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Enhanced deep learning model architecture for plant disease detection in Chilli plants

Sultanul Arifeen Hamim[1], *Akinul Islam* Jony[1]

[1]*American International University-Bangladesh, 408/1, Kuratoli, Khilkhet, Dhaka 1229, Bangladesh*

Abstract. A new deep-learning model for classifying and detecting plant diseases in chilli plants is described. It is built on a modified version of the MobileNet architecture. The model overcomes conventional diagnostic tools' high computing costs and restricted adaptability by combining sophisticated optimisation models and reliable training procedures. The model considerably reduces the time and resources needed for an accurate diagnosis while effectively managing complicated illness presentations, with a diagnostic accuracy of 97.18%. Using the chilli leaf picture dataset, data augmentation, and fine-tuning techniques, the model shows promise for real-time disease diagnosis in agricultural environments. The study underscores the importance of high-quality image data and extensive training datasets, calling for further evaluation across various climatic and environmental conditions to ensure robustness and adaptability. This research opens new opportunities for AI-based models in diverse agricultural contexts, potentially leading to significant advancements in precision farming.

Keywords: image processing, computer vision, Chilli plants, deep-learning, plant disease detection

1. Introduction

Diagnosing plant diseases by optical examination of the symptoms on the leaves of the plants involves a very high degree of intricacy. Owing to this intricacy and the vast array of domesticated plants and the phytopathological issues accompanying them, even highly skilled agronomists and plant pathologists frequently need to catch up in accurately diagnosing specific diseases, leading to incorrect conclusions and treatments. The agronomist, who must make these diagnoses by visually observing the leaves of afflicted plants, would greatly benefit from an automated computational system to detect and diagnose plant illnesses [2, 16]. The system, if designed for simplicity and accessibility through a basic mobile application, could be a valuable tool for farmers in regions lacking the necessary infrastructure to offer agronomic and phytopathological guidance. Furthermore, using continuous image capture, the system could integrate with autonomous agricultural vehicles in large-scale farming to accurately and promptly pinpoint phytopathological issues throughout the cultivation field. Agriculture is crucial to human civilisation as it provides food and essential materials for survival. Plant diseases pose significant hazards as they can significantly impact crop quality and output, affecting farmers' livelihoods and global food security. Pathogenic organisms, environmental pressures, and inappropriate agricultural practices contribute to plant diseases, necessitating

arifeenhamim@gmail.com (S. A. Hamim); akinul@aiub.edu (A. I. Jony)
https://cs.aiub.edu/profile/arifeen.hamim (S. A. Hamim); https://cs.aiub.edu/profile/akinul (A. I. Jony)
0009-0008-4402-0739 (S. A. Hamim); 0000-0002-2942-6780 (A. I. Jony)

advanced detection and intervention techniques [13, 14, 23].

Farmers have traditionally used manual examination, a labour-intensive and error-prone method, to detect and classify plant diseases. This conventional method frequently results in postponed interventions, which spreads illnesses and worsens crop productivity and health [8]. Leaf rust, stem rust, sclerotinia, powdery mildew, birds-eye spots on berries, damping down of seedlings, leaf spots, and chlorosis are typical plant disease signs. The physical state of the plant leaves can distinguish these diseases. Experts can identify defects by examining leaves, stems, or fruit. Many human resources are necessary for this specific task [2]. Convolutional neural networks (CNNs) are used in deep learning for image detection to evaluate and interpret visual data automatically. These models are very good at finding patterns and features in images, which makes them ideal for tasks like segmentation, classification, and object detection [5]. Deep learning models can precisely identify and categorise different aspects inside images by learning from enormous datasets. This greatly improves applications in agricultural diagnostics, autonomous driving, and medical imaging domains, e.g. [22].

It might be more effective in this age of technology and automation; having an automated system that can recognise plant disease independently is excellent. One of the significant advantages of deep learning over machine learning is that it does not have to have feature engineering in contrast to these conventional machine-learning techniques. Hence, domain expertise is not an issue, e.g. [7, 19].

