recognition through supervised classification. The below figure 13 is the internal process (black box) of CNN model which illustrates how the designed CCN model perform the tasks from image pre-processing up to classification. As shown the model repeats each process in testing phase as it does in training phase. This is indicated by the arrow from left to right. From here the task that the researcher is going to do manually are data acquisition and feeding training and testing data.

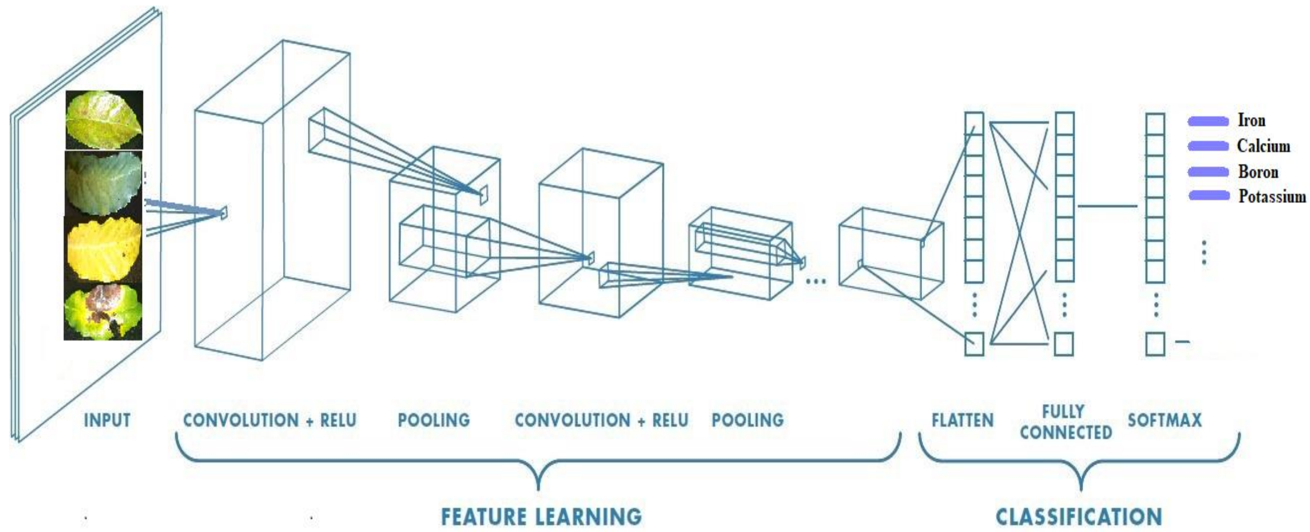


Figure 13: Framework for automatic detection of Coffee nutrition deficiency in Coffee leaves

3.12. System Evaluation

The model was evaluated by running a test dataset on the classifier built using the training dataset. The performance of the system is evaluated as an output that contains performance matrices and percentage accuracy measures for each grade obtained by from the system with comparison to experts, and summarized into a confusion matrix. Confusion matrix is a kind of a contingency table, used to drive true positives, true negatives, false positives and false negatives indicating the correct/incorrect values of samples into their respective classes. The system performance is evaluated by measuring accuracy rate.

$$\text{Accuracy rate} = \frac{Total\ number\ of\ samples\ correctly\ classified * 100\%}{Total\ number\ of\ samples\ used\ for\ testing}$$

CHAPTER FOUR

4. Experimental Result

4.1. Introduction

In this study, image processing technology is employed to detect nutritional deficiency of coffee leaf by characterizing and formulating distinct pre-defined classes that served as the basis for assigning the new sample leaves into their respective classes. The pre-defined classes depend on the values of the features computed from coffee leaf images. The captured and acquired images for the purpose of this research were pre-processed for noise reduction and image enhancement in order to improve the quality of coffee leaf images for accurate use in extracting the necessary features using image analysis and processing techniques.

