International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(5s) 2026 pp. 110-117
https://doi.org/10.70917/ijcisim-2026-2679
Article

ANN-Based Early Plant Disease Detection for Precision Crop Management in India

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Abstract: Agriculture is a very important part of our human society. In India, many people think of it as the backbone of the economy because it creates a lot of jobs. It not only protects food, but it also helps the economy stay strong. Food and the economy are very tightly related in some ways; thus, it is really important to keep farming going. But farming is not perfect. Like different industries have different issues same as agricultural field also have the issues related to the crops. One of the main issues in agriculture is keeping crops and plants healthy. Fungi, bacteria, viruses, nematodes, pests, and even severe weather can all make crops plants sick. Finding and treating diseases in agriculture is still a difficult and time-consuming task. With help of image processing techniques farmers can detect plant disease easily. For early detection and management researchers uses different techniques. Here in this research we have used some machine learning techniques like MobileNetV3, DenseNet201, VGG19 and ANN. We got an accuracy of 98% with DenseNet201.
Keywords: NA

1. INTRODUCTION

Agriculture is of paramount importance in meeting the food needs of a growing population. However, the prevalence of plant diseases is one of the major problems encountered by farmers. These diseases usually cause a considerable drop in crop quality and yield and can occur in crops at different growth stages. Researchers have long turned their attention to plant diseases. Many studies are available on development, transmission and harm of diseases on different crops. Yet, despite all these efforts, plant diseases remain a severe problem in agriculture. There are many causes of crop diseases. Viral, bacterial, fungal and insect infestations are the usual culprits. Besides them, the ambient factors also have a considerable influence. In some cases, unseasonably high temperatures, excessive humidity, heavy rains and unpredictable weather might generate conditions conductive to the development of disease. In such cases farmers often suffer financial loss and agricultural output decreases. These losses can be very high in many regions especially when disease outbreaks are not detected. The major way of detecting sickness in the traditional way is observation by human beings. Farmers will usually go to their fields and look for obvious signs on plants. This has been done for several hundred years and expert farmers can often recognize the common diseases easily. Still not the best strategy. Different diseases might seem extremely similar and early infections can sometimes be difficult to recognize. A tired farmer can miss the indicators, while someone else might see the same symptoms differently. This technique therefore contains some slight inaccuracies and subjectivity. As a result, experts have been seeking more accurate means of identification of the disease.

Artificial intelligence has been a beneficial tool for solving certain practical problems, especially those concerning agriculture. It has become very popular because it is able to process enormous volumes of data and find patterns that people would not perceive instantly. Artificial intelligence can assist in identifying plant diseases and make quicker judgments by noticing illness symptoms in photos of leaves. This has encouraged several researchers to explore for AI-based applications in agriculture. Among numerous ways, Artificial Neural Networks (ANN) have attracted a lot of attention, The networks are trained with examples. They get better at categorizing data over time.

Researchers have employed ANN models to diagnose and classify several plant diseases with promising results . Another technology that is extensively utilized is Convolutional Neural Networks (CNNs). CNN models are advanced yet when you are working with images, they are really useful as they can identify crucial visual aspects automatically. Hence, a lot of research has been carried out on ANN and CNN models for plant disease detection.

Never has there been a greater need for rapid and accurate diagnosis of disease. In some cases a few days' delay may permit a disease to cover a significant area of agriculture. Early discovery allows farmers more time to enhance overall output, minimize crop loss and take preventive steps. It can also cut the expenses of production and the unnecessary usage of pesticides. Accurate detection methods are particularly important for tomato crops where outbreaks of diseases can greatly affect the output and market value.

Tomatoes are one of the most important crops farmed worldwide due to their great nutritional and economic values. It is grown commercially in several countries and is a daily food for many households. But tomato plants can be affected by several illnesses that can spread swiftly if left unchecked. In certain circumstances, the farmer may not be aware that a disease has developed until the damage is very severe. This has made early disease detection a major research focus in tomato production and crop management. Most plant infections begin interestingly on the leaves. Actually, you can learn a lot about the health of a plant from its leaves. Little spots, unusual patches, yellowing, discolouration, curling or a change in texture might all be signs of a disease. distinct diseases cause distinct symptoms. Some may develop inconsistent patterns or color shifts, while others may develop dark round regions. Thus, leaves are one of the most studied plant parts in the context of disease detection.

