Plant Disease Detection using AI based VGG-16 Model

Anwar Abdullah Alatawi[1], Shahd Maadi Alomani[2], Najd Ibrahim Alhawiti[3], Muhammad Ayaz[4]
Industrial Innovation and Robotic Center (IIRC), University of Tabuk, Tabuk 47731, Saudi Arabia[1, 2 3]
Faculty of Computers and Information Technology, University of Tabuk, Tabuk, Saudi Arabia[1, 2, 3]
Sensor Networks and Cellular Systems (SNCS), Research Center, University of Tabuk, Tabuk, 47431, Saudi Arabia[4]

Abstract*—Agriculture and modern farming is one of the fields where IoT and automation can have a great impact. Maintaining healthy plants and monitoring their environment in order to identify or detect diseases is essential in order to maintain a maximum crop yield. The implementation of current high rocketing technologies including artificial intelligence (AI), machine learning, and deep learning has proved to be extremely important in modern agriculture as a method of advanced image analysis domain. Artificial intelligence adds time efficiency and the possibility of identifying plant diseases, in addition to monitoring and controlling the environmental conditions in farms. Several studies showed that machine learning and deep learning technologies can detect plant diseases upon analyzing plant leaves with great accuracy and sensitivity. In this study, considering the worth of machine learning for disease detection, we present a convolutional neural network VGG-16 model to detect plant diseases, to allow farmers to make timely actions with respect to treatment without further delay. To carry this out, 19 different classes of plants diseases were chosen, where 15,915 plant leaf images (both diseased and healthy leaves) were acquired from the Plant Village dataset for training and testing. Based on the experimental results, the proposed model is able to achieve an accuracy of about 95.2% with the testing loss being only 0.4418. The proposed model provides a clear direction toward a deep learning-based plant disease detection to apply on a large scale in future.

***Keywords*—Machine learning; VGG-16; disease detection; convolutional networks; Plant Village; modern farming**

I. Introduction

Agriculture has always been a basic human need ever since humans' existence as plants were a primary source of food. Even nowadays, agriculture is still considered an essential food resource and is the center of several aspects in humans' lives [1]. As a matter of fact, agriculture serves as the pillar of economy in many countries regardless of their developmental stages. The various domains that show the importance of agriculture include the fact that agriculture is a main source of livelihood where approximately 70% of the population depends on plants and their cultivation for livelihood. This great percentage reflects on agriculture being the most important resource that can actually stand a chance in the face of the rapidly increasing population [2].

One of the most critical challenges that face agriculture and affects it trade is plant diseases and how to timely detect them and deal with them to improve the health of crops. By definition, plant disease in a type of natural problems that occur in plants affecting their overall growth and might lead to plant death in extreme cases. Plant diseases can occur throughout the different stages of plant development including seed development, seedling, and seedling growth [3]. When diseased, plants go through different mechanical, morphological, and biochemical changes [4, 5]. Truthfully, there are two main types of plant stress classified as biotic stress represented by living creatures that interact with plants in a way that negatively affects their growth [6] such as bacteria, viruses, or fungi [7], or abiotic stress represented by the collection of non-living factors or the environmental factors. Fig. 1 illustrates the collection of factors that contribute to plant diseases.

Typically, the commonly used approach for farmers, scientists, and even breeders, to detect and identify plant disease was the manual inspection of plants. Of course, this process requires expertise and knowledge for the proper detection. With time, manual inspection became tiresome and time consuming and not as quite efficient especially when large amounts of plants needed to be inspected. Another factor that proves the inefficiency of manual inspection is the similar conditions that might be caused by different pathogens that might look alike in their effect on the plant [6].

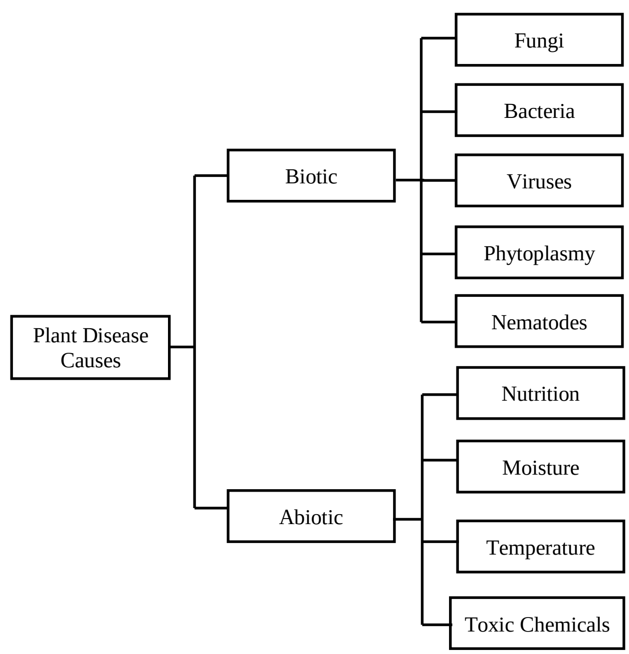

Fig. 1. Plant Disease Causes Detailed as Biotic and Abiotic Factors.

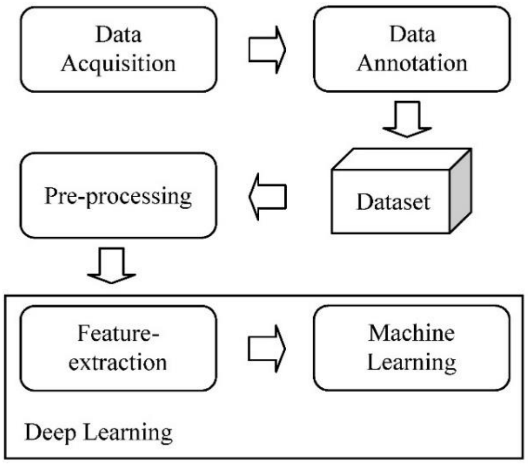

Fig. 2. Steps in the Implementation of Machine Learning Models in Plant Disease Detection.

For this reason, humans needed a better suited technique that can deliver effective plant detection results in less time.