Coffee leaf images that passed through image preprocessing techniques were used in the training phase. In addition, coffee leaf images were segmented to identify the region of interest (ROI). This section also presents the results associated to the obtained descriptors, according to their accuracy for detecting the nutritional deficiencies. Specifically, it presented the amount of correctly classified and incorrectly classified images, and the global accuracy. In addition, the evaluation metrics precision, recall obtained for each class, in this case, for each kind of nutritional deficiency. In all case it was used a 10-fold cross validation approach and confusion matrix was used to for this validation purpose.

4.2. Image preprocessing results

Image preprocessing is the operation with images at the lowest level of abstraction in which both input and outputs are intensity images usually represented by a matrix of image function values such as brightness. Filtering techniques were used to remove noise information from images. Median filtering was used in digital image preprocessing because, under certain condition, it preserves edges while removing noise.

The first tasks were subtracting background from the images to avoid blurs, light distortions and other noises that could be formed due to light effects during image capture and some external objects on the background. After background subtraction, conversion of the RGB images to 8-bit gray scale image and histogram thresholding for the purpose of extracting features from the original images were done. Conversion to gray scale images of the RGB images supports the production of binary images which help extraction of features the above listed task were done at the backend of deep learning.

4.3. Image analysis

Image analysis involves investigation of the image data specific to classify coffee leaf nutritional deficiency in to its appropriate class. Normally, the raw data of a set of images is analyzed how they can be used to extract desired information from coffee leaf images. In image processing and pattern recognition, feature extraction analysis is an important step, which is a special form of dimensionality reduction. Deep learning performed a great task of image processing, analysis and feature extraction activities of all the captured coffee leaf images. Enhanced and segmented coffee leaf images were outputs of the research, whereby same were used as inputs for the succeeding phase of feature extraction in the program.

4.4. Extracted coffee leaf features for detection

The output of enhanced images plays a great role in the generation and computation of the important and actual parameter's features of these agricultural products. Features of the coffee leaves were the focal concern in this research and were extracted accordingly to generate statistical values for raw quality value rank modeling. CNNs mainly consist of three type of layers: i) convolutional layers, where a kernel (or filter) of weights is convolved in order to extract features; ii) nonlinear layers, which apply an activation function on feature maps usually element wise in order to enable the modeling of non-linear functions by the network; and iii) pooling layers, which replace a small neighborhood of a feature map with some statistical information mean, max, etc. about the neighborhood and reduce spatial resolution. The units in layers are locally connected; that is, each unit receives weighted inputs from a small neighborhood, known as the receptive field, of units in the previous layer. By stacking layers to form multi-resolution pyramids, the higher-level layers learn features from increasingly wider receptive fields. The main computational advantage of CNNs is that all the receptive fields in a layer share weights, resulting in a significantly smaller number of parameters than fully-connected neural networks.

Figure15. Sample deep learning boron leaves feature extraction using threshold canny edge detection algorithm

4.5. Experimentation

For experimentation and constructing classification model Mobile-Net classifier, VGG NET 16 and Inception-Net-V3 classifiers were used. After separately testing morphological features and color features of coffee leaf images, a combination of these two features is used in this experimentation. The accuracy and efficiency of models relies on the procedures of setting up the model initialization and parameter value. The overall automated system modeling activity is conducted by using attributes that were either selected by the model itself or by the researcher based on their suitability to the particular model. Experimental result ensures the realization of the developed system architecture.

There are two basic phases of classification used in this study. Those are training and testing phases. Data was repeatedly presented to the classifier in the training phase. The trained system is applied to new data to check the performance of the classification in testing phase. Classifier was designed by partitioning the total dataset into training and testing dataset. From the total dataset of each grade, 80% was used for training and 20% was used for testing data.

4.6.1 Training and Testing datasets

After annotation, the researcher preprocessed and trained on the model. For training, the researcher needs training and validation split and for model evaluation, it requires test split test data. In this study the researcher split the data 80 by 20 as a result the researcher can get training 60 percent, evaluation 20 percent, and testing data 20 percent. The researcher used four hundred twenty two (422) total nutritional deficient Coffee plant leaves image data set, from this data first the researcher split 20 percent for testing which is 84 images and 338 training image data which is 80%, and further from the remaining training data, the researcher again split 20 percent validation data which is 10 images. So split our data 50 for training, 40 for testing unseen data during training, and 10 for evaluation.