2. RELATED WORK

Hassan Amin et al. (2022) applied data augmentation techniques to provide variations to the images in the dataset used to train the model, enhancing the diversity and amount of the images, and allowing the model to learn more complex situations of the data. The result achieved in this work is contrasted with existing pre-trained CNN models like ResNet152 and InceptionV3, which have a greater number of parameters than the proposed model and need more processing resources. The suggested model achieves a classification accuracy of 98.56% which shows the superiority of proposed model over ResNet152 and InceptionV3 that achieved a classification accuracy of 98.37% and 96.26% respectively. [1]

R. Karthik et al. (2024) suggested network captures the global and local features, which combines the contextual information and multi-scale feature learning capabilities of the Swin transformer with the local feature-extracting capabilities of the DAMFN track. In the DAMFN CNN track, attention methods are incorporated to enhance feature extraction and increase model generalization. To the best of our knowledge, this is the first article revealing the results of a dual-track architecture for agricultural disease and pest detection employing a combination of Swin transformer and DAMFN networks. The dual-track design of the transformer and proprietary CNN work together for better pattern recognition and less false positives and negatives. The TA module addition considerably boosts the network's ability to selectively concentrate on pertinent information. Thus, improving the accuracy and precision of disease classification. The model obtained a classification accuracy of 95.68% on the CCMT dataset, beating other state-of-the-art networks. [9]

Khaoula Taji et al. (2024) fills the research gap by giving an extensive overview of the plant diseases impacting fruits and vegetables. They also recognizes the limits of the proposed approach opening the path for further research and enhancements. The proposed strategy achieves a remarkable accuracy of 99.8% and outperforms the present state-of-the-art techniques. The research adds to the continuous efforts to increase food security and sustainability by providing an effective solution for the early detection and categorization of plant diseases thereby helping to reduce the adverse influence on the production and quality of the crops. [10]

Sudhakar Muthusamy et al. (2025) first trained and tested model on photos of dietary deficits and visually alike illness signs to tackle frequent categorization difficulties. They also tested it on a dataset of coffee crop from Mendeley to verify its resilience. The suggested approach D-PAN is a modified Pyramid Attention Network (PAN) using a dynamic attention mechanism for multi-scale input images. The performance of the model was tested against other vision transformer (ViT) based channel attention techniques and a weighted ensemble of Transformer models with a modified convolution neural network (CNN). The model registered top accuracies of 98.80% for banana and 94.60% for coffee, with reduced misclassification errors. [11]

Clecio Elias Silva et al. (2025) presents a new two-stage approach, detecting the diseased region of coffee leaf and classifying the illnesses into Miner, Rust, Cercospora and Phoma on coffee leaves. A new dataset was generated from the BRACOL and Diseases and Pests in Coffee Leaves datasets to increase class balance and robustness. In the first stage, the YOLOv8 model is employed for detecting the sick regions. For the second step, InceptionResNetv2, DenseNet169, Resnet50 and ShuffleNet models are trained and utilized to categorize the detected region and a modification to a low computational cost classification architecture termed SmallPavicNet-MC is proposed. The data obtained are compared and the performance analysis of the detection models shows that YOLOv8 had the greatest performance with a mAP(MeanAveragePrecision) of 85.1% and for classification the DenseNet169 model got the highest average accuracy with 97.93%. [12]