Technology and the rise of both deep and machine learning came as a benefit in various fields, most importantly medicine. Nonetheless, advanced technological approaches can also be implemented for the purpose of detecting diseases in plants. Thus, machine learning and deep learning approaches can be considered non-destructive disease detection methods since they are based on image-processing techniques, as opposed to destructive serology or molecular methods [8]. However, for these techniques to work, the disease must have already caused a visible change in the plant, particularly in the leaf area or stem [9].

Artificial intelligence, computer vision and machine learning utilizations can greatly enhance the process of plant disease detection, and is already applied in multiple research papers [10]. Such technologies are capable of not only detecting the presence of a disease, but it is also possible to determine its severity, and to classify exactly which kind of disease is present in a given plant sample [11].

Based on their depth, the plant disease detection methods can be divided into shallow architectures and deep architectures. Basic machine learning methods like Random Forest (RF), Support Vector Machine (SVM), Naïve Bayes (NB), and K-Nearest Neighbor (KNN) rely on specific design intended for features such that good features and patterns must be recognized. These specific features include hue saturation value (HSV), Histogram of Oriented gradient (HOG), linear binary pattern (LBP), and red-green-blue RGB color features [12]. In machine learning, according to the complexity of the classifier, the more data is required for its training in order to achieve satisfactory results. The Fig. 2 illustrates the general flow of the implementation of machine learning techniques in detecting plant diseases. Initially, the data is acquired and labeled according to disease classes or healthy class. A specific dataset is then created for the model, where the input images can be pre-processed before feature extraction can take place. Machine learning algorithms are capable of recognizing the changes in features upon comparison, and thus determining the output as diseased or healthy [13].

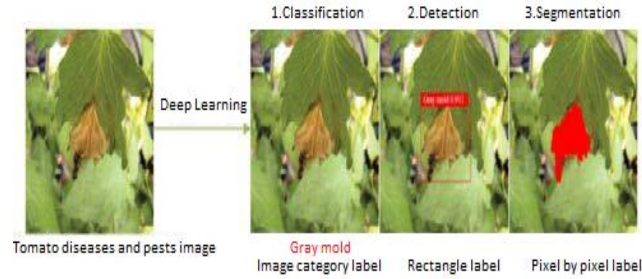

Fig. 3. Plant Disease Detection Phases through Deep Learning.

On the other hand, deep architectures like CNN (Convolutional Neural Networks) have also been heavily used in studies that are concerned with plant disease detection. These deep architectures differ from the shallow ones by not requiring hand-designed features since deep learning algorithms are able to learn the features themselves. Thus, deep learning approaches undergo three basic stages in detecting plant diseases (see Fig. 3): classification, detection, and segmentation [14].

After SVM machine learning approach was the most commonly used one for so long, approximately after the year 2015 CNN replaced SVM as the most popular ML technique for detection of diseases. CNN is considered state-of-the-art model that has been used in plant disease detection nowadays, especially since this task requires dealing with image data applications [13].

CNN can execute tasks such as classification of images, segmentation, object detection, and recognition. In their structure, CNNs are made up of artificial neural networks where tens and even hundreds of layers are used [15, 16]. CNNs is made up of an input layer, several convolutional layers, along with pooling layers in between them, and finally full connection layer in addition to activation function layers, and output layer. There exist several forms of CNN architectures like VGG-16, Inception-V3, ResNet50, and AlexNet. However, CNN architectures need large data numbers which is often considered as a challenge [17-19].

Since agriculture is essential there's a need to provide methods that enhance the agricultural methods in terms of planting, monitoring crop environment, detecting plant disease, and even harvesting. These important details led to significant research to be conducted and several papers to be published with the purpose of providing solutions to these agricultural challenges. This study proposes a model based on CNN, namely VGG-16 architecture in order to detect and classify a total of 19 plant conditions (several crop types and diseases) with the best accuracy possible.

Our contributions in this study can be summed up as follows:

1) Updating a large dataset based on Plant Village. The dataset comprises 15 thousand images of plant leaves which are captured on the field, which means that they are photographed within their surroundings, and thus it is efficient in terms of not needing to isolate the plant for disease detection.

2) Implementing the proposed VGG-16 model which is an effective convolutional neural network architecture, and it achieves a great accuracy. Our proposed model is capable of scanning through thousands of leave images in order to identify if a plant has a certain type of disease based on its leaf image. The proposed model achieves a great accuracy of detection among 19 different disease classes in a short period of time, and it doesn't require a long time in training either.

The arrangement of the current paper is as follows: section two is a description of some of the published similar studies about ML and DL in plant disease detection. Section three describes the proposed methodology including the dataset and the proposed model. Results are provided and compared theoretically with some of existing techniques in section four, while section five concludes the article by sharing the future research intentions.

II. Related Work

A large number of studies have been performed and published about the detection of diseases in plants, especially since disease detection and classification can help in treating the diseased plant. The more technology emerges, the more it will be implemented in the agricultural field, one of the reasons being the continuous enhancement of already existing machine learning and deep learning methods that identify and classify plant diseases. This section describes five studies conducted in this regard.

The study by Ashwin et al. [20] discussed the development of a machine learning approach for the detection of diseases in Soybean plant in Mazandaran province in Iran. The study aimed to illustrate the importance of incorporating physiological features as well as the morphological features in realizing the diseases presence in a plant. The dataset used by the authors contains two randomly chosen subsets one for the healthy soybean plants (negative) and one for the diseased soybean plants (positive), which makes up to 2,500 images total. These images were collected from 10 different regions in the Mazandaran province. Several features were selected based on one-way ANOVA F1-score which include stem length, root length, number of pods per plant, empty pods per plants and seed oil content. Six different machine learning techniques with ten-fold cross validation and internal cross validation, which are the binary Logistic Regression, Multilayer Perceptron with Adam optimization, Random Forest, Gradient Tree Boosting (GBT), and Support Vector Machine. These ML techniques are evaluated based on confusion matrix, precision, F1-score, AUC, etc. Out of the six techniques, GBT achieved the best results of 96.79% accuracy, 96.68% F1-score, and 97% sensitivity and specificity depending on 21 features. The same technique achieved similar results (96.13%) depending on 12 morphological features.

