Detection and Classification of Coffee Leaf Disease using Deep Learning

Conference Paper · November 2022

DOI: 10.1109/ICT4DA56482.2022.9971300

2 authors:

Eyobed Birhanu Paulos
Wolaita Sodo University

Michael Melese Woldeyohannis
Addis Ababa University

Detection and Classification of Coffee Leaf Disease using Deep Learning

Eyobed Birhanu Paulos
School of Informatics, Wolaita Sodo University
Wolaita Sodo, Ethiopia
eyobed.birhanu@wsu.edu.et

Michael Melese Woldeyohannis
School of Information Science, Addis Ababa University
Addis Ababa, Ethiopia
michael.melese@aau.edu.et

***Abstract*—Ethiopia is the leading coffee exporter in Africa which accounts for 22% of the country's commodity exports. Coffee is one of the crucial agricultural product in the global economy, particularly for Ethiopia. However, diseases like brown eye spot, wilt, and rust are the most determinant constraints the productivity and quality of coffee export. The disease detection requires specific attention from professionals, which is not achievable for mass production. As a result, an autonomous method for detecting and classifying coffee plant disease become very crucial for better productivity. To determine whether a particular image of a leaf has a brown eye spot, wilt, or rust or if it is healthy, we created a deep learning model trained with image dataset collected from the Wolaita Sodo agricultural research center consisting of 1,120 and augmentation technique also applied to handle data over-fitting problem and totally 3,360 images were used. In order to achieve the best results during the classification of such diseases, we compared training from scratch and transfer learning techniques. Because of this, training from scratch performs at a rate of 98.5%, whereas transfer-based learning offers accuracy rates of 97.01% and 99.89% when employing transfer learning through Mobilnet and Resnet50, respectively. The pre-trained Resnet50 model performs picture classification better than other methods. We are further working towards considering the other class of the Coffee leaf disease by incorporating additional data beside the other pre-trained models.**

***Keywords*—Coffee leaf disease, deep learning, transfer learning**

I. Introduction

Agriculture is essential to economic growth; it contributed 4% of the world's GDP, and in the least developed nations, it may even make up more than 25% of gross domestic product (GDP) in the future [1]. Agriculture is also one of Ethiopia's top economic sectors which accounts for around 68% of employment and 34% of GDP. According to World Bank[1], Agriculture is one of the leading source of income to reduce poverty, raise incomes and improve food security for more than 80% of the poor people who live in rural areas and work mainly in farming for the country like Ethiopia.

Additionally, more than 75% of Ethiopia's population heavily relies on agriculture to provide for their basic needs. Africa is a continent whose economy mainly relies on agriculture. Accordingly, for a nation like Ethiopia, the requirement for agricultural economic growth is rising at an alarming rate. Over the past decades, the demand of economic growth on agricultural center is increasing in an exponential rate. Thus, the rate of generation within the agriculture sector has doubled within the recent two decades [2], [3]. This resulted within the extension of land, labour and expansion worker close to the modern inputs for the agriculture sector. In like manner, the production of crops in final decade becomes three times more than that of the year 2017 whereas the demand delivered increased by 86% for an increase of the 70% area cultivated.

Among the agricultural products, Coffee is one of the crucial agricultural product in the global economy, particularly for Ethiopia [4]. In addition, many people uses Coffee as a refreshment and source of income beside the cultural value [5]. Ethiopia is the biggest maker of coffee in Africa and is the fifth biggest coffee maker within the world another to Brazil, Vietnam, Colombia, and Indonesia of add up to world coffee generation. Being the beginning of coffee Arabica, Ethiopia has gigantic potential to offer the world showcase a wide assortment of flavours of naturally delivered, washed and sun-dried coffee. Present days, Ethiopia is contributing approximately 7-10% of add up to world coffee generation [4]. Beside contribution to world coffee market, around 15 million individuals specifically or in a roundabout way, determining their jobs from a coffee framework in Ethiopia [5].