	Mobile Net	VGG-Net 16	Inception-Net-V3
Training Accuracy	0.9911	0.6677	0.9643
Training Loss	0.0157	0.4853	0.0889
Testing Accuracy	0.9882	0.6471	0.8095
Testing Loss	0.0761	0.5028	0.3820

Table 4: Accuracy and loss of both training and testing of the three models

4.6. Mobile-Net classifier and its output

Mobile-Net is a CNN architecture model for Image Classification and Mobile Vision. Mobile-Net uses depth wise separable convolutions**.** It significantly reduces the number of parameters when compared to the network with regular convolutions with the same depth in the nets. This results in lightweight deep neural networks. The experimental result tested with Mobile net classifier is shown on the below figure 18.

SampleTest Image

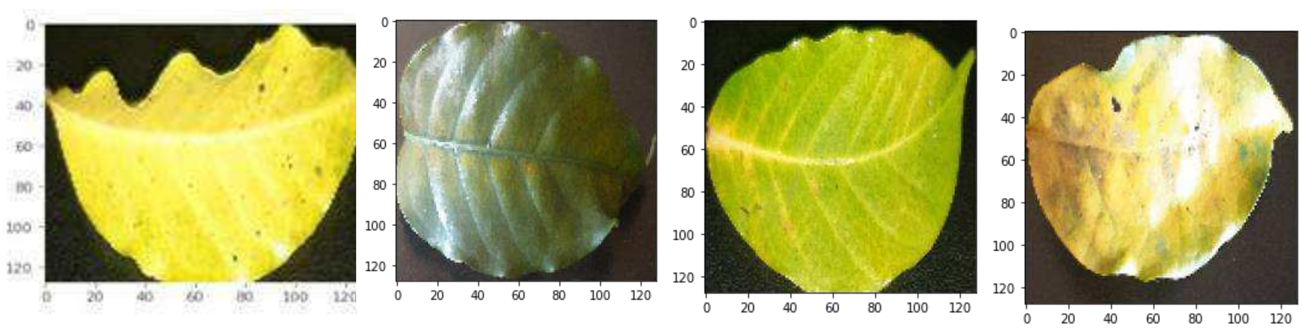


Figure 18: Mobile Net test image

Prediction

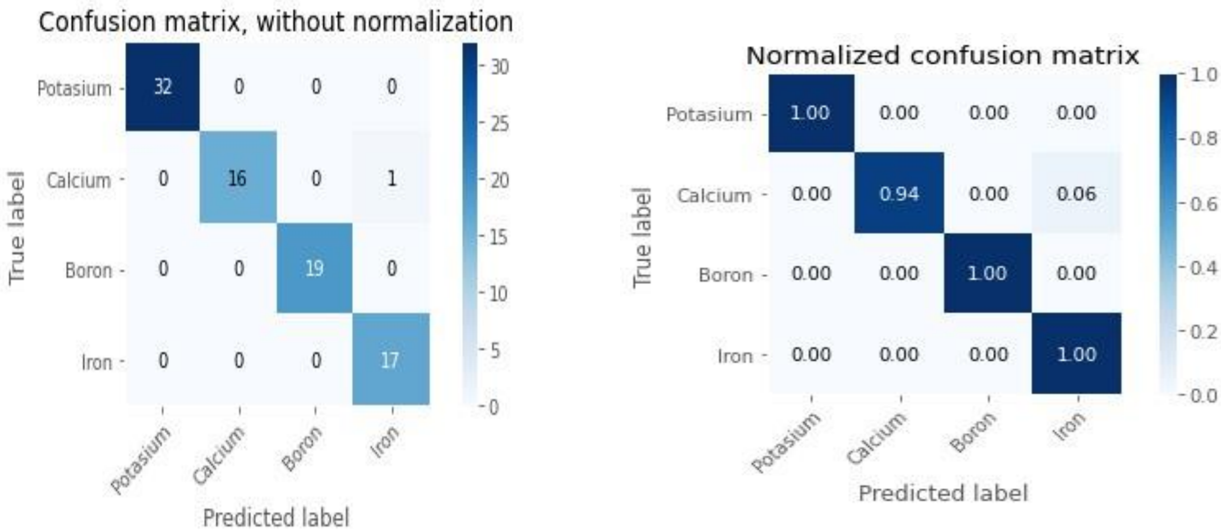
Iron = 0.999 percent

Calcium = 2.8e-05 percent

Potassium = 8.97e-06 percent

Boron = 3.76e-06 percent

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. The researcher compared model and showed the result in the below figure 21.