Xian et al. [21] relied on a supervised machine learning termed Extreme Learning Machine "ELM" to determine the presence or absence of tomato diseases. The developed system was based on analyzing tomato leaves; the whole dataset was acquired from Kaggle, specifically the Plant Village dataset. The dataset comprises 10 classes, which makes a total of 1,000 images. The model is a feed forward neural network made up of several hidden nodes with weights that connect and the complete neural network has no iterations. Image pre-processing is done on the images in the dataset including image resizing, segmentation, color space conversion, and HSV. A scatter plot of HSV is done on the resized image of tomato late blight, where a mask can be performed on the segmented image. 7,000 images of tomato leaves were selected for training (70%) whereas 3,000 were selected for testing (30%). The features HSV histogram, Haralick textures, and Colour Moments were selected and the labels were transformed into numerical values via the One Hot Encoding method. In the ELM model, using 1024 neurons and Sigmoid activation function yielded the best disease detection accuracy of 84.94%. When compared to Decision Tree model, ELM achieves better overall accuracies, 77.8% vs. 84.94%, respectively, in all of the 10 classes. On the other hand, SVM is slightly better in terms of accuracy (91.43%) when compared with this ELM model.

In their paper discussing plant disease detection, Bedi et al. [22] proposed a detection model based on convolutional auto encoder "CAE" and CNN as two parts of a hybrid system. The system was implemented on leaf images of peach plants specifically, but it can also be used to spot diseases in other plants. The dataset consists of two different classes healthy peach leaves (2160) and diseased leaves with bacterial spots (2297) which sums up 4457 images in total. 70% of the images in the dataset were used for training the system whereas the remaining 30% were kept for testing the detection performance. After gathering the data into the dataset, the usual pre-processing procedures are performed on the images. The next step is the training of the CAE model and getting compressed domain representations of leaf images from which, a CNN model will be trained afterwards. Upon testing, new leaf images will be used as input and their respective compressed representations will be compared for the CNN to determine if the leaf is healthy or not based on whether a defect is found. The CAE network was made up of 14 layers while the hybrid system was made up of 17 total layers through concatenating layers of the CAE with the CNN layers. Adam optimizer and binary cross entropy were used on the proposed system, where parameters such as NRMSE loss and accuracy measures were used for evaluation. As a result, the testing NRMSE loss was 0.0607, the testing accuracy reached 98.38%, and the F1-score was 98.36%.

Jeyalakshmi et al. [23] developed an approach based on machine learning for classification of diseases of potato and grape crops depending on their leaf images. The dataset was acquired from Pant Village dataset, consisting of 1000 healthy leaf images, as well as 2000 images of diseased potato leaves, and 3270 of diseased grape leaves. In the potato subset, there exist three different classes, while there are four classes in the grape leaves subset. From each RGB leaf images, the background was removed through using "enhanced GrabCut algorithm". Several features were selected from the images such as the intensities of red, green and blue, weighted mean and weighted standard deviation (belonging to histogram features), and texture features including contrast, entropy, etc. After that, the features were normalized and fed into several classifiers, namely KNN, Naïve Bayes, and SVM. It was observed that the number of features (ranging between 7 and

13) affects the accuracy of detection such that the higher the number of features, the better the accuracy. For instance, the highest accuracies were achieved by KNN at 94% considering 13 features, and 96.8% by SVM similarly in potato crops. On the other hand, in grape crops, SVM was superior achieving 96.02% accuracy with respect to 13 features.

Lamba et al. [24] published a paper discussing the implementation of several machine learning algorithms as well as deep learning techniques to properly detect diseases in crops. The images comprising the dataset are from Kaggle and rice dataset. In fact, four different datasets are created which are: the rice dataset containing 120 images, the pepper dataset containing 1,994 images, potato dataset containing 2,152 images, and tomato dataset containing 16,072 images. As usual, the images are pre-processed accordingly, and then auto-color correlogram filter is applied as an additional pre-processing step. After that, classification took place through machine learning techniques, or through deep learning methods with various activation functions to assess the overall performances. With respect to machine learning, fifteen different algorithms were tested including bayes net, random forest, and iterative optimized classifier to name a few. On the other hand, in the deep learning method, different activation functions were used including SoftMax, Softsign, ReLu, etc. The evaluation of performance was done relying on confusion matrix, specificity, F1-score, and accuracy. As a matter of fact, each of the models (ML and DL) was implemented on each one of the four datasets. In Pepper dataset, random forest and DL-Softsign achieved the best results as ML and DL techniques respectively. In rice dataset, random forest and DL-Softmax achieved the best results. SVM and DL-Softsign were responsible for the better results in the tomato dataset, and SVM and DL-Hard-tanh outperformed the rest in the potato dataset. In conclusion, from the large set of experiments, the authors concluded that in binary classification, DL with Softsign is the best, whereas Softmax is better suited for multi-class classifications. Table I compares between theses similar systems.

From the analysis of these previous studies, a group of limitations can be seen, as most of the studies focus on detecting the diseases in one type of crops. On the other hand, logically, most farms are interested in growing more than one crop, especially if the farmer is using these crops for the local market, whereas in some cases a field might be planted with one specific type of crop which is grown for a huge demand and can be used for exportation and national trade. However, the aim is to create a model that can be used by the various farmers, whether they have a small farm growing multiple crops, or they had large farms with more than one type of crop. For this reason, we chose to take into consideration a group of plants to be analyzed and to train our model to detect their diseases respectively. Furthermore, the second aim is to create a reliable model which achieves very accurate results with minimal loss and minimal false detection (both false positive and false negative), for this reason the majority of the studies focus on CNN models for the disease detection class. Similarly, our chosen CNN architecture in VGG-16 still stands as one of the best computer vision models. VGG provides better results while having smaller convolutional layers since it doesn't rely on a large number of hyper-parameters, yet it has several 3x3 filters with stride 1, and max layers and padding with stride 2 that are distributed throughout the architecture. In addition, the VGG16 model not only perform image recognition and detection, but it is also capable of localization, meaning that in our case and objectives, the model can be improved to detect the exact location of the classified disease on the plant leaf.