This paper introduces Advanced MobileNet, a novel deep-learning architecture that efficiently and accurately classifies plant diseases across various species. The model integrates advanced optimisation models and training strategies, significantly improving existing methods for handling the complexities of plant disease diagnosis. By enhancing MobileNet's architecture, this study seeks to establish new benchmarks in the field, offering a robust solution that supports precision farming and promotes agricultural sustainability. The rest of this essay is organised as follows: A thorough analysis of the pertinent literature is provided in Section 2, which also highlights the difficulties and developments in plant disease detection. The materials and techniques used to create the Advanced MobileNet architecture are described in Section 3, along with the steps involved in model training, dataset preparation, and validation. The results are shown in Section 4, and the model's efficacy is discussed. In conclusion, Section 5 offers a comprehensive synopsis of the study, deliberates on the results and proposes avenues for future research in agricultural technology and plant disease control.

2. Literature review

According to recent research, CNN designs are essential to advancing plant disease detection. CNN architectures are becoming increasingly common in agricultural technology, particularly plant disease detection. Cutting-edge designs like InceptionV3 and MobileNetV3 have shown incredible computing efficiency and adaptability. These models provide notable gains in accuracy and are feasible to use on a range of systems [9, 20].

Several studies emphasise the importance of these advancements and stress how these models can quickly adapt to contexts with limited resources without compromising their ability to identify disease. With its modifications, MobileNetV3 is notable for its capacity to handle subtle details in leaf images by utilising Efficient Channel Attention (ECA) modules and dilated convolutions [11, 17].

Using an enhanced Plant Image dataset and deep learning, researchers have created a method for detecting plant diseases that can differentiate between healthy and diseased leaves. With an 85:15 data split, their CNN model produced a 96.3% accuracy rate using numerous convolution and pooling layers [2]. With an accuracy of 96.3% and a precision of 96%, a deep CNN created to identify leaf blight was able to classify 13 different forms of leaf illnesses and healthy leaves [12]. A deep CNN model was utilised in a different study to categorise plant types into distinct categories using photos. The study demonstrated a 99.53% success rate for real-time disease diagnosis [4]. With a 96% accuracy rate, the ResNet18 model, which was trained by transfer learning, recognised different leaf types and related diseases. A deep CNN model achieved 95.81% accuracy in plant disease detection using a dataset of images across 38 classes [24]. Another study on citrus plant diseases found deep learning models, especially Inception v3 and VGG architectures, superior to conventional machine learning techniques [21].

The Plant Village dataset covers 38 disease categories across 14 crops. It demonstrated that the DENN model outperformed DenseNet 121 and InceptionV3 using a thorough evaluation system for pre-trained neural networks [25]. MobileNetV2, using its inverted residual structure and lightweight depth-wise convolutions to identify different plant leaf diseases, obtained 95% accuracy for ImageNet [11]. Lastly, for early and late stages of blight, the novel EfficientRMT-Net model achieved high accuracy rates 97.65% on the general Dataset and 99.12% on specialised datasets) for automatic detection and classification of potato leaf diseases [18]. Scientists are advancing technology in agriculture and creating more modern methods for identifying plant illnesses. Researchers are advancing transfer learning and architecture to make their computer models more accurate and efficient [15]. By enhancing the identification and management of plant diseases, these models could contribute to better crop management and sustainable agriculture. As a result, improving crop management and yield in many global farming contexts is possible [1].

3. Model and architecture

3.1. Data collection

The data for this study were collected from three separate datasets, each focusing on a specific type of crop disease. The datasets were meticulously assembled to encompass various disease manifestations, providing a comprehensive basis for training our deep-learning models.

Three hundred photos in the collection show chilli plant leaves in various settings. These illustrations represent four classifications of disease and one class of health. The pictures are as follows: 42 photos with a whitefly infestation, 92 photos with leaf spots, 50 photos of leaves afflicted by leaf curl, and 115 photos in good condition. This Dataset thoroughly depicts the many stages at which leaves on chilli plants can be found. As such, it is an invaluable tool for developing and testing machine learning models intended to identify plant diseases. This Dataset aids in the creation of a reliable and precise classification model because it covers a variety of states of illness and health. The range of picture settings aids in developing models that effectively generalise to actual situations, enhancing the potential for practical applications in agricultural technology and improving the efficiency of disease management strategies.