Even though area and demand increased, efficiency remained low because of a variety of issues, including disease-related harm, subpar management techniques, sterile soil, and cheap prices [6]. Diseases that are increasing in frequency as a result of environmental factors, economic factors, poor management, and hereditary factors are also linked to the low price of coffee [7]. Three principal diseases, Coffee Leaf Rust, Coffee Brown Eye Spot Disease, and Coffee Berry Disease, affect the coffee plant for different reasons [8]. Since it is a fact that plants can contract diseases, it is also very important for farmers to be aware of these problems [11]. Plant disease is one of the main factors that affects plant quality and can destroy the entire field's crops, generating an impressive resign incident within a few days after the initial damage manifests itself in the cultivate.

In today's world, the introduction of soft-computing technologies has provided a platform for plant professionals/pathologists to employ more intelligent tools and methodologies to diagnose and treat recognized plant leaf diseases, as well as identify and categorize crop leaf illnesses [11], [12].

[1] https://www.worldbank.org/en/topic/agriculture/overview

So, with the aforesaid issue of soft computing technology, it is necessary to come up with and merge Artificial Intelligence (AI). Currently, machine learning under the umbrella of AI setups is assisting in overcoming obstacles in each industry. The majority of agricultural start-ups are adapting the AI-enabled strategy to increase the efficiency of agricultural output [8]. The automated technique is assisting several segments to improve efficiency and competence. Similarly, machine learning in agribusiness is assisting growers to improve their adequacy while decreasing environmental adverse affects.

Computer vision innovation is widely used in the field of agricultural computerization as a result of the rapid advancement of artificial intelligence where a computer is made to observe and perceive. Instead of using the human common eye to detect, track, and degree targets for sophisticated image processing, this innovation uses an advanced camera and computer [8]. Because of the development of computer vision, such innovation is now widely used in the field of agricultural automation and contributes significantly to its advancement. A number Image processing helps computer vision to infer myore significant information from the image input and machine learning must learn from experience in order to execute computer vision tasks [8], [12]. Machine learning enables frameworks to organically learn and improve from experience with or without minor unambiguous human impediments, is necessary for machines to conduct computer vision operations [13]. It focuses on the development of computer systems that can gather data and build models to produce better choices through judgments in agreement with prior views or data records.

Deep learning is the study of machine learning algorithms and artificial neural networks that have more than one hidden layer [14], [15]. Different layers of neurons in deep learning accomplish diverse hierarchical learning of the information representation by means of non-linear changes [8]–[10], as opposed to Convolutional Neural Networks (CNN).

Therefore, it is frequently need to look closely at the leaf, stem, and occasionally the tree and perform some preventive work in order to identify potential reasons of the issue of a coffee [8], [9]. In a similar manner, conventional methods are frequently used by experts to prepare identifiable proof of disease through visual inspection. However, due to a lack of expertise and a large number of ranches, it is tedious, time-consuming, prone to error, and occasionally not practical [16]. Consequently, in order to solve those issues, we need a unique technique. In addition to this, a wide range of visible indicators, such as colored streaks or patches on various parts of the plants, can indicate that Coffee is diseased [9], [10]. Continually changing in color, shape, and size as the disease progresses are the visual symptoms of the illness, which makes it difficult to track the status. Thus, there is a need to detect and classify Coffee disease automatically.

Therefore, to boost the agricultural fields and the economy of the nation by raising the productivity and quality of Coffee, it is necessary to utilize a computerized early disease detection and classification in a short period by looking at the plant symptoms in an easier and cheaper way using the state-of-the-art AI technology which favours the high productivity and efficiency.

II. Related Works

Deep learning plays an important role in the agricultural sector for identifying plant diseases at different stages of cultivation. Numerous studies aimed to automatically identify and diagnose illness from various parts of the plant in an effort to address these various problems. This section gives a thorough explanation of the accomplishment.

The idea of using image processing to automatically identify the three main diseases affecting Ethiopian coffee leaves were attempted [11]. In the study, FCM, Otsu, Gaussian distribution, K-means, and a combination of Gaussian distribution and K-means clustering were five segmentation technique used. The standard traditional characteristics like color, shape, and texture, which perform badly when used alone, in addition to the Gray level co-occurrence matrix (GLCM) and color features to extract features from Ethiopian coffee leaves. The model was trained using Artificial Neural Networks (ANN), Nave Bayes, Self Organizing Map (SOM), and Radial Basis Function (RBF). The accuracy is 92.10% when Gaussian distribution and K-means clustering are combined with a mix of SOM and RBF classification techniques.