TABLE I. COMPARISON BETWEEN SIMILAR SYSTEMS

Study	Year of Publication	Crop Type	Dataset	Technique	Performance Results
A Machine Learning Approach to Prediction of Soybean Disease" [20]	2021	Soybean	Real samples from Mazandaran province	LR-L1, LR-L2, MLP, RF, GBT and SVM	Accuracy: 96.7% F1-score: 96.5%
Plant Diseases Classification using Machine Learning [21]	2021	Tomato	Plant Village	Extreme Learning Machine (ELM)	Accuracy: 84.94% F1-score: -
Plant diseases detection using hybrid model based on convolutional autoencoder and convolutional neural network [22]	2021	Peach	Plant Village	CAE and CNN	Accuracy: 98.38% F1-score: 98.36%
An effective approach to feature extraction for classification of plant diseases using machine learning [23]	2020	Potato and grape	Plant Village	Naïve bayes, K nearest neighbor and support vector machine classifier	Accuracy: 96% F1-score: 95%
"Classification of plant diseases using machine and deep learning [24]	2021	Rice, pepper, potato and tomato	Plant Village	Auto-color correlogram and deep learning	Accuracy: 99.4% F1-score: 95%

III. Implementation of the Model

In order to maintain constant care of plants in any farm, especially a vertical farm, you need to constantly keep a close eye on the crops and their leaves as well as their stems and all the surrounding conditions. Of course, detecting plant diseases from looking into plant leaves manually takes a lot of time and effort from the farmer, which is why automation could be a game changer in the field of plant disease detection. Computational techniques can be applied such that the images of the plants are being taken and analyzed or screened for diseases in a time efficient manner, without facing human effort or human error challenges.

In this project, we implement several deep learning technologies in order to classify the diseases in crops. Among machine learning techniques, deep learning is an interesting area since it can easily recognize patterns and perform complicated procedures, which makes it suitable for the disease classification task. In deep learning, deep neural networks are created, among which is the CNN, short for Convolutional Neural Networks, that can easily analyze images upon training. In our project, VGG-16 was selected to be the CNN classifier of different plant diseases.

A. Dataset

The chosen dataset for our study is the Plant Village dataset which contains numerous images of plant diseases totaling for 15,915 images. From these images, the dataset is divided into nineteen different classes, each class resembles a disease, and these classes do not overlap, meaning that a single image only belongs to one class and cannot simultaneously belong to two or more classes.

The nineteen classes include tomato, grape, apple, tomato, and corn diseases as well as healthy classes. The Fig. 4 and Fig. 6 demonstrate in detail the different classes and to which crop they belong.

The number of images per class varies between the classes, as shown in the Fig. 5. After the data had been selected, they are collected in a csv file, where each image is labeled with a path that indicates the health conditions of the crop within the image.

Fig. 4. Crop Disease Classes in Plant Village Dataset-1.

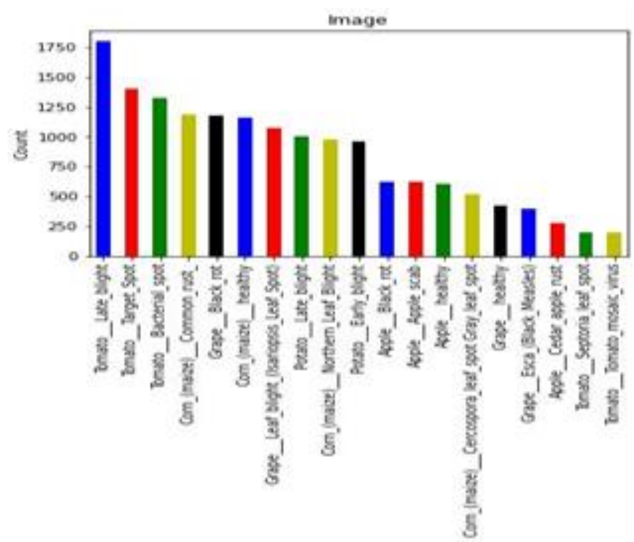

Fig. 5. Distribution of Images in Plant Village Dataset into Nineteen different Classes.

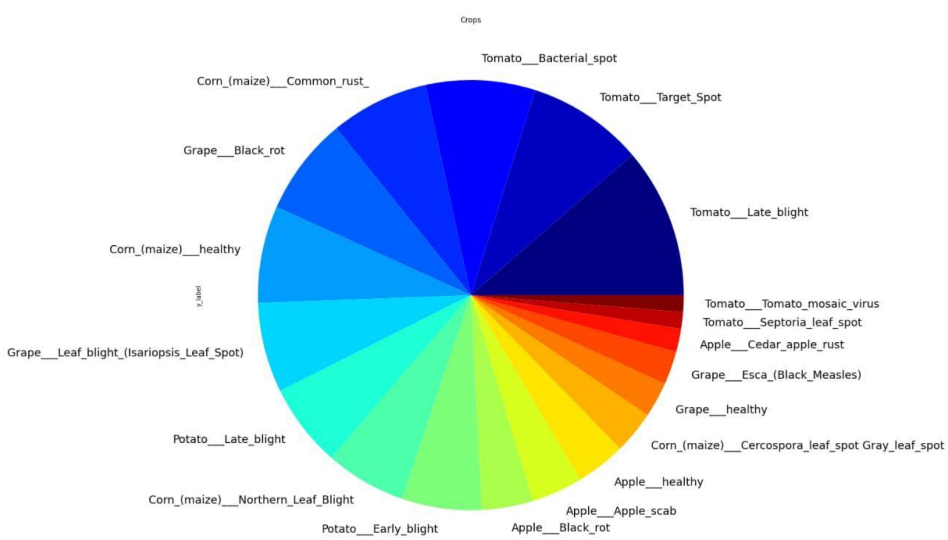

Fig. 6. Crop Disease Classes in Plant Village Dataset-2.

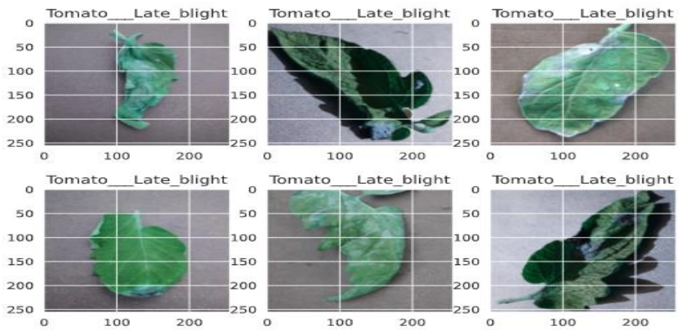

Fig. 7. Leaves with Diseases.