These datasets were used to ensure diversity in the conditions presented, which is essential for training robust and generalisable deep-learning models for plant disease detection and classification. Images were gathered using standard procedures for quality and resolution to maintain consistency and provide a reliable basis for the model development and validation stages. Sample images of Dataset are shown in figure 1.

Figure 1: Sample images of Chilli dataset.

3.2. Data preprocessing

The datasets on chillies underwent careful preprocessing to prepare them for deep learning research. A series of transformations were applied to each Dataset to ensure the best possible input quality for the models. The first step involved resizing each image to the exact dimensions to ensure consistency between datasets and expedite the training of deep learning models. The target dimensions for resizing were determined based on the input requirements of the deep learning models, balancing computational efficiency with the preservation of important characteristics. Standardising the input data through scaling was essential for the models to learn from and effectively generalise the photos. Consistency in image dimensions through preprocessing enhances the robustness of the model training process, ultimately contributing to the development of accurate and efficient plant disease detection systems. These procedures are the foundation for preparing the datasets for advanced deep-learning applications in agricultural technology.

The Dataset was artificially enlarged by applying a series of augmentations to each image. These augmentations included random rotations within a 40-degree range, a 0.2 brightness change, and a 0.2 contrast modification. Two augmented images were created and saved for every original image. The images were then scaled to 224x224 pixels to maintain important information while meeting the input requirements of the CNN. Normalising pixel intensities to a [0, 1] scale improved training stability and model convergence. The Dataset was split at 70:30

using randomisation for training, validation, and test sets. Class labels were one-hot encoded and converted to integers to be used with the definite cross-entropy loss function. Finally, the sizes and distributions of the training, validation, and test sets were confirmed to ensure the integrity and representativeness of the Dataset, which are essential components for an objective assessment of the model.

3.3. Environment setup

The research utilised the strong capabilities of Python to develop some of the critical detection models. Several pre-trained deep learning models were trained in Google Colab using TensorFlow and Keras, leveraging advanced computational resources like Tesla GPUs. The experimental setup was meticulously tailored to meet the specific requirements of each model, with MobileNet utilising the NVIDIA GPU. Input data was resized to dimensions between 224×224 and 299×299 pixels, depending on the model. Batch sizes, optimised with the Adam optimiser at a learning rate of 1×105, ranged from 32 to 64. Models were trained for 15 epochs by using the ReLU activation function. Data augmentation was applied to models on the GPU to enhance generalisation.

3.4. Model architecture

For better computational efficiency, a variant of MobileNet was used in this study, first trained on the Image dataset and then applying transfer learning to specific dataset features. By standard MobileNet input, the MobileNet base was changed to accept input dimensions of 224 x 224 pixels in RGB format. The network's width was decreased by setting the width multiplier (alpha) to 0.75. This reduced complexity and the number of parameters, which allowed processing to proceed more quickly with little loss of accuracy. A dropout rate of 0.001 and the elimination of pooling layers were among the modifications that allowed feature mappings from the final convolutional layer to flow through directly. The architecture includes a dropout layer at 0.5, a dense layer with 256 neurons employing ReLU activation, and a layer to convert outputs into a single vector to prevent overfitting. Softmax activation is used in the output layer for categorisation. While freshly added layers were trainable and could use MobileNet's feature extraction to adjust to new data, the base layers of MobileNet were initially frozen to preserve pre-trained weights. Figure 2 shows the visual representation of the model architecture.

3.5. Evaluation metrics

This study employed a confusion matrix for graphical representation and evaluation measures to evaluate each model's performance. The confusion matrix compares the model's predicted labels with the actual labels. Specific indicators from the confusion matrix presented in the table are essential to assess the efficacy of the model's predictions fully.

