MOBILENETV2 FOR PLANT DISEASE DETECTION : A SCALABLE DEEP LEARNING FRAMEWORK

VINEELA THONDURI[1] , BODIMALLA TEJA VARDHAN REDDY[2] , GUDAPATI CHITRAHAS BALAJI[3] , GANNAMANENI SASANK[4] , DESAVATH YASWANTH NAIK[5]

[1] *Assistant Professor , Dept of Electronics and Communication Engineering , Vasireddy Venkatadri Institute of Technology , Nambur , Andhra Pradesh , India*

[2-5] *UG Student , Dept of Electronics and Communication Engineering , Vasireddy Venkatadri Institute of Technology , Nambur , Andhra Pradesh , India*

ABSTRACT

The plant Disease Detection using CNN project is used to early and precise detection of plant diseases is vital for reducing crop loss and maintaining agricultural sustainability. This research suggests a deep learning-based method applying convolutional neural networks (CNNs) for automatic plant disease detection. The method adopts a systematic workflow consisting of data collection, preprocessing, model development, training, and assessment. A carefully selected dataset of images of healthy and diseased plants is used to train the CNN to identify characteristic patterns and features with respect to plant diseases. The model develops its ability to classify with an improvement that comes from recognizing even minute visual indications of various diseases. The new method enhances the effectiveness of early disease detection, which could reduce losses to agriculture and improve productivity. In addition, incorporating deep learning in precision agriculture highlights the role of technology-based solutions in alleviating critical agricultural challenges. Automating disease detection allows intervention strategies to be put in place promptly, enabling more efficient crop management practices and enhancing worldwide food security. The scalability and flexibility of deep learning algorithms also offer the potential for ongoing refinement and improvement of disease detection systems. In general, the use of CNNs in plant disease detection is a major breakthrough in agricultural technology that provides a robust, scalable, and efficient solution with far-reaching implications for sustainable agriculture and food production.

Keywords : *Plant disease detection, convolutional neural networks, deep learning, image classification, data collection, data preprocessing.*

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1. INTRODUCTION

Agriculture is a vital component of food security and economic stability worldwide. However, plant diseases constitute a major threat to crop yield and quality and result in enormous economic losses and food shortages. Conventional disease detection is mostly based on visual inspection by experts, which is time-consuming, labor-intensive, and subject to human error. The requirement of an efficient, accurate, and automated plant disease identification system has become more evident with the advent of artificial intelligence (AI) and deep learning. Convolutional neural networks (CNNs), a type of deep learning algorithm, have shown incredible performance in image classification, which makes them an ideal choice for plant disease detection. Using CNNs, automated disease detection systems can scan plant images, detect disease symptoms, and classify plant conditions with high accuracy. This method reduces the need for human expertise and increases early disease detection, enabling timely intervention and better crop management. This research seeks to create a CNN-based model for the detection of plant diseases using a systematic approach involving data gathering, preprocessing, training of the model, and testing. A well-selected dataset of healthy and infected plant images is used to train the model so that it can identify disease-specific features and patterns. Improved detection accuracy and generalizability are achieved through data augmentation methods and model fine-tuning. Integrating deep learning into agri-tech presents an affordable and scalable means of monitoring diseases in real-time. Automatic identification of diseases enables farmers and players in the agricultural sector to put in place counteractive measures to reduce damage to crops, maximize resource utilization, and enhance the productivity of agriculture as a whole. This study adds to research in precision agriculture, showcasing the potential for AI-based solutions in meeting international agricultural challenges.