The Fig. 7 illustrates some images of the tomato late blight class which refers to a disease in the tomato crop.

In order for the data to be convenient for our chosen model, all the text value had to be converted into numeric values that are suitable for the model. Moreover, the majority of dataset's images (80%) were utilized in the training procedure, and the rest 20% were kept for testing.

B. Proposed Model

VGG-16 is one of the most commonly used CNN architecture, especially since it works well with the ImageNet, which is large project utilized for visual object recognition procedures and it is considered one of the best models to be proposed so far due to its extreme usefulness in the image classification's field in the deep learning domain. Initially, this model was created by Karen Simonyan and Andrew Zisserman in 2014, where they developed in during their work in Oxford University titled "Very Deep Convolutional Networks for Large-Scale Image Recognition". In fact, "V" means Visual," G" Geometry while "G" stands for research group who contributed in the development of this Convolutional Neural Network model, whereas the number 16 refers to the neural network layer's number. ImageNet is so large that it contains more than fourteen million images distributed over thousand classes. This architecture is one of the top 5 models in terms of performance achievement in the ImageNet dataset, where its accuracy reached 92.7%. As an approach for the AlexNet enhancement, this architecture was submitted to ImageNet.

Large Scale Visual Recognition Challenge (ILSVRC), where this model has replaced the large kernel-sized filters of numbers 11 and 5 in both first and second convolutional layer, respectively by a multiple three × three kernel-sized filters consecutively. Moreover, the training of this model was trained by utilizing NVIDIA Titan Black GPUs for several weeks.

C. VGG-16 Architecture and Training Procedure

The training Procedure is made up of three consecutive steps as shown in Fig. 8:

- Preparing the images.
- Classifying the photos.
- Printing the decision.

Image Processing: The input of the convents is 224 × 224 RGB image with a fixed size where the value of each pixel is subtracted from the RGB mean value of the training image.

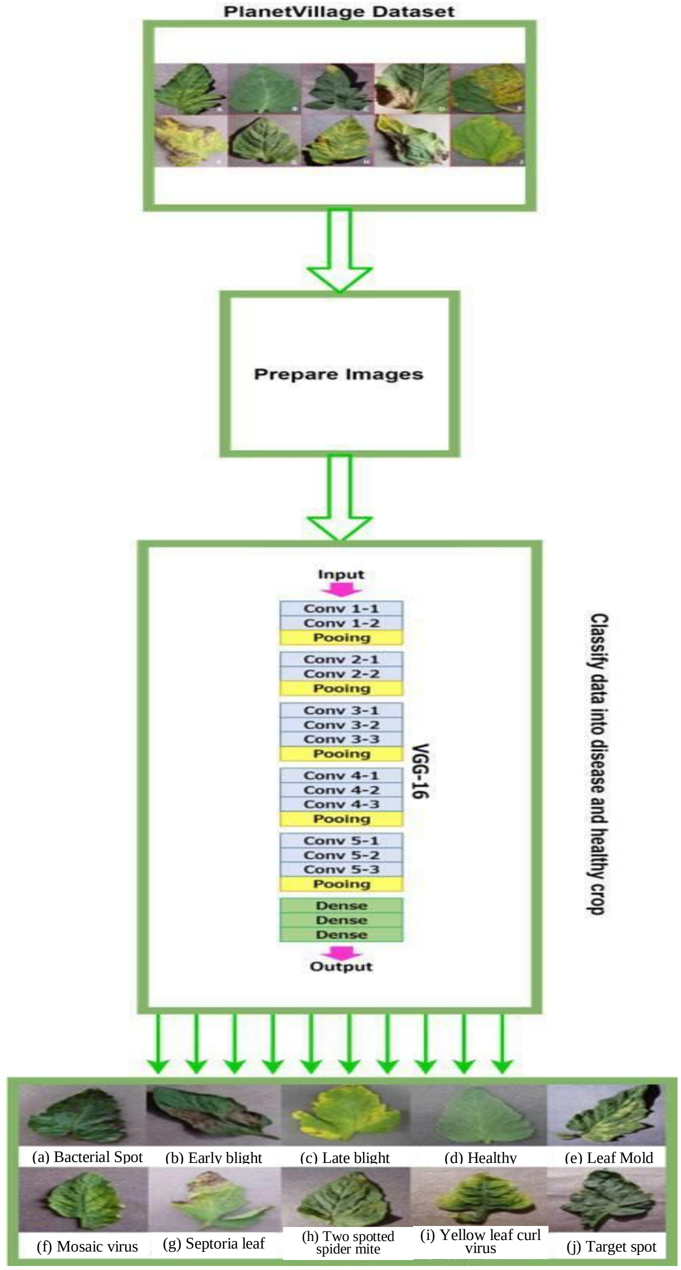

Fig. 8. Training Steps.

Classifying the data: The proposed model is made up of thirteen convolution layers, two batch normalization layers, along with five max-pooling layers and three full connection layers.

The processed image passes through several convolutional layers that contains filters that are characterized by a receptive field of size 3 × 3 for capturing the notions of left and right, up and down along with the center. Despite its small size of the mentioned filter, this filter is accompanied by the same efficiency as that of a receptive field of size 7 × 7 due to its deep characteristics such as including more nonlinearities and lesser parameters. In addition to that, a 1x1 convolution filter was used as an input channel's linear transformation in a certain configuration. On the other hand, both spatial padding and the convolution stride are fixed to 1 pixel for 3 × 3 convolutional layers, in which the spatial resolution's preservation becomes easy to occur. Also, spatial pooling is easier in case of a five max-pooling layers' addition after some of the convolutional layers and the Max-pooling layer takes place over a 2×2-pixel window, with stride 2.

In addition to that, a total of three varying FC (Fully Connected) layers in depths are fixed behind a group of convolutional layers, where the first two FC layers is made up of 4096 channels per FC layer, and the third performs 1000-way ILSVRC classification and is made up of 1000 channels for each class. Finally, the final layer is the soft-max layer, it's important to say the Fully Connected Layer's configuration does not vary among different networks.