Rubina Rashid et al. (2025) proposed a practicable lightweight model which is designed for an Android application to recognize the unhealthy areas in the image. This research is designed to improve the efficiency and accuracy of tomato leaf disease detection by the modification of mobile-based Convolutional Neural Networks (CNNs). This model is constructed from two concurrent streams of networks based on the key ideas of MobileNetv3 by using inverted residual blocks (IRBs) to better the accuracy of the low and high level features working for varied image sizes . In addition, inverted residual connections are used to increase the receptive field of the model. To fully utilize features, cross-layer connections are added between two parallel streams and Efficient Channel Attention (ECA) module is embedded to reduce the number of parameters. The model is trained using transfer learning with particular modification to reduce detection errors and fine-tuned with a dataset of tomato leaf disease images taken from Plant Village. Then the proposed feature integration and data analysis scheme is used to develop an Android application for tomato leaf disease diagnosis. The model is evaluated based on the number of correct predictions and quality criteria. The achieved mean training accuracy is 98.77% for the 10 classes. [13]

Satish Kumar et al. (2025) gathered and expert validated dataset of 8000 apple leaf photos from orchards in Himachal Pradesh and Uttarakhand, India, consisting of three prevalent diseases: Marssonina leaf blotch, Alternaria leaf spot and powdery mildew. They offer a new approach for the categorization of Apple Leaf Disease (ALD) and disease detection using a Transfer Learning (TL) Enhanced Residual BottleNeck Vision Transformer (RBVT-Net) model with YOLOv7 for high-precision identification. Extensive studies showed the efficiency of the proposed model, attaining 98.58% classification accuracy for disease detection using YOLOv7. [14]

3. PROPOSED MODEL

In this work, we proposed an efficient plant leaf disease classification framework by integrating deep features and Artificial neural network (ANN) classifier. The proposed method uses three pre-trained deep learning architectures namely DenseNet201, VGG19 and MobileNetV3 to extract meaningful and discriminative features from plant leaf images. The reason for choosing these designs is that they are capable of learning complex visual patterns and representing image information, which is suitable for plant disease identification applications. Image pre-processing is very important to improve the performance of classification model. The leaf pictures were then scaled and standardized for homogeneity in the dataset before training. This preprocessing procedure minimizes the variability of quality of images and allows to learn the sickness characteristics better by the models. The deep features extracted from the pre-trained networks were then used as input to an Artificial Neural Network (ANN) which was employed as the final classifier for disease prediction.

The research was conducted on the efficiency of DenseNet201, VGG19 and MobileNetV3 in extracting representative properties of plant leaf pictures. DenseNet201 is based on dense connected layers which promote reuse of features and efficient flow of information through the network. VGG19 It employs an extremely deep sequential architecture with a large number of convolution layers to extract detailed visual patterns. MobileNetV3 is a light-weight architecture that is designed to satisfy the computation and classification efficiency. Experimental results suggest that DenseNet201 observed the best overall performance of the analysed models with a precision of 0.9846, recall of 0.9841 and F1-score of 0.9841. The VGG19 model attained precision of 0.8302, recall of 0.8249 and F1-score of 0.8223. MobileNetV3 performed substantially worse with precision of 0.7095, recall of 0.6486 and F1-score of 0.6333 . The results reveal that DenseNet201 is particularly powerful in extracting disease-related characteristics from plant leaf pictures, and combined with ANN classification, it provides higher disease recognition performance than VGG19 and MobileNetV3. The proposed method demonstrates the feasibility of integrating deep feature extraction methods with Artificial Neural Networks for accurate and reliable plant disease detection thereby laying the ground for intelligent agricultural monitoring and crop management systems.

We used a dataset of tomato image data from Kaggle for the suggested model, which is free for all and easily available on the Internet. There was a total of 22931 images, from which we used 18346 images for training and 4585 images for testing. There was different folders of the different diseases of the plant like mosaic virus, target spot, leaf mold, late blight, early blight bacterial spot and others and also the healthy images. Folders were the same for the training and testing.

DenseNet 201 model

DenseNet201 is a 201-layer convolutional neural network with dense connectivity between layers. In this architecture, every layer is connected to all other layers in a feed-forward way. This leads to efficient feature reuse and better information flow across the network. DenseNet201 is able to overcome the vanishing gradient issue and extract highly discriminative features from plant leaf photos. The model's dense linkages can well reflect the low-level and high-level aspects of sickness.