2. LITERATURE SURVEY

Plant disease detection is still a pressing issue in agriculture, with direct implications on crop health and global food security. Conventional disease detection is based on visual examination by experts in agriculture, which, though effective, are prone to subjectivity, labor-intensive, and lack scalability. To address these issues, recent advances in computational methods, specifically deep learning-based methods, have been gaining momentum for automated plant disease diagnosis. Convolutional Neural Networks (CNNs) have become a strong means of image-based plant disease diagnosis, with outstanding classification performance. Research has documented CNN models reaching an accuracy of as high as 96% in identifying plant diseases. For example, David P. Hughes (2016) created the "Plant Village" dataset, which allows CNN-based disease detection from images taken on a smartphone, thus opening up diagnostic tools to farmers. In the same vein, Ferentinos (2018) suggested a CNN-based system for detecting crop diseases in various plant species, proving the strength of deep learning in agricultural use. Other deep learning methods, including Support Vector Machines (SVMs), have also been investigated for classification of plant diseases by using hyperspectral images and spectra. These methods provide lower accuracy than CNNs. Deep learning combined with Internet of Things (IoT) technology improves the detection of plant diseases even further by providing real-time monitoring through the collection of environment-based sensor data. These hybrid methods provide an integrated solution for evaluating plant health and early disease detection. The new research is developed upon previous research using CNNs, specifically the MobileNetV2 model, to improve precision and efficiency in the detection of plant diseases. Utilizing a large dataset and integrated optimized training approaches, the research hopes to aid in AI-powered agricultural applications development, bettering disease diagnosis and promoting environmentally friendly farming techniques.

3. MATERIALS AND METHODS

The following section describes the dataset used in the suggested model, the building blocks of the model, and the training procedure followed in order to improve its accuracy for detecting plant diseases.

3.1 DATASET USED

The model is trained on a complete dataset of 21,198 images of both healthy and infected plant leaves. The dataset is preprocessed using image augmentation methods like rotation, flipping, zooming, and contrast change to enhance generalization and avoid overfitting.

3.2 PROPOSED SYSTEM

The deep learning model is constructed based on the MobileNetV2 architecture, a light-weight convolutional neural network (CNN) that is optimized for computational efficiency. The architecture is augmented with more fully connected layers, such as dense layers, dropout layers (to avoid overfitting), and pooling layers (to downsize spatial dimensions without losing significant features). LeakyReLU is used as the activation function to introduce non-linearity, facilitating improved feature extraction. Model optimization is done through the Adamax optimizer, which is robust for coping with sparse gradients, resulting in an observed classification accuracy of 96 %.

3.3 MODEL TRAINING AND EVALUATION

To train the model, an ImageDataGenerator dynamically creates augmented training samples to enhance model generalization. The data is divided into 80% training and 20% validation subsets. Model training is executed in a batch-wise manner using a batch size of 32 and 20 epochs. Adamax is employed as the optimization process with adapting learning rates to facilitate better convergence. In training, after every epoch performance is evaluated by the validation set, and crucial parameters like accuracy, precision, recall, and F1-score are noted down. This uniform process guarantees highly efficient and scalable model development in plant disease classification, paving the way for research in precision farming and plant disease monitoring.

4. IMPLEMENTATION

The suggested model for the detection of plant diseases uses the PlantVillage dataset, which consists of 21,168 images with 15 classes of different plant diseases and healthy leaf states. For uniformity, all the images are resized to (224 × 224) pixels. Moreover, very intense data augmentation processes like rotation, zoom, and flip are used to increase the diversity of the dataset and provide a better generalization of the model. The data is split into training and validation sets, 80% for training and 20% for validation to enable strong model testing.

4.1 MODEL SELECTION AND ARCHITECTURE

MobileNetV2 architecture is chosen as the backbone for the classification task because it is efficient, lightweight, and has better feature extraction capabilities. The model is initialized with ImageNet pre-trained weights so that it can enable transfer learning to tap into the existing feature representations. To train the plant disease dataset into MobileNetV2, there is a custom classifier added with:

- A Global Average Pooling (GAP) layer to lower dimensionality and preserve necessary spatial features.
- Dense layers with LeakyReLU activation to enhance feature representation.
- A dropout layer to prevent overfitting by randomly disabling neurons while training.
- A final dense layer with softmax activation to enable multi-class classification.