The architecture of the VGG-16 model is portrayed in details in the Fig. 9.

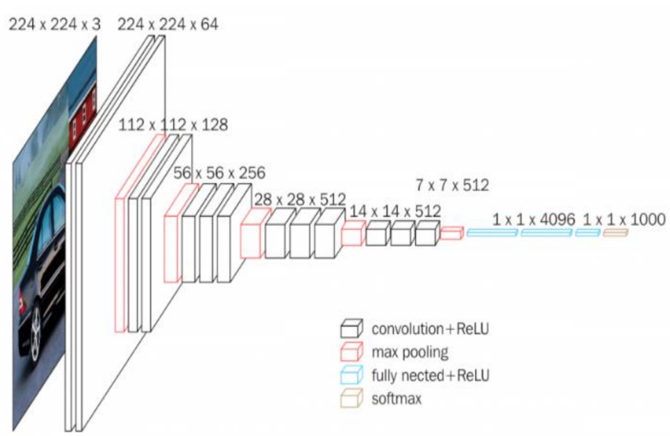

Fig. 9. VGG-16 Detailed Architecture showing the Various Layer and their Positioning.

D. Activation Function Used

Two activation Functions were used for our model training where the Softmax activation and the ReLU function.

The ReLU function was used at the fully connected layers, where the ReLU or "Rectified Linear Unit" is one of the popular activation functions used in Neural Networks and specifically in Convolutional Neural Networks and is defined as in (1):

$$y = max\,(0, x) \tag{1}$$

Moreover, the Softmax activation function is used for the output layers and this activation function is a type of logistic regression that is able of normalizing the inputted vector to a new vector where its probability distribution is equal to 1 and it is defined as in (2):

$$\sigma(\vec{a})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{2}$$

E. Loss Functions used

In the machine learning domain, the cost functions tend to optimize the model in the training procedure and the aim of the training procedure is to minimize the loss function and the model obtained is better as much as we tend to minimize this loss function. Therefore, one of the most important loss functions is the Cross Entropy Loss Function where it is used for Classification model's optimization and the complete understanding of this loss function depends on the Softmax activation function understanding. Moreover, in our project, the Sparse Categorical Cross Entropy is used for training our model where it has the same loss function as that of the cross entropy as in (3):

$$Loss = -\sum_{i=1}^{output\ size} y_i log\widehat{y_i} \tag{3}$$

However, the truth labelling procedure is what differs between the two loss functions, where in the case of a one hot encoded true labels ([1,0,0], [0,1,0] and [0,0,1] in 3 classification problem) the categorical cross entropy is used, while the cross entropy is used in the case of an integer truth labels coding ([1],[2],[3]).

F. Accuracy Calculation

The accuracy of the model is calculated as in (4):

$$Accuracy = \frac{True\ Positive}{True\ Positive + True\ Negative} \times 100 \tag{4}$$

IV. Results

The performance of our proposed model was assessed in terms of Loss Function and Accuracy, which was measured during the training/validation step as well as during the testing step. The Fig. 10 shows the performance during the training phase.

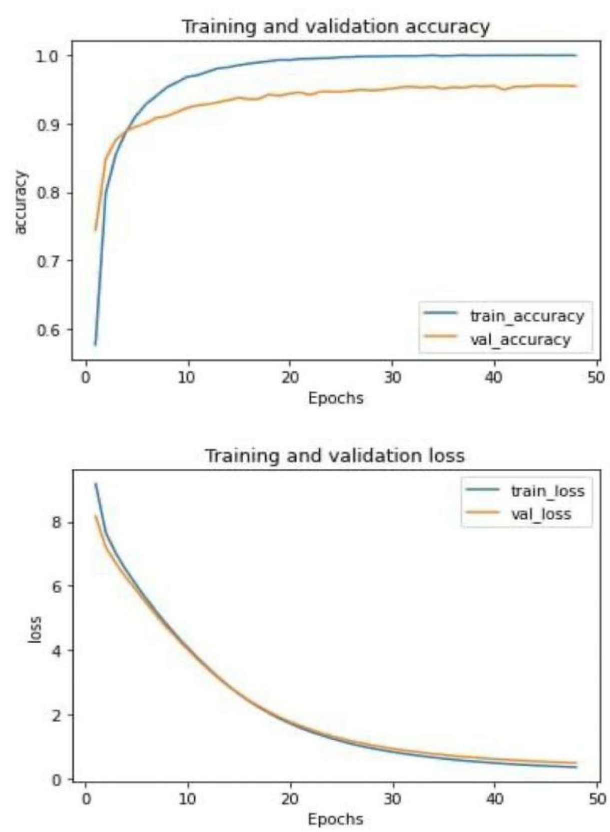

Fig. 10. The Performance of Proposed Model in Terms of Training and Validation Loss and Accuracy.

In the testing phase, the proposed VGG-16 model achieves the 93.5% accuracy, taking into consideration that the model performs classification on 19 different classes. The performance of our model is excellent for detecting diseases automatically from plant images. On the test set, which is excellent accuracy for classifying 19 items of plant images where the Test loss has reached 0.44 while the Test accuracy has reached 0.95. Moreover, the test accuracy was also computed for each of the 19 cases as well as the estimated distribution for the prediction and probability is shown in the Fig. 11 and Fig. 12.

A. Discussion

In the light of these results, and taking into consideration all of the parameters such as the big dataset and the variety of used crops, we can compare our results with those of similar studies that also used VGG networks for plant disease detection. For instance, the study by Iftikhar Ahmad implemented the VGG-16 model among others for the detection of diseases that infect tomato leaves, where the VGG16 network achieved a 76.2% accuracy by using feature extraction on augmented field dataset of 15 thousand images, and 84% accuracy for VGG16 when using parameter tuning [25]. Another study also used VGG and achieved an accuracy of 95.32% when using the Plant Village dataset of 4062 grape leaf images [26]. Narayani Patil and his colleagues also used VGG-16 networks for detection of plant diseases, and it achieved 97.53 % accuracy [27]. Finally, a pretrained VGG-16 model achieved an accuracy of 94.3% compared to 96.5% for the fine-tuned VGG-16 while using the Plant Village dataset but only for tomato leaves [28]. Taking into consideration that in our model we used a large dataset and multiple crops, it can be concluded that our VGG-16 model performed better in terms of accuracy than these studies.