Table 1 illustrates the confusion matrix concept, where TN is an appropriately expected negative consequence, FN denotes an inaccurately forecasted negative outcome, TP represents a correctly predicted positive outcome, FP represents an incorrectly predicted positive outcome, and so on. Below is a description of the accuracy, precision, and recall formulas (e.g. [3, 6, 10]).

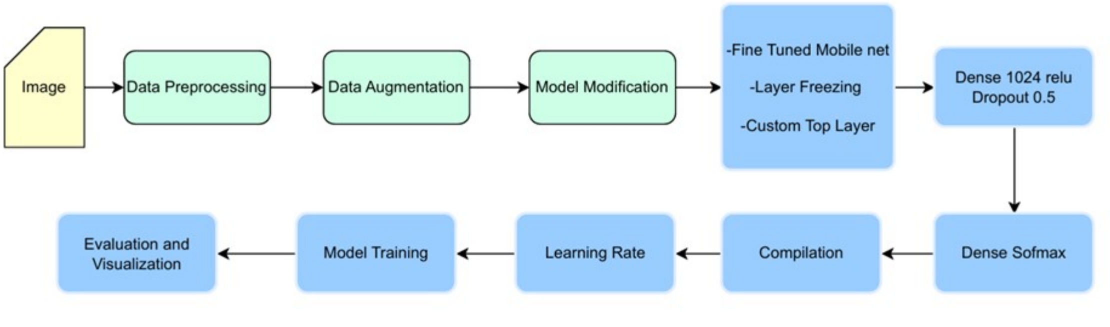


Figure 2: Model architecture of proposed MobileNet model.

Table 1
The table illustrates the concept of confusion in the matrix.

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

4. Results and discussion

Neural network models were created and evaluated based on a Chilli dataset to improve plant disease identification. The models involved were base architectures and modifications of MobileNet. Across the Dataset, the adjusted MobileNet models continuously outperformed the base versions in terms of accuracy and data loss reduction. The modified MobileNet performed remarkably well on the chilli dataset, achieving 97.18% accuracy with a loss of 0.0466, compared to 90.65% accuracy and 0.28% loss for the base MobileNet. The optimised architecture of the upgraded MobileNet models is responsible for their consistently better performance. Several modifications were made to improve feature extraction and generalisation skills and provide a more comprehensive and nuanced knowledge of the signs of chilli sickness in the images.

The performance outcomes of the base and modified MobileNet models, shown in table 2, highlight the effectiveness of the proposed MobileNet model. Here, the modified model shows a significant improvement for the Chilli dataset, soaring to 97.18% across precision, recall, F1-score, and accuracy metrics from the base model's livery of 90.65%. Table 2 highlights

Table 2
Performance outcomes of the base and modified MobileNet models.

Model	Precision	Recall	F1-Score	Accuracy
Base (chilli)	90.25%	90.65%	90.25%	90.65%
Proposed (chili)	97.12%	97.28%	97.12%	97.18%

the quantifiable advancements of the proposed MobileNet model and attests to its augmented predictive proficiency, positioning it as a formidable tool in agricultural disease surveillance.

Figure 3 is a bar graph that visually shows the performance outcomes for the base and modified MobileNet models shown in the table. The graph identifies precision, recall, F1-score, and accuracy for both the base and proposed models, represented as 'chilli' and 'chilli', respectively. This shows a significant improvement in the proposed model over the base for all metrics.