VGG 19

VGG19 is a deep convolutional neural network with 19 layers. It adopts a simple and homogeneous design that learns picture properties sequentially with small 3×3 convolution filters. The model can learn fine visual details such as spots on leaves, discoloration and texture changes owing to plant diseases. It is a common solution for picture classification challenges because to its basic construction.

MobileNetV3

MobileNetV3 is a light-weight convolutional neural network for efficient image classification with reduced processing costs. It offers a trade-off between accuracy and efficiency using depthwise separable convolutions, squeeze-and-excitation modules and better activation functions. MobileNetV3 is notably beneficial for mobile and embedded applications with limited computational resources while still achieving respectable classification performance. **Artificial Neural Network (ANN)**

The last classification model for the proposed framework is the Artificial Neural Network (ANN). ANNs are inspired by the structure and function of the human brain and are composed of interconnected neurons organized into input, hidden and output layers. The features are extracted by using the pre-trained models and these features are passed to the ANN which learns the association between the picture features and the disease classifications. From this procedure ANN learns and finds the matching disease category for each plant leaf image. In an ANN, the prediction process for a single neuron can be described by the following formula:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

Where:

- y is the output of the neuron.
- f is the activation function.
- wi are the weights of the inputs.
- xi are the input features.
- b is the bias term

Assessment Tools

The proposed model is measured using Precision, Recall and F1-Score.

Precision is the ratio of the number of correctly predicted positive samples to the number of all the predicted positive samples.

Precision = TP / (TP + FP)

TP (True Positives) – The number of correct positive predictions

FP (False Positives) – The number of incorrect positive predictions

Recall is the ratio between the number of true positive samples and the total number of actual positive samples.

Recall = TP / (TP + FN)

FN (False Negatives)

TP (True Positives) – The number of correct positive predictions

FP (False Positives) – The number of incorrect positive predictions

The F1-Score is a measure of the classification performance, and is the harmonic mean of Precision and Recall.

$$F1Score = 2 * [(precision * recall) / (precision + recall)]$$

The DenseNet201-based framework obtained the best performance with Precision, Recall, and F1-Score of 0.9846, 0.9841, and 0.9841, respectively, which indicates that it is an excellent framework for plant disease classification compared to VGG19 and MobileNetV3.

4. RESULTS AND DISCUSSION

The model was trained on a dataset of plant images and the data augmentation techniques were used to improve the robustness and generalization of the model. The results of our study with different models are shown in Table 1. The high accuracy and good performance indicators illustrate the efficiency of the proposed model for plant disease classification. The system uses advanced pre-trained models for feature extraction which enable to extract complex and high-level information from plant pictures that are essential for accurate disease identification. The data is taken from three different models in the same environment (e.g. epochs were 10 and 20 in the models, batch size 16 was taken and layers in ANN were comparable with neurons 1024, 512, 256 and 128) using the same dataset.

Table1. Comparison of different models

Feature Extraction Method	Accuracy (%)	Precision	Recall	F1 Score
DenseNet201	98.40	0.9846	0.9841	0.9841
MobileNetV3	64.86	0.7095	0.6486	0.6333
VGG19	82.48	0.8302	0.8249	0.8223