Increasing agricultural movement is becoming more and more important by the day due to the rapid increase in population which increases the food demand, and ultimately means the need for more crops. Maintaining crop health is a very important field, since growing the plants in their ideal conditions leads to better yield which comes with greater benefits. New technologies are invested in the agricultural domain to take care of the wellbeing of plants.

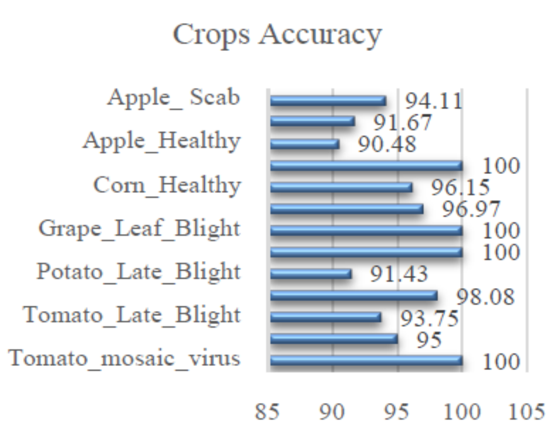

Fig. 11. Crops Accuracy.

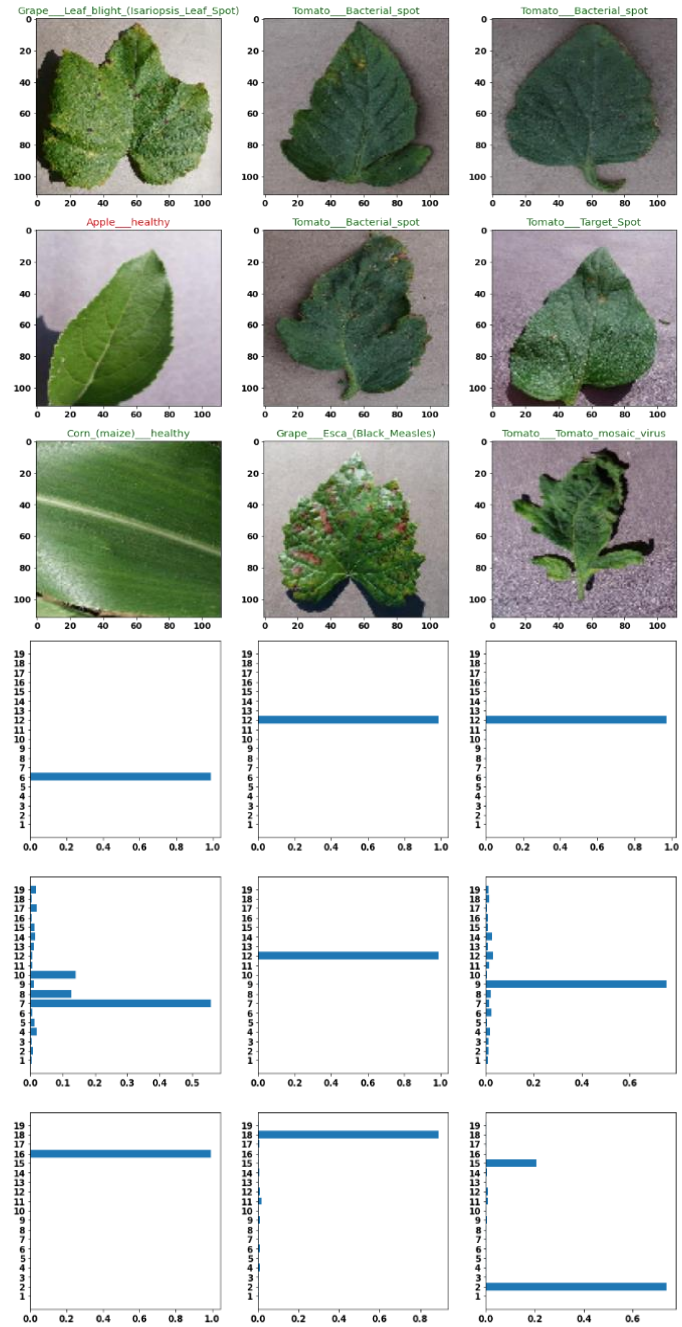

Fig. 12. Probability Estimated Distribution.

One of the domains where technology can have a large impact is the detection of plant diseases. Machine learning and deep learning are often implemented in systems for this specific purpose especially since ML techniques have an important image processing capability.

V. Conclusion

In this study, we proposed a system for the detection of plant diseases through analyzing leaf images of plants to determine not only if they are healthy or diseased, but rather to classify which kind of disease exists in each crop type. Our model is based on a VGG-16 architecture that classifies 19 classes of plant diseases, according to the data acquired from the Plant Village dataset. The model was able to achieve a 95.2% accuracy with a loss of 0.4418.

Despite achieving a high accuracy with a low loss, our model faces some limitations since the input images must have certain illumination conditions and a complex background behind them due to the fact that they are collected from actual leaves from planted plants. These conditions pose as a challenge for any model used for plant disease detection and they can be considered as areas for improvement when designing or trying to enhance the existing model. Furthermore, in the future studies, our efforts will be focused on achieving more precise disease detection, particularly through training our machine learning model to identify the exact location of the disease on each leaf, especially if more than one disease is detected in one plant leaf. In addition to that, the plant disease dataset can be further increased to take into consideration even more plant diseases and to incorporate additional crop types. Moreover, we can consider some advanced methods to increase the accuracy of processing of leaf images by applying technologies like Faster region-based convolutional neural network (Faster R-CNN), which is a unified network designed for object recognition. Faster R-CNN creates a network that proposes a region for the detection which is then fed to the developed model for training, and after that according to the features, the optimal detection region is selected for classification purposes. Another method that can be implemented is the You Only Look Once YOLO technology which presents a very fast detection in real time with approximately 45 frames for second. Another technique similar to YOLO is the Single Shot Detector (SSD) which provides a fast detection of objects from a single frame. SSD achieves its high accuracy by producing detection at different scales and separates between the predictions by aspect ratio.