(a) Confusion matrix without normalization (b) Normalization confusion matrix

Figure 21: Mobile Net Confusion Matrix

4.7. VGG16 classifier and its output

VGG16 is CNN architecture. It is considered to be one of the excellent vision model architecture. Most unique thing about VGG16 is that instead of having a large number of hyper-parameter they focused on having convolution layers of 3x3 filters with a stride 1 and always used same padding and max pool layer of 2x2 filter of stride 2. It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture. In the end it has 2 FC (fully connected layers) followed by a soft max for output. The 16 in VGG16 refers to it has 16 layers that have weights. This network is a pretty large network and it has about 138 million (approx) parameters. For the purpose of this study the researcher experiment and test VGG16 classifier.

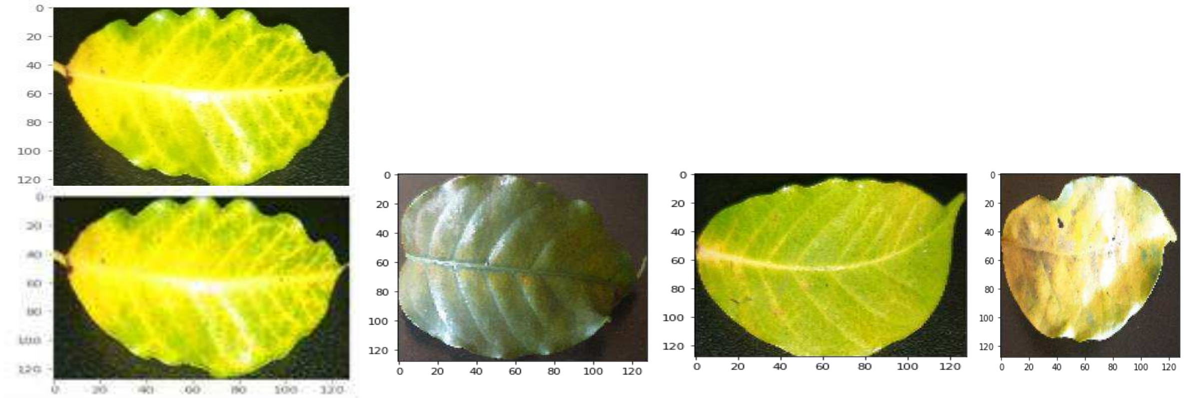
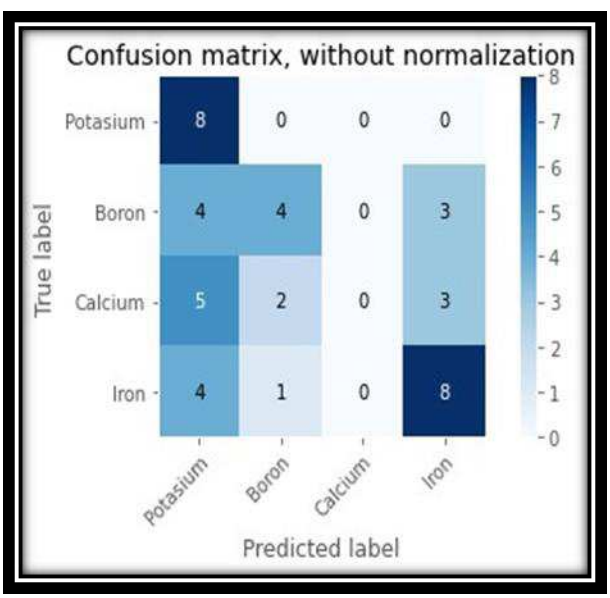


