Artificial Intelligence Based Multi Classification of Diseases from Different Plant

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Abstract: The development of an economy's agricultural sector is directly proportionate to the growth of that economy's potential for innovation, which in turn is directly related to the progress of that agricultural sector. The primary purpose of this investigation is to apply deep learning models for a process of constructing Plant Disease Detection and Classification Networks (PDDC-Net). The preprocessing step also involves the elimination of various kinds of noise, which ultimately leads to the standardization of the pictures that are a part of the dataset. In addition, the PDDC-Net puts the operation into practice by using a residual network based convolutional neural network (ResNet-CNN) for the purpose of feature extraction and classification. This allows the operation to be carried out more effectively. This contributes to ensuring that the operation is carried out correctly. The PDDC-Net model that was suggested obtained an accuracy rate that was adequate to detect and classification of plant leaf diseases, as shown by the outcomes of the tests that were carried out.

Keywords: Plant disease classification, preprocessing, convolutional neural network, Plant disease detection.

1.0 INTRODUCTION

Plant pests and diseases generate major problems for ecosystems and farms. Commercial farms and orchards have a vested interest in the early detection and prevention of a wide variety of plant diseases, making this a key objective of agricultural technology. Up until recently, the gold standard for disease diagnosis was time-consuming, inconvenient, and costly manual visual screenings [1]. Computer vision for precision agriculture has allowed for the relatively recent addition of a disease detection tool to crop health monitoring data collecting. As a result, this has led to significant improvements in the efficiency of disease detection and the output of agricultural production [2].

Because early detection and prevention of plant diseases may effectively eliminate any growth challenges, they are essential components of crop harvesting. This is because they allow for pollutant-free agricultural production with less pesticides. Automated plant disease diagnoses employing a suite of ML algorithms has emerged as a potent resource for precision farming. Many different machines learning methods, including as K-means clustering and support vector machine (SVM), have been used to attempt to solve the issues of plant categorization and disease identification. However, when used to real-time illness detection, their efficiency and speed are hindered owing to the significant picture preprocessing and feature extraction procedures needed by these algorithms [3]. Furthermore, most machine learning methods struggle to adjust to detecting situations that include complicated, non-uniform environments. This is a major issue with the state of the art in machine learning. Recent developments in deep learning have enabled substantial advances in computer vision that have broad applicability. In addition, it has applications in automated agricultural technologies, such as crop categorization, fruit recognition, and picture segmentation. More people are interested in these kinds of systems since CNN-based models have been found to be more accurate at detecting things [4]. CNNs may save significant amounts of time compared to traditional methods by automatically extracting characteristics from the input pictures. Their efforts in recent years have substantially aided in the identification of agricultural diseases. Recent developments in CNN-based object recognition models may be generally split into two types of detectors: those that need two stages and those that require just one. One well-known two-stage detector [5] is the region convolution neural network (RCNN), also known by a few other names. There has been a significant effect on automated farm management, crop and fruit identification, and production and growth evaluations thanks to these models. On the other hand, quicker R-CNN is made up of many sub-components such as categorization networks and region proposal networks (RPNs). Although these methods save a lot of time overall, they are not yet fast enough to detect high-resolution photos in real time. A relatively recent method called "You Only Look Once" (YOLO) has emerged. Classification and localization are two types of regression issues that are jointly addressed by this strategy. Because it doesn't have RPN, YOLO may utilize regression to quickly find targets in a picture, which contributes to its fast object identification speed. The cutting-edge YOLOv4 shines in a variety of real-time object recognition applications [6], and its fast detection speed is only one of its many outstanding characteristics.

This study aims to improve our understanding of apple plant disease detection, since apples have significant economic worth due to their wide range of health benefits. However, apple trees are prone to a variety of diseases when they are still young. Scab (caused by Venturia inadequacies) and rust (caused by Gymnosporangium juniperi-virginianae) are two particularly harmful and common fungal diseases. The quantity and quality of fruit might be drastically impacted by any of these illnesses. Consequently, the ability to detect disease spots in apple trees at an early stage allows for more efficient disease prevention and treatment, making it a crucial component in the creation of autonomous agriculture [7]. However, due to the similarity of color texture between illnesses and the background, the presence of several diseases in the same leaf, the diversity of the morphology of diseases, and the fine-grained multi-scale distribution, real-time early disease identification in apple leaf remains challenging. High-precision disease detection in apple leaves is further hindered by a variety of environmental factors, such as overlapping leaves and soil, fluctuations in light in a natural situation, and so on. Furthermore, there is a trade-off between real-time detection speed and accuracy in existing illness detection algorithms [8]. Thus, there is a substantial space between the presently used paradigm and the ability to provide timely in-field diagnoses of diseases utilizing mobile computing equipment.