Another effort has been made to gauge the degree of severity utilizing a mobile phone system that can instantly recognize and classify Coffee Leaf miner and rust [17]. They employed k-means clustering, the Otsu Technique, and an iterative threshold technique over two color spaces (HSV and YCbCr) to segment the diseased and pest-infested areas of the coffee leaves from the healthy ones. To train the model, they used extreme learning machines (ELM), back propagation neural networks (BPNN), and artificial neural networks (ANN). Finally, ELM outperforms ANN and BPNN by a small margin.

Beside artificial neural network [18], the traditional machine learning method that was suggested on a machine vision-based approach to identify papaya disease is used. Five different diseases, including black spot, powdery mildew, brown spot, phytophthora blight, and anthracnose, could be identified and categorized using Support Vector Machine (SVM) with an accuracy more than 90%. The approach has a problem of detecting automatic illumination feature, back ground clustering of an objects that have similar appearance, intra-variation and view point variation.

Furthermore, diagnosis of the vegetable disease and insect pest recognition were made through the images captured on smartphones [19]. A new extraction and classification technique used to distinguish leaves from photographs. A region-labeling technique was then used to calculate the number of insects and sick areas in the segmented images. To separate the objects in the zones of adhesion, a mathematical morphology approach was used. The proposed approach was field-tested and implemented on mobile smart devices. The experimental result is 91.96% accurate. The method's accuracy is limited in some difficult conditions, such as leaf occlusion, color similarity between the object and the leaves, aberrant illumination, and low image quality.

The study revealed that disease identification and classification have been routinely done using computer vision, which has produced quite interesting results in the sector of agriculture. Deep learning algorithms such as CNN and ANN are also often used. So, a plant that has leaf indications as well as bacterial leaf wilt, fungal leaf rust, and fungal brown eye spot, but there is currently a desire to develop a model that is more correct and effective. In general, more precise and effective model development is required for a plant with leaf symptoms such as bacterial leaf wilt, fungal Leaf Rust, and fungal brown eye spot.

III. Material and Methods

In this article, we used experimental research to develop a deep learning model that can identify and categorize Coffee leaf disease employing a series of step-by-step procedures from data collection through model creation and evaluation. Accordingly, Section III-A, presents the detail image data collection and preparation for experiment while IV presents the proposed system architecture as part of the study.

A. Data Collection and Preparation

Due to unavailability of sufficient open dataset for Coffee leaf disease detection and classification, we opted to collect and prepare a data from Wolaita Sodo agricultural research in addition to Kaggle[2] dataset. Deep learning, as opposed to traditional machine learning, necessitates a vast amount of data to train the model which might have direct impact on the experiment. For this, Image data sets is collected with the help of domain experts such as extension agents, and agricultural researchers for the aim of training the model. As a result, a total of 1,120 images from the Wolaita Sodo agricultural farming sector, Southern Nation and Nationality of People Region (SNNPR) of Ethiopia. The images dataset collected are from four different categories. These categories are; healthy images, images with brown eye spots, images with wilt, and images with rust. The images dataset were taken using mobile-phone, specifically Samsung A50 camera.

In capturing the Coffee leaf images, we settle the smartphone on a stand to diminish hand development and make a difference to capture uniform. All images were captured in the same situation of lighting and only single leaf per image. Only one leaf per shot and the identical lighting conditions were used for all images. Figure 1 presents the sample Coffee leaf image collected from onsite for brown eye, leaf rust, leaf wilt and healthy images.

[2]Online dataset collected from Kaggle available at https://www.kaggle.com/code/jtaglione/coffee-leaf-diseases/data

(a) Brown eye

(b) Leaf rust

(c) Leaf wilt

(d) Healthy

Fig. 1: Sample image dataset collected for experiment

As depicted in Figure 1, the data includes 287 images with brown eye spots (22 online and 265 onsite), 285 images with rust (49 online and 236 onsite), 278 images with wilt (72 online and 206 onsite), and 270 images with healthy eyes (46 online and 224 onsite).

After gathering the dataset, the leaf image is subjected to a number of image-preprocessing tasks, including noise reduction, resizing, and data splitting, which are considered to be the most significant and crucial steps when working with image preparation and processing. Following labeling, data augmentation were used to add additional images and address the issue of over-fitting. Table I presents the detailed data collected from online and Wolaita Sodo agriculture research center.