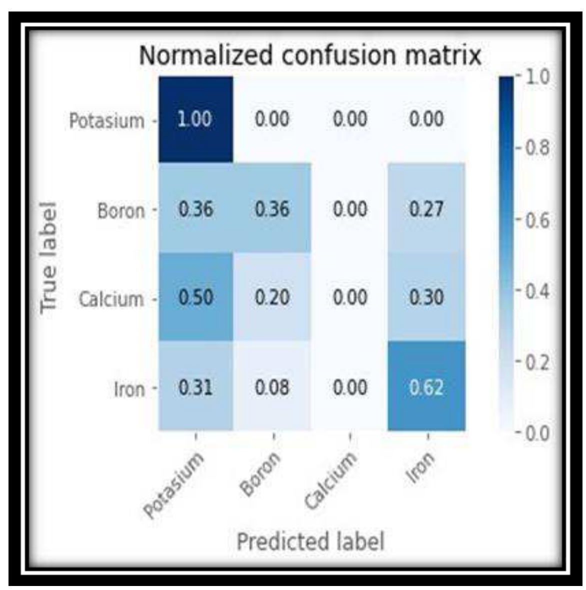
Figure 19: VGG Net 16 test image

Prediction

Iron = 0.336 percent Potassium = 0.256 percent Calcium = 0.226 percent Boron = 0.184 percent

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. The researcher compared model and showed the result in the below figure 22.





(a) Confusion matrix, without normalization (b) Normalization confusion matrix

Figure 22: VGG Net 16 Confusion Max

4.8. Inception-V3 classifier and its output

Inception v3 is a convolutional neural network for assisting in image analysis and object detection, and got its start as a module for Google-net. It is the third edition of Google's **Inception** Convolutional Neural Network, originally introduced during the Image-Net Recognition Challenge. Inception v3 is a widely-used image recognition model that has been shown to attain greater than 78.1% accuracy on the Image-Net dataset. The model is the culmination of many ideas developed by multiple researchers over the years.

The model itself is made up of symmetric and asymmetric building blocks, including convolutions, average pooling, max pooling, con-cats, dropouts, and fully connected layers. Batch-norm is used extensively throughout the model and applied to activation inputs. Loss is computed via Soft-max. The study employed the model and its output is showed below.