To address these issues, we propose a multi-scale illness identification model built on top of an improved version of the cutting-edge YOLOv4 algorithm. This technology has been put to use in the field to detect diseases in apple trees in near real time. The provided model is a modified version of CSPDarkNet53 that incorporates Dense Net blocks, resulting in Dense-CSPDarkNet53. This adjustment was made so that smaller targets may be identified with greater ease by transferring and reusing features [9]. In order to boost redundancy, reduce computation cost, and optimize efficiency, the number of network layers has been minimized by modifying the convolution blocks. In addition, a certain tweaks has been built to better fuse features from different levels of abstraction and keep track of fine-grain localization details. The receptive field is further enhanced due to the model's use of a spatial pyramid pooling (SPP) block. The proposed model uses Mish as a major activation function in both the neck and the backbone, which greatly improves feature learning capacity and detection technique accuracy. Overfitting is prevented during training via a data augmentation strategy [10] that also improves the model's robustness. The provided model has a high degree of accuracy in a complex orchard scenario, automatically recognizing the unique properties of each disease of varied sizes and the presence of many illnesses within the same image. The combined detection result shows that the state-of-the-art method performs better than the YOLOv4 baseline. The results of this study might be utilized to develop a method for rapidly and accurately diagnosing a wide range of plant diseases in apple trees, with good detection performance in a wide range of orchard settings.

Rest of the paper is organized as follows: Section 2 details about literature survey, section 3 details about the proposed methodology, section 4 details about the results with discussion, and section 5 concludes article with references.

2.0 LITERATURE SURVEY

A new deep learning model was created by Hassan et al. [11] using the inception layer and the residual connection. The number of parameters is decreased by using depth-wise separable convolution. Model has been trained and validated by using the data on plant diseases from three different sources. We discover that the plant village dataset has a 99.39% yield, the rice disease dataset has a 99.66% yield, and the cassava dataset has a 76.59% yield in terms of performance accuracy. The suggested model outperforms the current state-of-the-art deep learning models while using less parameters. Terentev et al. [12] have pioneered recent enhancements to the use of hyperspectral remote sensing for the early diagnosis of plant diseases. Some of the issues that now plague experimental approaches are described in this study. Expanding experimental and methodological standards is advocated as an alternate path forward. This article contrasts the findings of previous studies and provides a concise table summarizing the disease detection capabilities of hyperspectral remote sensing applied to several plant species. Here we present some of the most common wave bands and sensor models. Veerendra et al. [13] examined both leaves and stems as part of their study of the detection process. There are two main advantages to using techniques that include dealing with seeds and roots. The optimal set of suggestions has been divided into three parts: grading the severity, finding it, and labeling it. These categories are subdivided further considering the algorithm's central technical description. This publication aims to provide researchers working on vegetable pathology and pattern recognition with a comprehensive, readable, and comprehensive review that will aid their efforts. Seventy papers on deep learning applications and the patterns related with their usage are analyzed in [14], providing a complete look at their potential impact on agricultural disease detection and control. These experiments were conducted by scientists like Ahmad and Anais. The research was found using Xplore, Science Direct, Scopus, Google Scholar, and IEEE. Eleven keywords emerged as particularly prevalent, including "plant diseases," "precision agriculture," "unmanned aerial system," "imagery datasets," "image processing," "machine learning," "deep learning," "transfer learning," "image classification," "object detection," and "semantic segmentation." To aid in the development of deep learning-based tools for the identification of plant diseases, this article will serve as a comprehensive research and set of recommendations. The investigation will be structured around seven primary queries that will cover issues like (i)dataset needs, accessibility, and utility; (ii)imaging sensors and data collection platforms; (iii)deep learning methods; (iv)model generalizability; (v)disease severity estimation; and (vi)a comparison of deep learning model accuracy. The answers to these questions may help close some of the gaps in the current body of research by directing the development and implementation of instruments to improve plant disease detection and offer farmers with support for disease management. If you're looking for a full taxonomy of the performance of several pre-trained neural networks and the performance of a weighted ensemble of those models for detecting illnesses in plant leaves, go no further than [15]. The research was conducted by Vallabhajosyula and colleagues. In addition, the recommended approach is tested using a publicly accessible dataset sourced from plant village. There is a total of 38 categories in this data collection, which correspond to 14 different plant species. Examples of state-of-the-art pre-trained models that DENN outperforms include ResNet 50 and 101, InceptionV3, Dense Net 121 and 201, MobileNetV3, and NasNet. When compared to pre-trained models, the suggested model exhibits significant improvement in its ability to classify a variety of plant diseases.