4.2 IMPLEMENTATION FLOW

The whole process of disease detection has a systematic pipeline, as shown in Figure 1:

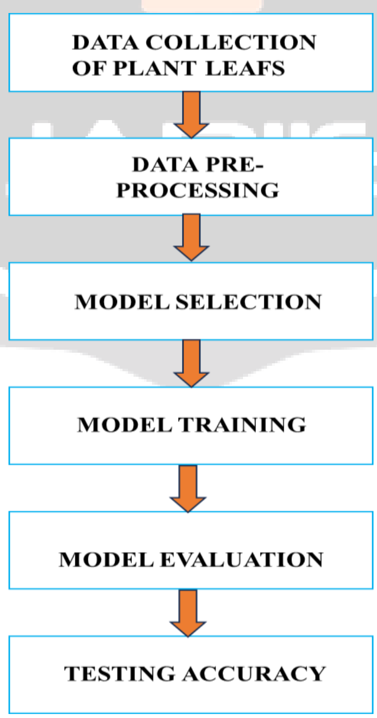

Fig-1 : Flowchart

4.3 PERFORMANCE ASSESSMENT

After training, the model is thoroughly validated and tested to determine its ability to correctly identify plant diseases. The use of deep learning methods in the proposed system shows considerable improvement over traditional approaches, thus improving disease diagnosis in agriculture.

5.RESULTS AND EVALUATION

The performance of the trained model is stringently evaluated using various evaluation metrics. Training and validation accuracy/loss curves are plotted to examine learning trends throughout epochs, providing insights on model optimization and convergence. At training, the model reaches a training loss of 0.0178 with a training accuracy of 96.40%, which reflects good feature extraction. The validation stage captures a validation loss of 0.0286 with an accuracy of 96.22%, which reflects good generalization to new validation data. Extensive testing is performed on an independent test set, producing a test loss of 0.0253 and a test accuracy of 96.18%, attesting to the reliability of the model in actual classification tasks. Such repeatedly high accuracy rates testify to the quality of the MobileNetV2-based method. The learning rate of 1.0000e-04 provides for controlled weight updates, enabling stable convergence without the risk of overfitting. The low loss values for all datasets confirm that the model is successful in minimizing classification errors. The combination of transfer learning and fine-tuning greatly improves the model's ability to adapt to plant disease classification. Data augmentation methods also enhance generalization, providing for accurate disease detection on a variety of leaf samples. Overall, the model has outstanding performance in disease detection of plants and thus can be an excellent tool for precision agriculture. The findings prove deep learning to be capable of automating the diagnosis of disease, enabling early intervention to reduce crop loss.