REFERENCES

[1] Ramsanthosh, A. S. Laxmi, S. A. Chepuri, V. Santosh, V. Kothareddy, and S. Chopra, "Review and further prospects of plant disease detection using machine learning," International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 7, pp. 105-115, 2021.

[2] B. V. Gokulnath and G. Usha Devi, "A survey on plant disease prediction using machine learning and deep learning techniques," Inteligencia Artificial, vol. 23, pp. 136-154, 2020.

[3] J. Liu and X. Wang, "Plant diseases and pests detection based on deep learning: A review," Plant Methods, vol. 17, p. 22, 2021.

[4] T. Su, W. Li, P. Wang, and C. Ma, "Dynamics of peroxisome homeostasis and its role in stress response and signaling in plants," Frontiers in Plant Science, vol. 10, p. 705, 2019.

[5] Ayaz, Muhammad, et al. "Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk." IEEE access 7 (2019): 129551-129583.

[6] S. Roy, R. Ray, S. R. Dash, and M. K. Giri, "Plant disease detection using machine learning tools with an overview on dimensionality reduction," in Data Analytics in Bioinformatics, R. Satpathy, T. Choudhury, S. Satpathy, S. N. Mohanty, and X. Zhang, Eds. Beverly, MA: Scrivener Publishing LLC, 2021, pp. 109-144.

[7] D. B. Collinge, H. J. L. Jørgensen, M. A. C. Latz, A. Manzotti, F. Ntana, E. C. Rojas, et al., "Searching for novel fungal biological control agents for plant disease control among endophytes," in Endophytes for a Growing World, B. R. Murphy, F. M. Doohan, M. J. Saunders, and T. R. Hodkinson, Eds. Cambridge: Cambridge University Press, 2019, pp. 25-51.

[8] A. M. Abdu, M. M. Mokji, and U. U. Sheikh, "Machine learning for plant disease detection: an investigative comparison between support vector machine and deep learning," IAES International Journal of Artificial Intelligence, vol. 9, pp. 670-683, 2020.

[9] L. Mohamed, E. Ahmed, and A. Mohamed, "Deep learning in plant diseases detection for agricultural crops: A survey," International Journal of Service Science, Management, Engineering, and Technology, vol. 11, pp. 41-58, 2020.

[10] R. D. S. Chowdary, V. Yogeshwari, V. Varsha, M. R. B. Priya, and S. Chinnappan, "Plant disease detection using image processing and machine learning algorithm," Journal of Xidian University, vol. 14, pp. 79-91, 2020.

[11] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70-90, 2018.

[12] B. S. Kusumo, A. Heryana, O. Mahendra, and H. F. Pardede, "Machine learning-based for automatic detection of corn-plant diseases using image processing," in 2018 International Conference on Computer, Control, Informatics and its Applications (IC3INA), Tangerang, Indonesia, 2018, pp. 93-97.

[13] H. F. Pardede, E. Suryawati, D. Krisnandi, R. S. Yuwana, and V. Zilvan, "Machine learning based plant diseases detection: A review," in 2020 International Conference on Radar, Antenna, Microwave, Electronics, and Telecommunications (ICRAMET), Tangerang, Indonesia, 2020, pp. 212-217.

[14] M. Turkoglu, D. Hanbay, and A. Sengur, "Multi-model LSTM-based convolutional neural networks for detection of apple diseases and pests," Journal of Ambient Intelligence and Humanized Computing, 2019.

[15] M. Syarief and W. Setiawan, "Convolutional neural network for maize leaf disease image classification," Telkomnika (Telecommunication, Computing, Electronics and Control), vol. 18, pp. 1376-1381, 2020.

[16] Sharif, Z., Jung, L. T., Razzak, I., & Alazab, M. (2021). Adaptive and Priority-based Resource Allocation for Efficient Resources Utilization in Mobile Edge Computing. IEEE Internet of Things Journal.

[17] A. Abdalla, H. Cen, L. Wan, R. Rashid, H. Weng, W. Zhou, et al., "Fine-tuning convolutional neural network with transfer learning for semantic segmentation of ground-level oilseed rape images in a field with high weed pressure," Computers and Electronics in Agriculture, vol. 167, p. 105091, 2019.

[18] Uddin, M., et al. "Cloud-connected flying edge computing for smart agriculture." Peer-to-Peer Networking and Applications 14.6 (2021): 3405-3415.

[19] Sharif, Z., Jung, L. T., & Ayaz, M. (2022, January). Priority-based Resource Allocation Scheme for Mobile Edge Computing. In 2022 2nd International Conference on Computing and Information Technology (ICCIT) (pp. 138-143). IEEE.

[20] N. Ashwin, U. K. Adusumilli, N. Kemparaju, and L. Kurra, "A machine learning approach to prediction of soybean disease," International Journal of Scientific Research in Science, Engineering and Technology, vol. 9, pp. 78-88, 2021.

[21] T. S. Xian and R. Ngadiran, "Plant diseases classification using machine learning," Journal of Physics: Conference Series, vol. 1962, p. 012024, 2021.

[22] P. Bedi and P. Gole, "Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network," Artificial Intelligence in Agriculture, vol. 5, pp. 90-101, 2021.

[23] S. Jeyalakshmi and R. Radha, "An effective approach to feature extraction for classification of plant diseases using machine learning," Indian Journal of Science and Technology, vol. 13, pp. 3295-3314, 2020.

[24] M. Lamba, Y. Gigras, and A. Dhull, "Classification of plant diseases using machine and deep learning," Open Computer Science, vol. 11, pp. 491-508, 2021.

[25] I. Ahmad, M. Hamid and S. Yousaf, "Optimizing Pretrained Convolutional Neural Networks for Tomato Leaf Disease Detection," Complexity, 2020.

[26] K. Akshai and J. Anitha, "Plant disease classification using deep learning," in International Conference on Signal Processing and Communication (ICPSC), 2021.

[27] N. Patil, S. Kelkar and M. Ranawat, "Krushi Sahyog: Plant disease identification andCrop recommendation using Artificial Intelligence," in 2nd International Conference for Emerging Technology (INCET), 2021.

[28] H. Agh Atabay, "Deep residual learning for tomato plant leaf disease identification," Journal of Theoretical and Applied Information Technology , 2017.