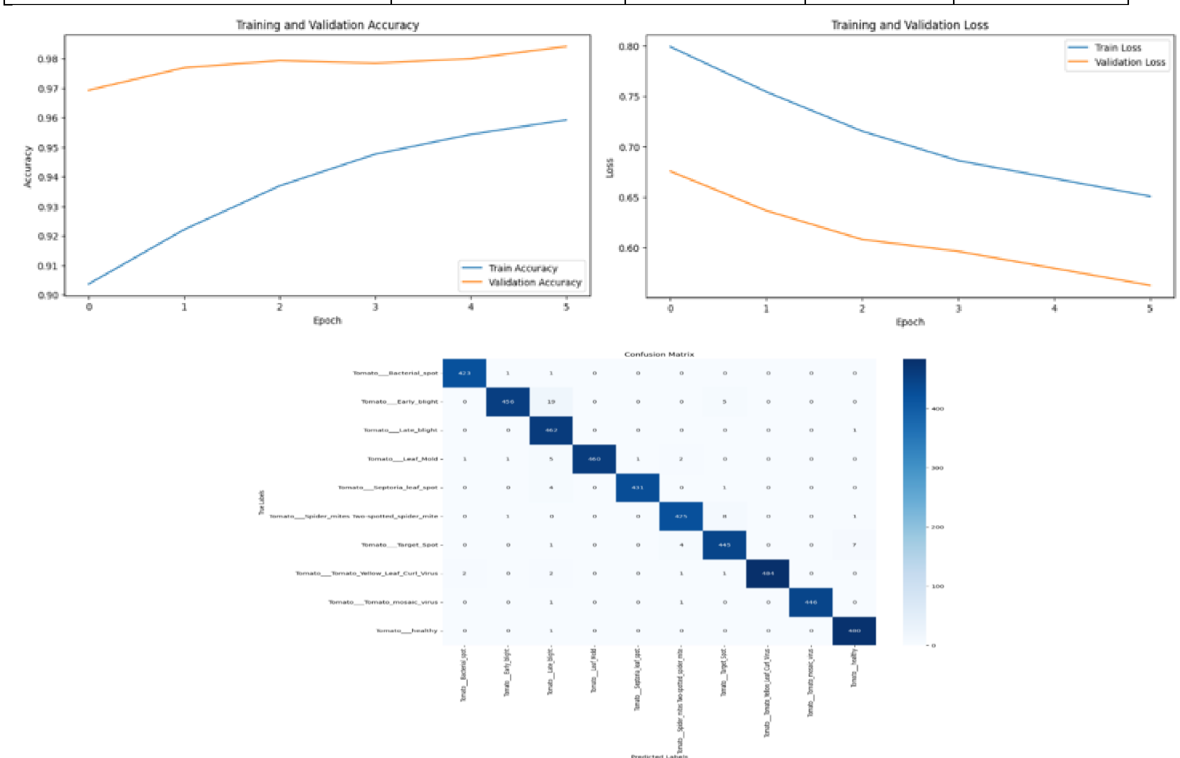


Image 1. Accuracy, Loss, and Confusion Matrix of DenseNet201 Model