Test Image

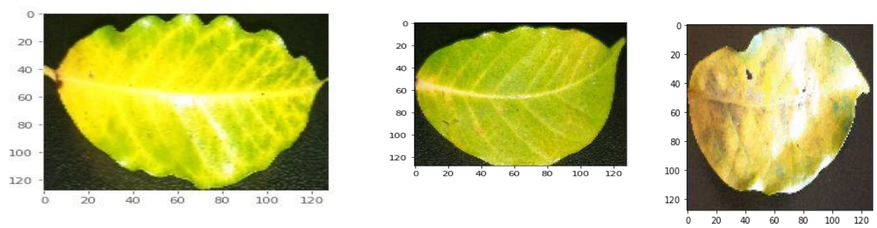


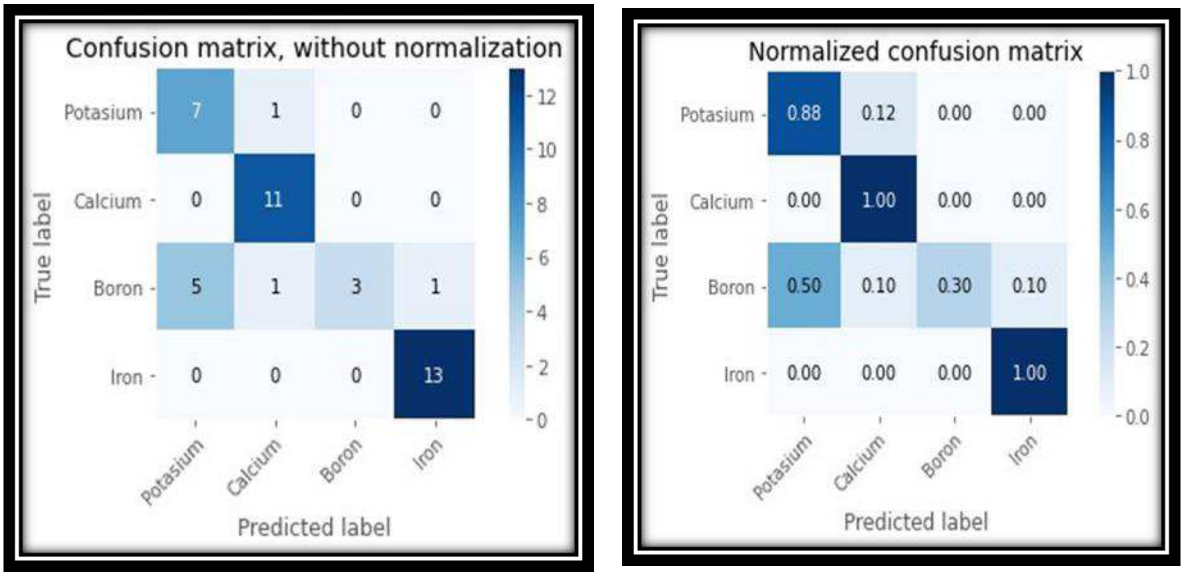
Figure 20: Inception-Net-V3 test image

Prediction

Potassium = 0.47 percent Calcium = 0.289 percent Iron = 0.206 percent Boron

= 0.154 percent

A confusion matrix is a table that is often used to describe the performance of a classification model (or “classifier”) on a set of test data for which the true values are known. The researcher compared model and showed the result in the below figure 22.



(a) Confusion matrix, without normalization (b) Normalization confusion matrix

Figure 23: inception Net V3 Confusion Max

4.6. Classification performance of the models

The researcher evaluated the performance of nutritional deficiency model via Accuracy, Precision, Recall and F1 Score metrics.

Mobile Net				
	precision	**Recall**	**f1-score**	**support**
Potassium	1.00	1.00	1.00	32
Calcium	1.00	0.94	0.97	17
Boron	1.00	1.00	1.00	19
Iron	0.94	1.00	0.97	17
accuracy			0.99	85
macro-avg	0.99	0.99	0.99	85
weighted-avg	0.99	0.99	0.99	85
VGG Net 16				
	precision	Recall	f1-score	support
Potassium	0.38	1.00	1.00	32
Calcium	0.57	0.94	0.97	17
Boron	0.00	1.00	1.00	19
Iron	0.57	1.00	0.97	17
accuracy			0.48	42
macro-avg	0.38	0.49	0.40	42
weighted-avg	0.40	0.48	0.40	42
Inception Net V3				
	precision	**Recall**	**f1-score**	**support**
Potassium	0.58	0.88	0.70	8
Calcium	0.85	1.00	0.92	11
Boron	1.00	0.30	0.46	10
Iron	0.93	1.00	0.96	13
accuracy			0.81	42
macro-avg	0.84	0.79	0.76	42
weighted-avg	0.86	0.81	0.78	42

Table6 : Performance evaluation of nutritional deficiency model.

Finally, MobileNet showed best performance and 0.99 accuracy when compared with others as it is depicted in the above table. Therefore, the model was developed using MobileNet convolutional Neural Network.

4.9. Discussion

This section presents a brief discussion on the accuracy in the detection of the mentioned nutritional deficiencies, as well as the performance of the used image descriptors and the pre-trained models.

Summarizing, the referred experiments obtained the better results at the identification of Iron (Fe) and Boron (B) nutritional deficiencies. These results could be related to the fact that the symptoms associated to the Boron and Iron deficiencies are more remarkable than those associated to the other nutrients; therefore they could be identified in an easier way. Specifically, the best results associated to the Mobile-Net descriptor were notably obtained in the identification of deficiencies, with a large difference in relation to other pre-trained models which means VGG16 and inception v3.