J. Arun Pandian, et al. [16] This study demonstrates the significance of developing a DCNN with an appropriate number of layers and filters. The importance of data augmentation strategies and hyperparameter optimization approaches is further shown by the experimental outcomes. The study used many performance metrics to determine the efficacy of the proposed DCNN, including classification accuracy, precision, recall, and F1-Score. Fan, Xijian, and coworkers [17] present a general strategy for identifying plant diseases. Our first step is to propose a deep feature descriptor that may offer a high-level representation of the latent features through transfer learning. Next, we use a technique called feature fusion to combine the deep features with the regular handmade features in order to extract the local texture information from the images of plant leaf surfaces. The addition of center loss improves the discriminating ability of the fused feature. Due to the Centre loss that results in lower class numbers within each subject and bigger class sizes overall, students are able to learn about both related and unconnected subjects. The suggested technique has been extensively tested on three publicly accessible datasets: two Apple Leaf datasets and one Coffee Leaf dataset. Asad, Saeed Ahmad, et al. [18] highlight this option as being more sustainable. Farmers often employ Trichoderma-based biological control agents (BCAs) to prevent the spread of illnesses that may be transmitted by the soil. These BCAs may be found in supermarkets, where they are marketed in several different ways, such as growth stimulants, bio-fertilizers, and bio-pesticides. They also can increase resistance in plants. Biological methods to plant disease control have improved agricultural output and quality while also benefiting ecosystem health in the long run. These BCAs shield plants against pests and diseases and boost photosynthesis, plant development, and nutrient usage efficiency, all of which contribute to bumper crops. Despite these variations, nothing is known about the mechanisms through which Trichoderma inhibits the growth of diseases and promotes plant growth. This study's overarching purpose, therefore, is to specify this central objective. This study also considers Trichoderma-based fungicides that may be purchased in various areas. Finally, we highlight the research priorities and knowledge gaps that need to be addressed if Trichoderma-based BCAs are to achieve greater success. Using a unique technique based on DL, [19] can detect plant diseases using a mix of RGB and segmented pictures. Yasin Kaya and his colleagues at Google developed this method. To take both pictures into account, a multi-headed Dense Net-based architecture was created. The system was put through its paces using Plant Village, a publicly available dataset. There are 54183 images in total, organized into 38 groups. A low complexity CNN architecture for autonomous plant disease classification is presented by Bensaadi, Soumia, and colleagues in [20]. As a result, classifications made online may proceed more quickly. We utilized almost 575,000 pictures of tomato leaves for the training process, each of which was labeled with one of nine different categories. The backdrops of the training photos were not changed in any way after they were taken.

3.0 PROPOSED METHOD

Human disease monitors for plants are being phased out in favor of automated technology. The early findings of the application of real-time testing by researchers from several institutes to monitor plant diseases are promising. The goal of this research was to create a dataset representative of Pakistan to identify guava plant and fruit diseases. To get around this issue of employing enormous volumes of data, data augmentation was used. Model overfitting problems were also addressed with its help. Affine transformation was used all through the data augmentation process. The ROI was narrowed down with the use of unsharp masking and histogram equalization. The ROI was refined with the use of these procedures, and the noise in the supplemented data was cleaned out. Following its completion, the enhanced and supplemented dataset was put through a variety of fine-tuned state-of-the-art classification techniques. Figure 1 depicts the whole process from start to finish.