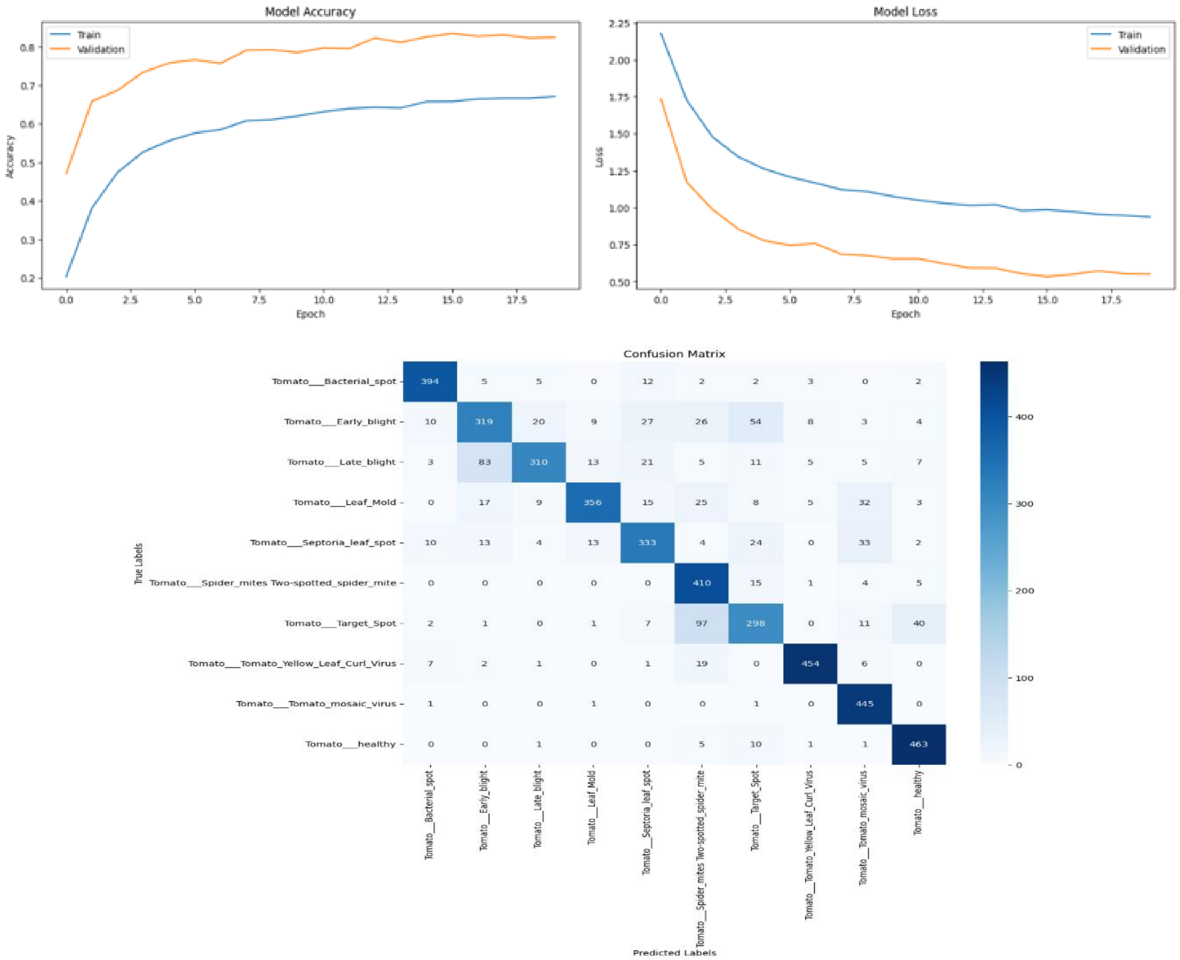
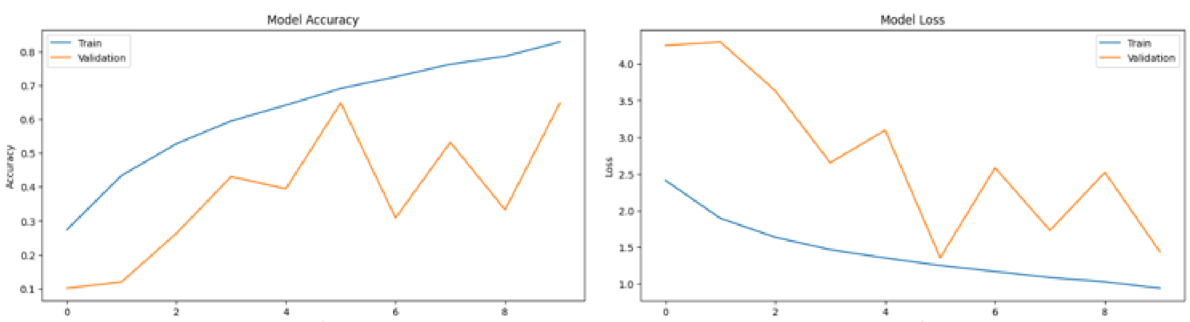