	Data Source		Total
	Online	Onsite	
Healthy	46	224	270
Rust	49	236	285
Wilt	72	206	278
Brown eye spot	22	265	287
Total	189	931	1,120

TABLE I: The coffee leaf datasets

As depicted in Table I, a total of 1,120 image dataset from four different category. From these, 189 of the image from Kaggle while the remaining 931 collected by the researcher. Before creating a model using the data collected, we implemented noise reduction on an image, resizing to the same dimension and labelling with appropriate labeling to respective classes with the help of domain expert for onsite collected data.

After implementing data augmentation, the final dataset size is 3,360 as shown in Table II.

Coffee leaf Dataset	Size of Dataset
Healthy	810
Rust	855
Wilt	834
Brown eye spot	861
Total	3,360

TABLE II: Total coffee leaf datasets

IV. Proposed System Architecture

Given sufficient data for learning, deep learning techniques have achieved very high performance in a variety of fields such as image identification and segmentation, speech recognition, natural language processing beside the emotion recognition [14]. We assess the usefulness of deep learning method, which is the state-of-the-art for digital image processing tasks. Traditional strategies for training classifiers need explicit extraction of the features to be studied from the image prior to categorization and prediction. A deep neural network with specialization in handling data that has a grid-like representation, such an image and multi-dimensional data, is known as a convolution neural network (CNN), also called ConvNet [20], [21]. In contrast to other networks with fully connected layers, CNN has profound feed-forward engineering and has incredible generalizing capacity.

The genuine reality is that CNNs give automatic feature extraction, which is the essential advantage. The desired input information is at first sent to a feature extraction network, and after that the result extracted features are sent to a classifier network. The feature extraction network comprises loads of convolutional and pooling layer sets. Convolutional layer comprises of a collection of digital filters to perform the convolution operation on the input information. The pooling layer is utilized as a dimensionality decrease layer and chooses the threshold.

CNN has a numerous hidden layer that mimics and gets it stimuli as the visual cortex of the brain processes. The output layer of CNN regularly uses the neural network for multiclass classification. The more the layer the deeper the network for better image recognition. The neural network classification block then works on the premise of the image features and produces the output. The neural network for feature extraction incorporates convolution layer heaps and sets of pooling layers. As its name shows, the convolution layer changes the image utilizing the method of the convolution. Pooling layer changes the neighboring pixels to a single pixel. Then this layer decreases the dimension of an image.

A digital image refers to visual data made up of a grid-like arrangement of pixels, each of which carries a value that indicates how bright and what color it should be. CNN is made up of four main departments [23]. These procedures include feature extraction from an input, activation functions such the Rectified Linear Unit (ReLU), Sigmoid, and Softmax, pooling, which reduces the layer size, and dense layers (completely linked layers), in which each node is connected to every node on the adjacent levels. In pre-processing, we used median filter to filter salt and pepper noise on the collected image.

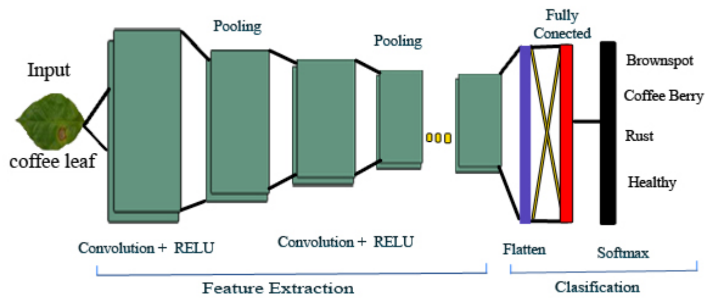

Fig. 2: CNN architecture adopted and modified from [22]

To collect additional images, address the issue of limited data, and improve the training and classification model, data augmentation techniques were used to the original image data to avoid the data imbalance and data over-fitting problem. The data augmentation is made using 90 degree rotation and horizontal flipping the original data. After data augmentation, the resources are divided in to training and validation. From the total dataset, 80% of the data used for training while the remaining 20% of the data are further divided for validation and testing the classification.