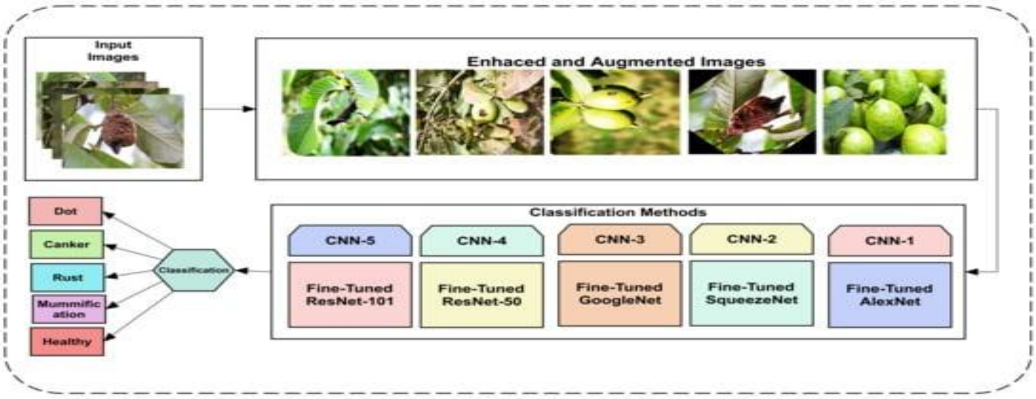

Figure 1. Proposed framework for guava plant disease detection.

The upgraded and augmented photos were partitioned among five distinct predefined structures inside the framework, with the topmost layer of each structure modified with data-specific labels. Alex Net was the first to use deep learning models to win the ImageNet competition, which had previously been considered unwinnable. Squeeze Net, Google Net, and ResNet are just a few of the networks that followed in its footsteps. The quality of a locally collected guava dataset was evaluated and compared to that of more popular datasets. Using a newly gathered dataset from Pakistan, the presented approach demonstrated a first step. In the future, further approaches using diverse machine learning and deep learning technologies may be used.

3.1 Crop disease dataset

Drone and cell phone data were collected in each zone from 8:00 to 10:00 in the morning to determine the extent of the tomato disease. Tomato diseases such as blossom end rot were photographed using mobile phones and were found to be prevalent in the Changing district and the Tong Zhou region. The UAV views of tomatoes are mostly represented, but images of tomato diseases are limited. The phone's 4k pixel camera was used to take pictures of the sides and bottoms of various tomatoes. Extensive tests were conducted on the Changing, Shunyi, and Thouzhou datasets to prove the efficacy of the suggested technique, and the results are shown here. Information about these data sets is included in Table 1. Tomatoes may not all be susceptible to the same diseases since they are not all ripe at the same time. There are a total of 10 different disease types in the tomato datasets; seven are exclusive to one location, while the remaining one is shared by the other three.

Table 1. Datasets used for image classification tasks.

Dataset	Train Size	Test Size	Classes
Shunyi	4800	1200	7
Tong Zhou	5680	1420	7
Changing	6720	1580	7

Cracked fruit, blossom end rot, bacterial spot, gray mold, striped rot, anthracnose, citrus canker, early blight disease, and leaf mold are only few of the diseases cataloged in tomato disease databases.

In the Changing region, tomato disease data may be sorted into seven distinct groups. Diseases such as striped rot, blossom end rot, anthracnose, bacterial spot, gray mold, and citrus canker fall under these groups.

The selected images represent three distinct regions affected by tomato leaf disease, each of which is brought on by a different pathogen. Following this, human comparisons were done across all diseases, and sample maps were constructed to gather data on the locations of visually interpretable hotspots. The degree to which computer-generated graphical maps reflect human knowledge is not yet quantifiable. So, even though gradient-based methods yield useful insights into the network training process for disease classification in tomatoes, there are still limitations to using neural networks, and human experts are needed to assess the accuracy of the resulting computer visualizations. This is true even if the findings of gradient-based approaches for training a network to classify tomato disease are relevant.

3.2 Image pre-processing

In order to effectively assess plant diseases, it is necessary to process aerial photos received by UAVs in a way that decreases the number of mistakes and enhances the picture quality.

Before the images are utilized as input for the model, they must undergo preprocessing such as picture mosaicking, geo-referencing, and radiometric calibration. Sometimes, image tiling is necessary as well. Mosaicking is the practice of combining many outdoor images into one seamless image. A perspective inaccuracy in distance calculation may be avoided with the use of an Orth mosaic picture. Orth mosaics may be made using well-known and reliable software like Agisoft Metashape, PIX4Dmapper, and DJI Terra. The process of assigning geographical coordinates to each pixel in a picture is known as "geo-referencing." Field georeferencing is impossible without GCPs. Applying this method, we may make the picture seem more as it does in real life by adding precise geoinformation and modifying its overall shape. Such programs as ArcGIS, Agisoft Metashape, PIX4Dmapper, and ENVI are all examples of georeferencing software. After that, a radiometric calibration has to be performed. Only digital numbers (DN) may be collected by a hyperspectral camera; these DN must be transformed into radiation to be considered raw data. Converting the radiation value to the reflectance value ensures a constant output. There is always going to be some fluctuation in the total amount of light intensity from flight to flight, and it's feasible that the field observations will take place on various days. In this example, the reflectance of the radiation measurement is calibrated in the field using a reflectance tarp. We get the intended result because of this.