Finally, a direct comparison between the three classification approaches concludes that using the information associated descriptor, for all the deficiencies the classifier with best accuracy results was the Mobile-Net (98.82 %). However, for the descriptor the results do not evidence the superiority of some classifier over the remaining two. In contrast, the best results associated to each nutritional deficiency, were shared across the three classifiers. In related to this study as Setiawan, W., Syarief, M., & Prastiti, N. (2019) depicted in their study on the title of maize Leaf Disease Image Classification Using Bag of Features by using 200 images and convolutional neural network (VGG 16, VGG19, GoogleNet, Inception-V3). They got similar result that accuracy, sensitivity, specificity of 93.5%, 95.08%, and 93%, respectively. In addition, Zhang et *al.,(*2018), conducted the study entitle Identification of maize leaf diseases using improved deep convolutional neural networks achieves performance evaluation of an average accuracy of 98.8%. Moreover, as Rajbongshi *et al.,* (2020) stated in their study on the title of rose diseases recognition using MobileNet they got model performance evaluation result achieves 95.63% accuracy.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

The researcher analyzed the nutritional deficiency of coffee plant by image processing and deep learning techniques convolutional neural network to classify as: Iron, Potassium, Calcium and Boron. First, the researcher prepared the dataset by using less than thousand images for both the training and the deep learning, due to the shortcomings the researcher faced from the data sources. On the other hand, the deep learning technique requires more than thousand images to learn and classify accurately. However, the researcher managed the problem by classifying the fewer datasets for both training and testing. Then, the researcher compared the testing results of three pre-trained deep learning models. Finally, the researcher concluded that testing and training value of Mobile-Net model showed best performance with accuracy of Mobile Net 0.9882 than the rest of two models.

5.2. Recommendation

The researcher recommends that nutrition deficiency and disease of coffee plantations can be done by using others deep learning models such as Dense-Mobile-Net. In addition, the researcher recommends that further researches should be done to upgrade this system into mobile apps for fast and best results. The researcher further adds that the coffee leaves data documentation culture of the coffee producing and researching organizations should be promoted both qualitatively and quantitatively. Since, the researcher used few number of dataset because of there is no already captured and stored dataset. Therefore, further plant pathology researches can be conducted to gain better results in the field.

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Appendix 1 sample code

Importing pre processer

```
import keras
import tensorflow as tf
from tensorflow.keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Activation,BatchNormal
from keras.layers import Conv2D, MaxPooling2D, MaxPool2D
#from keras.utils import to_categorical
from keras.preprocessing import image
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from tqdm import tqdm
%matplotlib inline

from keras.applications.vgg16 import VGG16
from keras.applications.vgg16 import preprocess_input
from keras.applications.mobilenet import MobileNet
from keras.applications.mobilenet import preprocess_input
from keras.preprocessing.image import ImageDataGenerator
from keras import regularizers, optimizers
from keras.optimizers import Adam,Adamax,RMSprop,Adagrad,Adadelta,SGD
import seaborn as sns
```

Training the images

```
import numpy
from numpy import loadtxt
from numpy import asarray
from numpy import save
train_image = []
with tf.device('/gpu:0'):
  for i in range(train.shape[0]):
      img = image.load_img('/content/drive/My Drive/colab/coffee_nutrition_deficiency/'+train['Image'][i]+'.jpg',
                           target_size=(128,128,3))
      img = image.img_to_array(img)
      img = img/255 #RGB
      train_image.append(img)
  X = np.array(train_image)
# save to npy file
save('422_data_with_4_deficiency.npy', X)#save
```

Mobilenet

```
from keras import models
from keras import layers

#Load the MobileNet model
IMAGE_SIZE=[128,128]
Mobilenet = MobileNet(input_shape=IMAGE_SIZE + [3], weights='imagenet', include_top=False)

# Freeze the layers except the last 4 layers
for layer in Mobilenet.layers:
  layer.trainable = False

# Create the model
with tf.device('/gpu:0'):
  mobilenet = tf.keras.models.Sequential()
  mobilenet.add(Mobilenet)
  # mobilenet.add(BatchNormalization())
  # Add new layers
  mobilenet.add(layers.Flatten())
  #mobilenet.add(layers.Dense(1024, activation='relu'))
  # mobilenet.add(BatchNormalization())
  #mobilenet.add(layers.Dense(1024, activation='relu'))
  mobilenet.add(layers.Dense(1024, activation='relu')) #addition of layer
  # mobilenet.add(BatchNormalization())                # addition of BN layer
  mobilenet.add(layers.Dropout(0.5))
  mobilenet.add(layers.Dense(4, activation='sigmoid'))
  # Show a summary of the model. Check the number of trainable parameters
  mobilenet.summary()

lr = 0.0001
epoch = 30
with tf.device('/gpu:0'):
  opt = Adam(lr = lr, decay = 1e-6)
  mobilenet.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
  HMN = mobilenet.fit(X_train, y_train, epochs=epoch, validation_split = 0.2, batch_size=32)
```