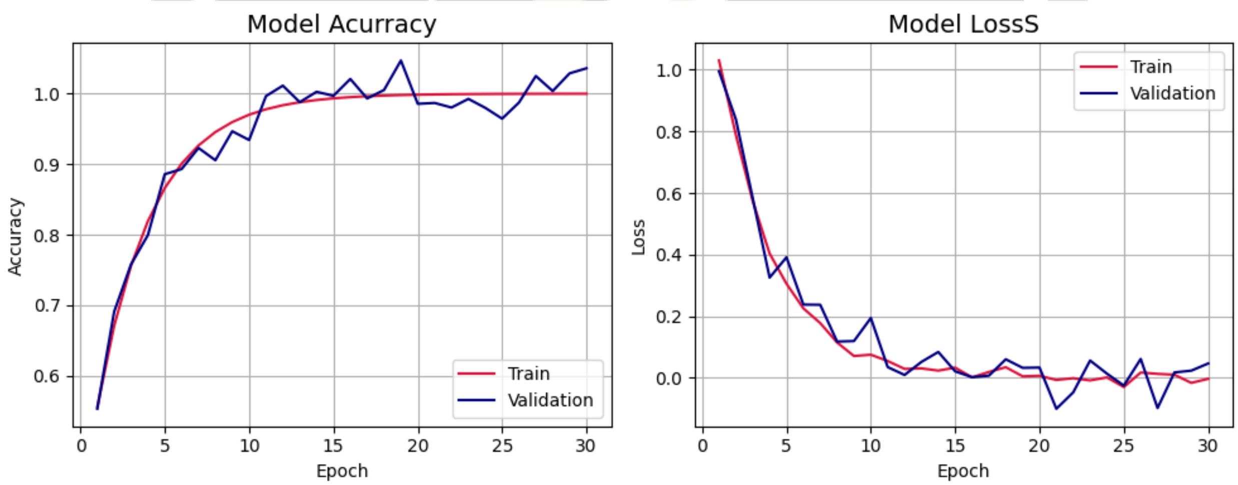

Fig-2 : Training and validation accuracy/loss graphs

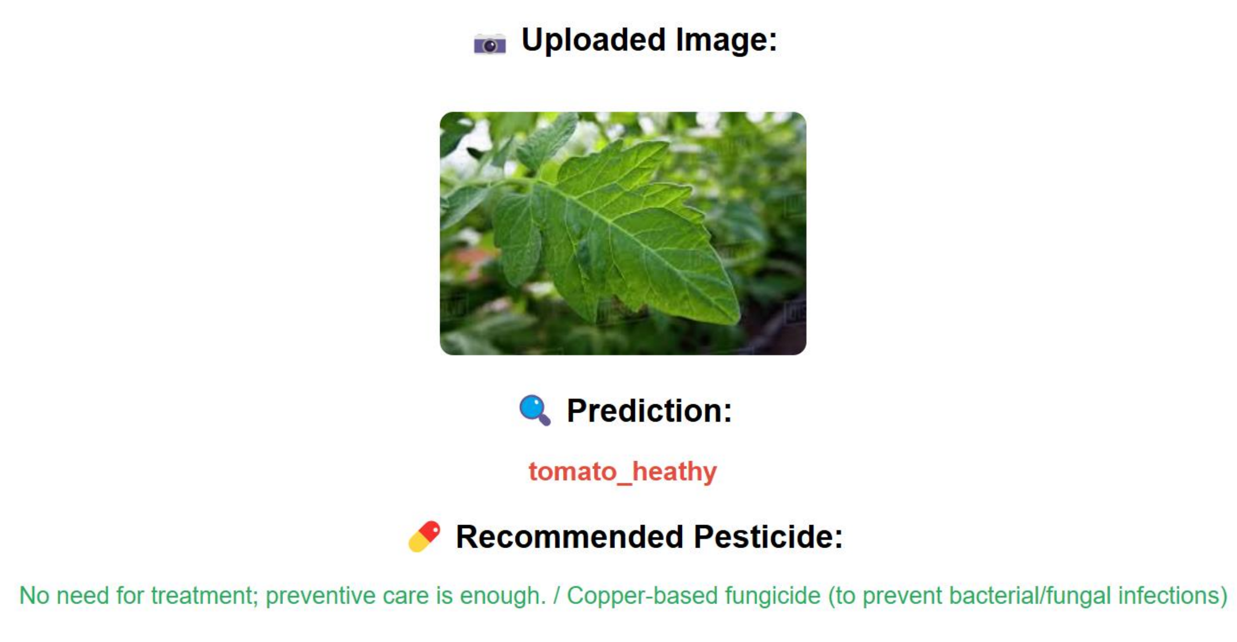

Fig – 3 : Tomato Healthy Leaf

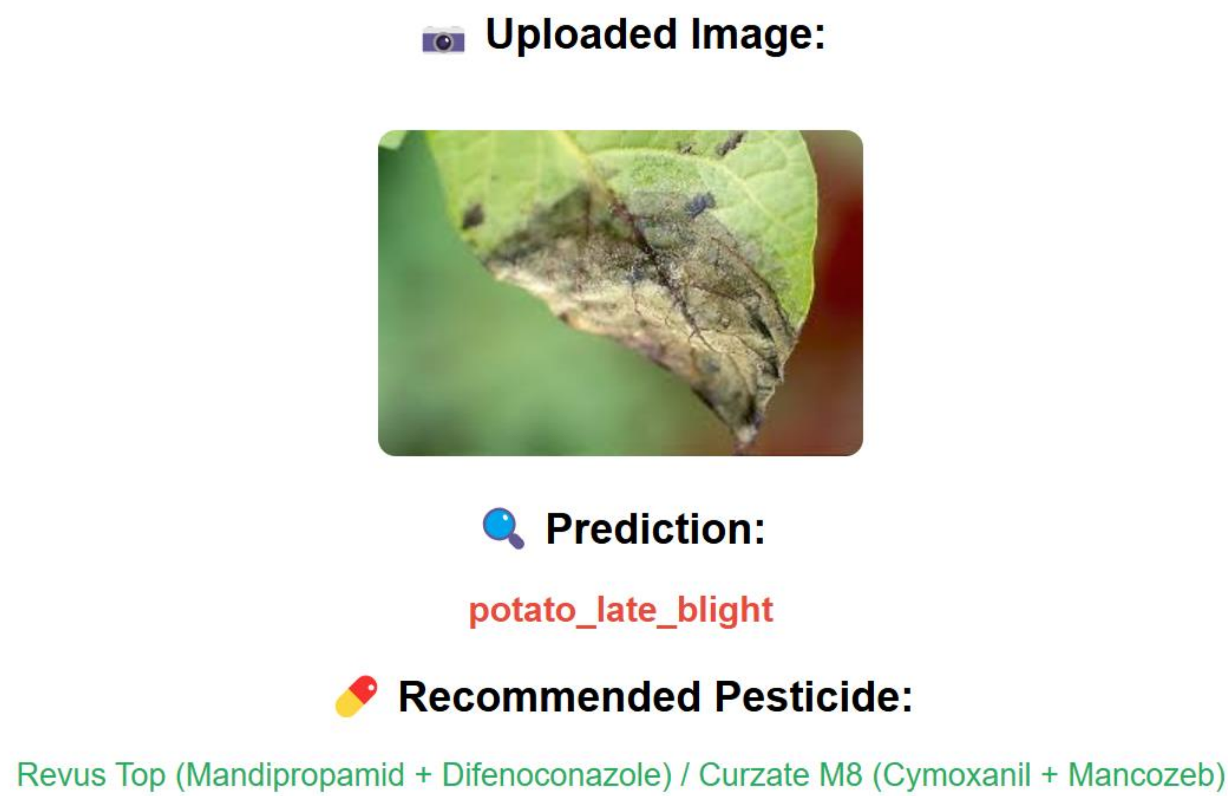

Fig – 4 : Potato Late Blight Disease Leaf

6. CONCLUSION

The successful deployment and development of the plant disease detection model for plant malfunction detection point to a major breakthrough in utilizing deep learning to solve agricultural problems. With an accuracy of 96.18%, the model proves to be highly reliable in classifying plant conditions such as diseases, pests, and abnormalities. By combining MobileNetV2 architecture, transfer learning, and data augmentation, the model is able to capture complex patterns in plant images. This ability enables farmers and agricultural stakeholders to make informed decisions, implement proactive management practices, and maximize resource allocation, thereby enhancing crop health and yield. Aside from agriculture, the model has the potential for large-scale applications in healthcare, cybersecurity, finance, and environmental monitoring. Its ability to make predictions can support innovation, improve decision-making mechanisms, and help solve complicated real-world issues in various sectors of the economy. The study highlights the revolutionary role of artificial intelligence and machine vision in precision agriculture. More refinements, further enhancements to the datasets, and interfacing with the current agricultural frameworks can make the model more robust and scalable. Ongoing research in this area can lead to sustainable solutions, enhance food security, and support global agricultural progress, making AI-based plant disease detection a precious asset for future farming.

7. REFERENCES

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