3.3 Proposed ResNet-CNN

3.3.1 Residual Network (ResNet)

The first ResNet models were created by him and his colleagues [11]. The deep architectures used in these models have shown to be very accurate and exhibit exceptional convergence capabilities. The ILSVRC and the COCO classification challenge, both held in 2015, were won by the group. ResNet's construction spanned a broad range of layer counts, from 18 to 1202. ResNet is built from concatenated residual units. However, due to the varying nature of designs, the total number of operations may vary. The residual units in each of these examples represent the result of an iterative process including convolutions, pools, and layers. Both ResNet and VGG are very deep networks, but ResNet is around eight times deeper. The ResNet 18 strikes a good balance between complexity and efficiency. Five convolutional layers, an average pooling layer, and a fully connected layer with a SoftMax make up the architecture. ResNet 50 has 49 convolutional layers altogether, the final of which is completely coupled. Finally, to maximize efficiency in terms of time and computer resources, ResNet 18 and ResNet 50 were selected as the platforms on which to carry out this task.

3.3.2. CNN Settings

Changes to the parameters, which often include many distinct elements, produce different CNN designs. The fundamental building blocks of a CNN and its general layout are shown graphically in Figure 2. Input layer, convolutional layer, pooling layer, and flattening process are all instances of such components. The data is flattened and then stored in many layers, the last one being the outcome.

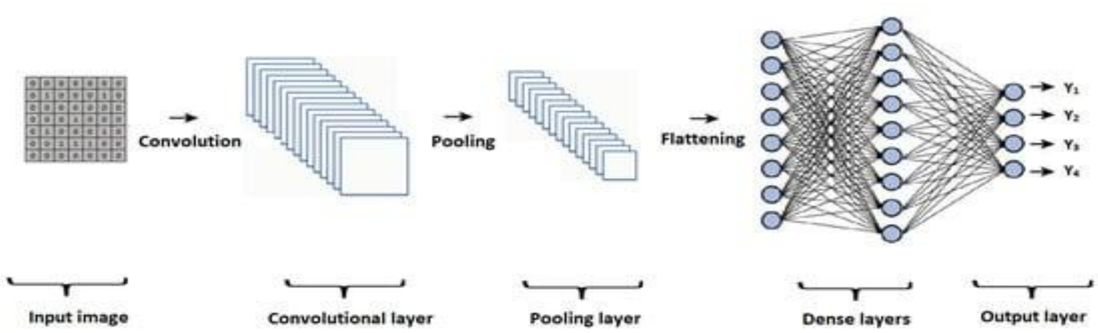

Figure 2. Representation of the architecture of a convolutional neural network (CNN).

Therefore, the characteristics of the architectures used are described in the Table 2.

Table 2. Summary of the utilized architectures.

Network	**Image Input Size**	**Parameters (Millions)**	**Depth**
Google Net	224 × 224	7	22
Inception V3	224 × 224	23.9	48
ResNet 50	227 × 227	25.6	50
ResNet 18	224 × 224	11.7	18
Alex Net	299 × 299	60	8

To facilitate a more meaningful comparison across trials, we also tried to standardize the hyper-parameters used throughout by utilizing the hyper-parameters listed in Table 3. This was done so that a comparison could be made more easily.

Table 3. Hyper-parameters of the experiments. * Stochastic Gradient Descent with Momentum (SGDM).

Hyper-Parameters	**Value**
Momentum	0.9000
Optimization algorithm	SGDM *
Epochs	30
Batch size	32

L2 Regularization	1.0000 × 10−4−4
Initial learning rate	1.0000 × 10−3−3

Several scientific fields have made great gains because to DL. Because of its unrivaled ability to strike a balance between accuracy and speed, the stochastic gradient descent (SGD) method has emerged as the de facto standard in optimization. Although the SGD is simple to apply, it still needs careful tuning of the model's hyper-parameters, particularly the initial learning rate. This optimization parameter controls the rate at which weights are changed to seek a local or global minimum in the loss function. The momentum helps SGD accelerate to the right and suppresses oscillations. Regularization is a method that may be used to reduce the likelihood of overfitting. L2 Regularization is used more often than any other kind of regularization. When used with SGD, this regularization causes weight decay. Each iteration involves subtracting a small fraction of a unit from all the weights. There are a total of 30 training iterations (epochs) available for each experiment. Insightful direction was offered by the work of Mohanty et al., which demonstrated that their approach led to permanent convergence after the first reduction in learning pace. This factor proved decisive in determining the winner. The maximum recommended batch size for training a CNN is 32, thus that's what's used for all of them.