MobileNet result

	precision	recall	f1-score	support
Potasium	0.00	0.00	0.00	32
Calcium	0.28	0.65	0.39	17
Boron	0.00	0.00	0.00	19
Iron	0.29	0.76	0.42	17
accuracy			0.28	85
macro avg	0.14	0.35	0.20	85
weighted avg	0.11	0.28	0.16	85

Android code

```
# TensorFlow Lite Android image classification example

This document walks through the code of a simple Android mobile application that
demonstrates
[image classification](https://www.tensorflow.org/lite/models/image_classification/overview)
using the device camera.

## Explore the code

We're now going to walk through the most important parts of the sample code.

### Get camera input

This mobile application gets the camera input using the functions defined in the
file
[`CameraActivity.java`](https://github.com/tensorflow/examples/tree/master/lite/examples/image_classificati
This file depends on
[`AndroidManifest.xml`](https://github.com/tensorflow/examples/tree/master/lite/examples/image_classificati
to set the camera orientation.

`CameraActivity` also contains code to capture user preferences from the UI and
make them available to other classes via convenience methods.

```java
model = Model.valueOf(modelSpinner.getSelectedItem().toString().toUpperCase());
device = Device.valueOf(deviceSpinner.getSelectedItem().toString());
numThreads = Integer.parseInt(threadsTextView.getText().toString().trim());
```
```

Image recognition

```java
private static List<Recognition> getTopKProbability(
    Map<String, Float> labelProb) {
  // Find the best classifications.
  PriorityQueue<Recognition> pq =
      new PriorityQueue<>(
          MAX_RESULTS,
          new Comparator<Recognition>() {
            @Override
            public int compare(Recognition lhs, Recognition rhs) {
              // Intentionally reversed to put high confidence at the head of
              // the queue.
              return Float.compare(rhs.getConfidence(), lhs.getConfidence());
            }
          });

  for (Map.Entry<String, Float> entry : labelProb.entrySet()) {
    pq.add(new Recognition("" + entry.getKey(), entry.getKey(),
                entry.getValue(), null));
  }

  final ArrayList<Recognition> recognitions = new ArrayList<>();
  int recognitionsSize = Math.min(pq.size(), MAX_RESULTS);
  for (int i = 0; i < recognitionsSize; ++i) {
    recognitions.add(pq.poll());
  }
  return recognitions;
}
```

Display results

```
protected void processImage() {
  rgbFrameBitmap.setPixels(getRgbBytes(), 0, previewWidth, 0, 0, previewWidth,
      previewHeight);
  final int imageSizeX = classifier.getImageSizeX();
  final int imageSizeY = classifier.getImageSizeY();

  runInBackground(
      new Runnable() {
        @Override
        public void run() {
          if (classifier != null) {
            final long startTime = SystemClock.uptimeMillis();
            final List<Classifier.Recognition> results =
                classifier.recognizeImage(rgbFrameBitmap, sensorOrientation);
            lastProcessingTimeMs = SystemClock.uptimeMillis() - startTime;
            LOGGER.v("Detect: %s", results);

            runOnUiThread(
                new Runnable() {
                  @Override
                  public void run() {
                    showResultsInBottomSheet(results);
                    showFrameInfo(previewWidth + "x" + previewHeight);
                    showCropInfo(imageSizeX + "x" + imageSizeY);
                    showCameraResolution(imageSizeX + "x" + imageSizeY);
                    showRotationInfo(String.valueOf(sensorOrientation));
                    showInference(lastProcessingTimeMs + "ms");
                  }
                });
          }
          readyForNextImage();
```