V. Experiment and Result Discussion

As part of the experiment result and discussion, the specification used in the development of the Coffee leaf disease classification presented in Section V-A, the different hyper-parameter used in the development beside the experiments attempted are presented in V-B followed by the detail of experimental result and discussion under the Section V part.

A. Experimental setup

The experiment was carried out using a PC with an Intel(R) Core(TM) i7-8550U CPU running at 1.80GHz and 1.99GHz, 8GB RAM, and the Windows 10 Pro operating system. Beside these, different tools have been used for the development of classification model such as Python, Tensorflow, and Keras.

TensorFlow is a complete open source machine learning platform which is feature rich, adaptable ecosystem of tools, libraries, and community resources that enable researchers to push the boundaries of ML and developers to quickly build and deploy ML-powered applications [24], [25]. Similarly, Keras adheres to best practices for lowering cognitive load using Tensorflow as a backend [24], [25]. It also provides consistent APIs that reduce the amount of user activities necessary for typical application. On the other hand, Python is a dynamically typed programming language that is high-level, interpreted, and general-purpose programming language.

B. Experimental setting

In this part, we modified the experimental setup and assessed and tested the performance of the offered methods in order to find the best performing approach for our dataset. The experiment is carried out by contrasting both ways of training from scratch and transfer learning. In transfer learning, the researcher used Residual Network with 50 layer (Resnet50) and Mobilenet for transfer based learning.

In training from scratch, the researcher used a 224x224 image as an input for training, and the model was built from fifteen hidden layers consisting of six 2D convolution layers interspersed with six 2D max-pooling layers, then a flattening layer, and two dense layers, producing a single array with four items containing the probability of the image being healthy, rust, brown eye spot, or wilt leaf. Similarly, in pre-trained model of ResNet 50 which is the backbone of the network for the computer vision tasks. Mobilenet is a class of CNN that was open-sourced by Google, and therefore, this gives us an excellent starting point for training our classifiers that are insanely small and insanely fast. MobileNets are little, low-latency, low-power models parameterized to meet the asset imperatives of assortment of use cases [20].

To explore and build a deep learning model, we chose a number of epochs equal to 20, a batch size of 32, dropout is equal to 0.5, loss function of Categorical Cross-Entropy, a learning rate of 0.001, and a dataset split of 80% for training and 20% for testing. In addition, the adam optimizer, the Relu activation function, the Softmax classifier, the max pooling, verbose of one, and the 3 channel RGB image were used.

C. Experiment

In this study, three different deep learning experiment conducted using Convolutional Neural Network using the Experimental setup and setting discussed in Section V-A and Section V-B, respectively. The first experiment is conducted using training from scratch/baseline without using any pre-trained model. The result obtained from the experiment shows a 97.92% test accuracy and 5.25% test loss. The training result shows 97.43% training accuracy with 7.19% training loss.

Unlike the first experiment, the two deep learning algorithm takes the advantage of pre-trained transfer based to benefit from sufficient resource for the detection and classification of Coffee leaf disease. Accordingly, the experiment result of Resnet50 shows a 99.86% training accuracy and 2.50% training loss with 99.89% test accuracy and 1.40% test loss. Similarly, Mobilenet experment achieved a 97.01% training accuracy and 7.60% training loss with 98.96% test accuracy and 6.20% test loss. The experiment comparison of baseline, Resnet50 and Mobilenet against the accuracy in training and testing is presented in Figure 3.

As depicted in Figure 3, the result obtained from the three experiment using convolutional neural network shows a promising result despite the small amount of data collected and used for Coffee leaf disease detection and classification, this is specially true for the training from scratch. The results of the leaf disease detection and classification demonstrate that it is feasible to identify and categorize leaf disease at the earliest stages of planting in order to maximize output and implement suitable treatment measures before the condition worsens. Accordingly, the Resnet50 provides an improved result performance over by 2.85% from the MobileNet while

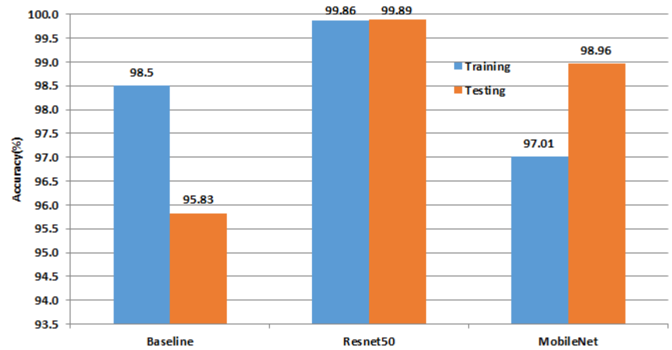

Fig. 3: Experiment result comparison

1.35% from scratch training. This achievement over the training from scratch and MobileNet is a result of pre-trained model used to train the data over the large one though the performance of the MobileNet gets better with higher epoch. By the same token, training from the scratch has resulted a better performance by 1.49% over the MobileNet.