Training a convolutional neural network (CNN) system is computationally intensive. Test results from a workstation are summarized in Table 4 for convenience. The Deep Learning (DL) Toolbox in MATLAB 2018b was used for the training phase. This infrastructure may be used to construct and deploy CNNs. It is possible to display network activations and monitor their growth during training with the help of apps and visualizations. For statistical analysis, we utilized the open-source program R (3.5.2), with its pROC and caret package additions, to compare the various blueprints.

Table 4. Machine specifications.

Hardware and Software	**Characteristics**
Processor	Intel Core i7-7700 CPU @ 3.60 GHz
Operating system	Windows 10, 64 bits
Graphics	GeForce GTX 1070 X 8 Gb
Memory	16 Gb

4.0 RESULTS AND DISCUSSION

This section contains details of proposed simulation results, which are carried out using the Spyder software and python programming environment. The modules used in this work also discussed. Further, productivity of proposed PDDC-net is compared to state of art approaches.

4.1 Modules

- Upload Crop Disease Dataset: This module is used to select the dataset.
- Image Processing & Normalization: The image pre-processing and normalization of dataset is achieved by this module.
- Build Crop Disease Recognition Model: Either selection of trained model or retraining of module is achieved by this module.
- Upload Test Image & Predict Disease: This module is used to identify the disease class from the test image.
- Accuracy & Loss Graph: This module is used to plot the accuracy and loss comparison graph various iterations (epochs).

4.2 Results and Discussions

Figure 3 displays some representative photos from the dataset. Figure 4 shows the classification outcome of test image, where class name is recognized as potato healthy. Figure 5 shows the classification outcome of test image, where class name is recognized as potato with early blight. Here, both the plant names and disease names were predicted. Figure 6 illustrates epochs and iterations, and the y-axis depicts accuracy and loss. The green line illustrates accuracy, while the blue line illustrates loss. If we look at the above graph, we will see that while the number of iterations increases, accuracy improves while loss decreases. Table 2 examines how well the suggested approach performs in comparison to other ways already in use. In this case, the proposed ResNet-CNN produced results that were superior to those produced by the current NB, RF SVM in terms of accuracy, recall, precision, and F1-SCORE. Figure 6 is a depiction of the graphical form of Table 5, which can be found above. In conclusion, the results of the simulations showed that the performance achieved by the suggested ResNet-CNN was superior to that achieved by SVM, naive Bayes, and random forest.

Figure 3. Sample dataset.

Figure 4. Crop recognize as Potato healthy.

Figure 5. Crop recognize as Potato early blight.

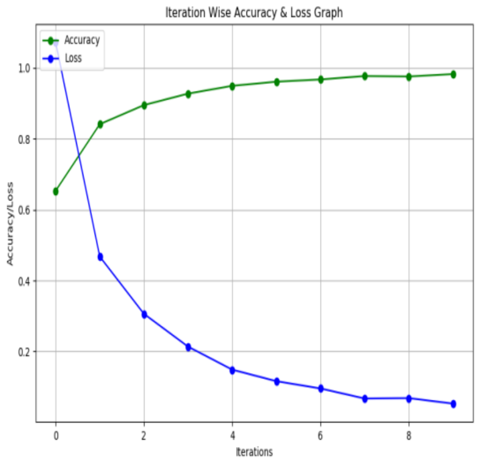

Figure 6. Iteration wise accuracy & loss graph.

Table 5: Performance comparison.

Method	Accuracy (%)
SVM [17]	87.4585
Decision Tree [16]	72.495
XGBoost [14]	99.485
Random Forest [15]	78.384
Naive Bayes [13]	89.239

5.0 CONCLUSION

Totally, 27 different types of crop diseases were investigated in this paper. Deep learning theory as well as ResNet-CNN technologies were used in the construction of the model. Experiments have shown that the model is capable of accurately recognizing the data set, and the model has attained an overall identification accuracy of up to 98.23%. Results showed that compared with traditional models, the recognition accuracy of the hybrid network model is much higher. Additionally, this model has the potential to be efficiently used for the purpose of identifying and detecting plant diseases. There are two areas that need to be improved in the work that will be done in the future. These are the expanded data set and the optimized model.

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