Image 2. Accuracy, Loss, and Confusion Matrix of VGG19 Model



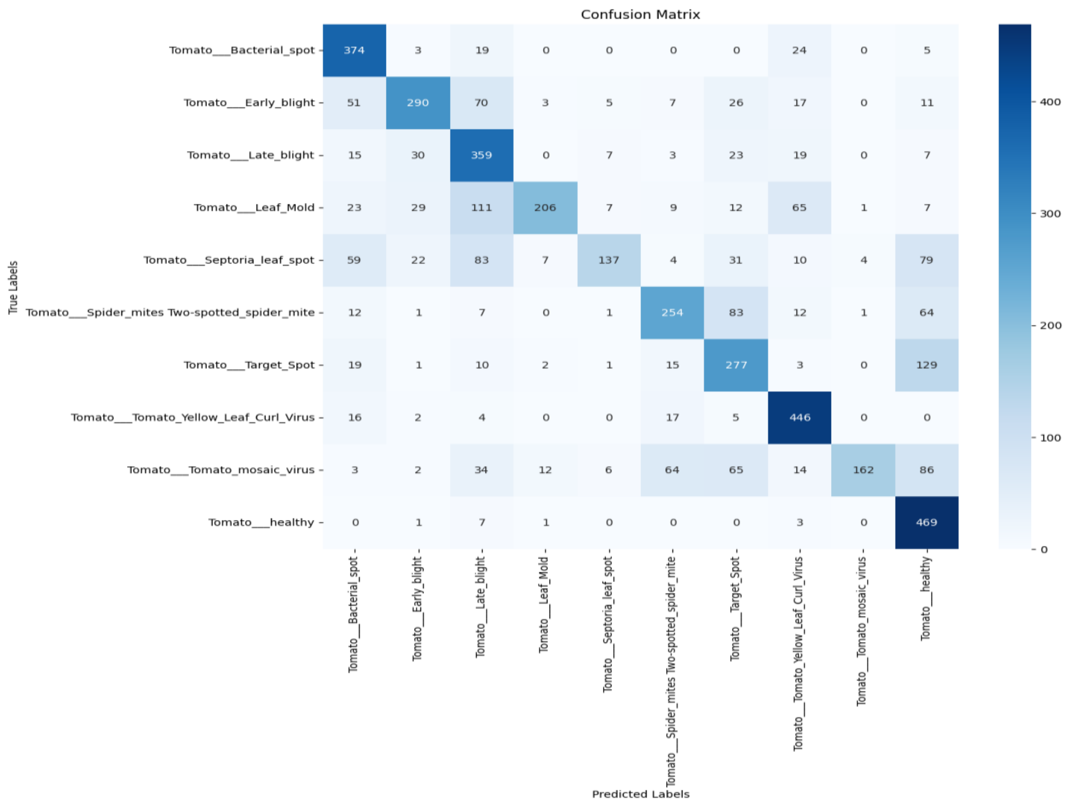


Image 3. Accuracy, Loss, and Confusion Matrix of MobileNetV3 Model

5. CONCLUSION

In this work DenseNet201, VGG19 and MobileNetV3 are utilized as feature extraction models and Artificial Neural Network (ANN) for plant disease classification. The experimental findings demonstrated that the DenseNet201 model performed better than the other two models and can effectively extract the disease-related properties from the plant leaf photos. Results indicate that the combination of deep learning-based feature extraction and ANN classification can offer accurate and dependable plant disease detection, which can be helpful for farmers in early disease diagnosis and crop management. Results however are promising but there are many areas for further exploration and enhancement.

Suggestions and Future Scope

Bigger & More Diverse Data: More plant species, disease categories and images taken under different climatic situations can be incorporated in the future studies to improve the model's generality. **Real Time Disease Detection:** The proposed model can be incorporated with mobile applications and IoT devices to provide real time disease monitoring directly in the agricultural fields. **Hybrid Deep Learning Models:** Combining features from several deep learning models can enhance classification accuracy and robustness.

Explainable AI Techniques: Future work can focus on improving the interpretability of the model's predictions to better the understanding of the decision making process by farmers and agricultural specialists.

Field Validation: The model should be validated on real field images instead of controlled datasets to assess the model for its practical applicability and dependability.

Cloud Based Agricultural Systems: Model can be hosted on the cloud platforms which provide the disease detection services to the farmers through the cellphones and web applications. Overall, the proposed framework has a significant potential to be used for automated plant disease diagnosis and can help towards the development of smart and sustainable agriculture systems.

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