Since the performance of the CNN based on Resnet50 pre-trained performs with a better performance over the two deep learning, Figure 4 presents the performance and loss measure of the testing and validation of the Resnet50.

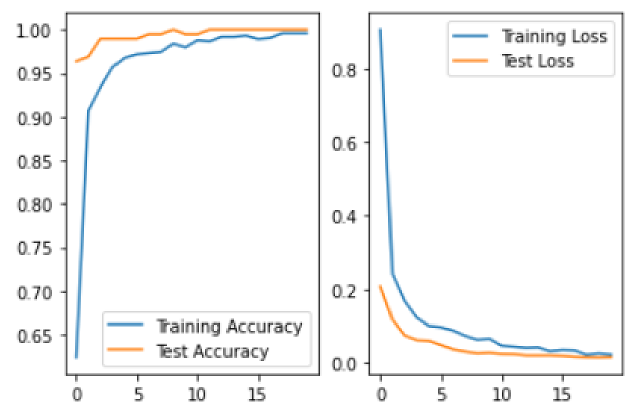

Fig. 4: The training and testing accuracy and loss of best result Resnet50

As depicted in Figure 4, the performance of test accuracy increase at the increasing rate until the twenties iteration and at a decreasing rate after the tenth iteration. Similarly, the loss of training is decreasing at the rate of decreasing rate until the twenties iteration and at rate of increasing rate.

VI. Conclusion and Future Works

On the basis of the symptoms seen on the leaves, a limited amount of study has been done on the automated diagnosis of coffee leaf diseases. Therefore, the goal of this article was to create a model to identify coffee leaf disease at its early stage. This model would be extremely helpful to farmers, extension agents, and agricultural experts, and it will also boost the quality and quantity of coffee crops produced for the export market. As a result, we put forth a method for employing a convolutional neural network to identify and categorize coffee leaf disease in Ethiopian coffee leaves. The Resnet50 model's experiment on transfer learning produced a 99.89% accuracy result, outperforming the approaches that were examined over training from scratch and MobileNet. As a result, the four classes of coffee leaf diseases can be readily identified and classified with high performance utilizing our constructed model employing Resnet50.

In this paper, we only examined three classes of diseased coffee beans and one healthy class. However, these are not the only coffee leaf diseases that exist. Therefore, in order to enhance performance, we advise future researchers to add more classes for Coffee Leaf Disease and expand the size of the dataset. Future studies may also compare other deep learning algorithms with other pre-trained models to obtain even greater categorization accuracy.

REFERENCES

[1] Worldbank. World Development Indicators Data Catalog (2021). https://datacatalog.worldbank.org/search/dataset/0037712, Accessed 10 July 2022

[2] Degaga, Jima. "Review on coffee production and marketing in Ethiopia." J. Mark. Consum. Res 67 (2020): 7-15.

[3] Amamo, Alemayehu Asfaw. "Coffee production and marketing in Ethiopia." Eur J Bus Manag 6, no. 37 (2014): 109-22.

[4] Minten, Bart, Seneshaw Tamru, Tadesse Kuma, and Yaw Nyarko. Structure and performance of Ethiopia s coffee export sector. Vol. 66. Intl Food Policy Res Inst, 2014.

[5] Ayalew, Tewodros. "Characterization of organic coffee production, certification and marketing systems: Ethiopia as a main indicator: a review." Asian Journal of Agricultural Research 8, no. 4 (2014): 170-180.

[6] Fekadu, Gemechu, Maryo Melesse, and Benti Girmaye. "The prevalence and impact of coffee arthropod pests in the gedeo indigenous agro forestry systems, Southern Ethiopia." International Journal of Biodiversity and Conservation 8, no. 10 (2016): 233-243.

[7] Ababa, Addis. "CONTROL OF COFFEE BERRY DISEASE (CBD) IN ETHIOPIA." (2000).

[8] Ongsulee, Pariwat. "Artificial intelligence, machine learning and deep learning." In 2017 15th international conference on ICT and knowledge engineering (ICT&KE), pp. 1-6. IEEE, 2017.

[9] Mengistu, Abrham Debasu, Dagnachew Melesew Alemayehu, and Seffi Gebeyehu Mengistu. "Ethiopian coffee plant diseases recognition based on imaging and machine learning techniques." International Journal of Database Theory and Application 9, no. 4 (2016): 79-88.

[10] Mengistu, Abrham Debasu, Seffi Gebeyehu Mengistu, and Dagnachew Melesew. "An automatic coffee plant diseases identification using hybrid approaches of image processing and decision tree." Indones. J. Electr. Eng. Comput. Sci. 9, no. 3 (2018): 806-811. doi: 10.11591/ijeecs.v9.i3.pp806-811.

[11] Rutherford, Mike A., and Noah Phiri. "Pests and diseases of coffee in Eastern Africa: A technical and advisory manual." Wallingford, UK: CAB International (2006).

[12] Gupta, Jyoti. "The Role of Artificial intelligence in Agriculture Sector." customer think, October 11 (2019).

[13] Anzai, Yuichiro. Pattern recognition and machine learning. Elsevier, December 2, 2012.

[14] Goodfellow Ian, Yoshua Bengio, and Aaron Courville. Deep learning. MIT press, 2016.

[15] Yigezu, Mesay Gemeda, Michael Melese Woldeyohannis, and Atnafu Lambebo Tonja. "Early Ginger Disease Detection Using Deep Learning Approach." In International Conference on Advances of Science and Technology, pp. 480-488. Springer, Cham, 2021.

[16] Kamilaris, Andreas, and Francesc X. Prenafeta-Boldú. "Deep learning in agriculture: A survey." Computers and electronics in agriculture 147 (2018): 70-90.

[17] Türkoğlu, Muammer, and Davut Hanbay. "Plant disease and pest detection using deep learning-based features." Turkish Journal of Electrical Engineering and Computer Sciences 27, no. 3 (2019): 1636-1651, doi: 10.3906/elk-1809-181.

[18] Manso, Giuliano L., Helder Knidel, Renato A. Krohling, and Jose A. Ventura. "A smartphone application to detection and classification of coffee leaf miner and coffee leaf rust." arXiv preprint arXiv:1904.00742 (2019).

[19] Habib, Md Tarek, Anup Majumder, A. Z. M. Jakaria, Morium Akter, Mohammad Shorif Uddin, and Farruk Ahmed. "Machine vision based papaya disease recognition." Journal of King Saud University-Computer and Information Sciences 32, no. 3 (2020): 300-309., doi: 10.1016/j.jksuci.2018.06.006.

[20] He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778. 2016. doi: 10.1109/CVPR.2016.90.

[21] Patterson, Josh, Adam Gibson, Mike Loukides, and T. McGovern. "Major architectures of deep networks." Deep Learning A Practitioner's Approach (2017): 117-164.

[22] Hussain, Mahbub, Jordan J. Bird, and Diego R. Faria. "A study on cnn transfer learning for image classification." In UK Workshop on computational Intelligence, pp. 191-202. Springer, Cham, 2018.

[23] Wang, Kaiyi, Shuifa Zhang, Zhibin Wang, Zhongqiang Liu, and Feng Yang. "Mobile smart device-based vegetable disease and insect pest recognition method."Intelligent Automation & Soft Computing 19, no. 3 (2013): 263-273. doi: 10.1080/10798587.2013.823783.

[24] Gulli, Antonio, Amita Kapoor, and Sujit Pal. Deep learning with TensorFlow 2 and Keras: regression, ConvNets, GANs, RNNs, NLP, and more with TensorFlow 2 and the Keras API. Packt Publishing Ltd, 2019.

[25] Hodnett, Mark, and Joshua F. Wiley. R Deep Learning Essentials: A step-by-step guide to building deep learning models using TensorFlow, Keras, and MXNet. Packt Publishing Ltd, 2018.