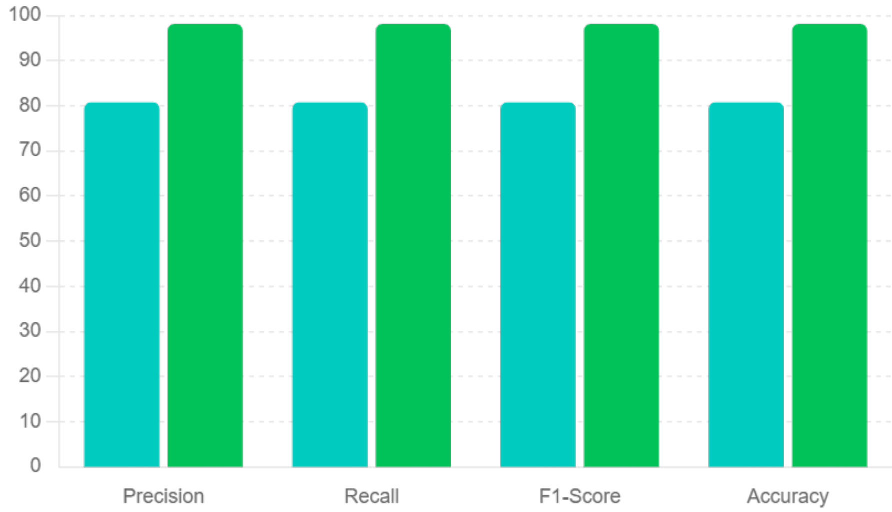
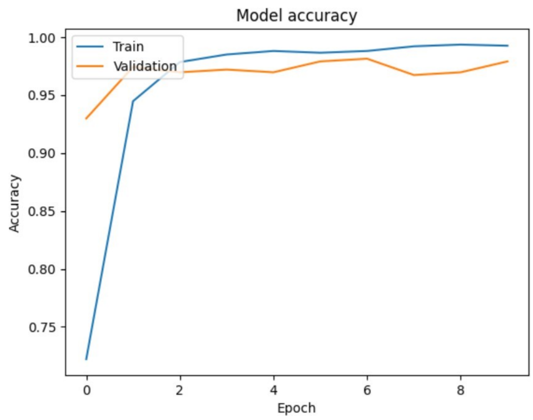


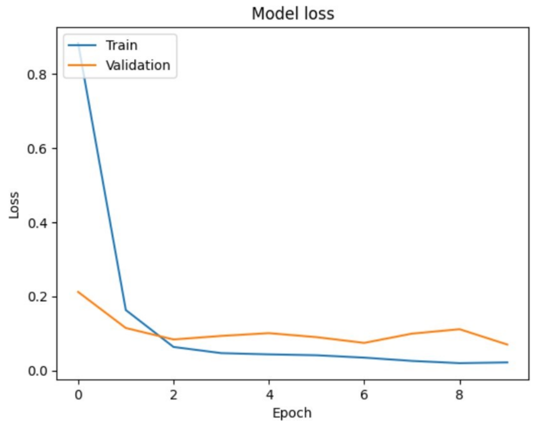
Figure 3: Sample images of chilli Dataset.

Figure 4 shows the learning curves that describe the architectural optimisation and enhanced predictive performance of the MobileNet models in assessing the models over the Chili dataset. Figures 4a and 4b show the base model's training and validation accuracy and loss, and figures 4c and 4d show the modified model's training and validation accuracy and loss. The modified MobileNet shows an expeditious elevation to peak training accuracy, with a notable generality to validation data, as seen in the chilli dataset. This model's training and validation accuracies combine closely, eschewing the overfitting marked in the base MobileNet, where a noticeable difference between training and validation curves shows a less generalisable approach.

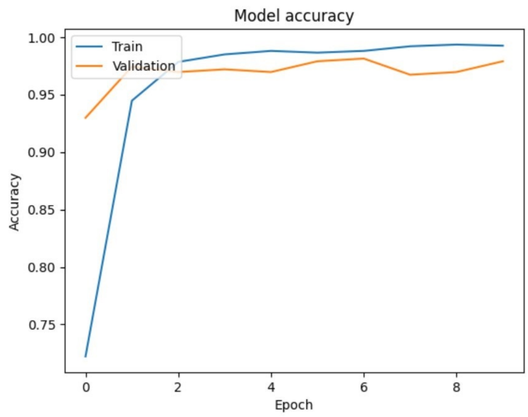
The modified MobileNet's early and tight convergence of accuracy metrics in the Chili dataset Figure 4 emphasises its robustness, in sharp contrast to the standard model's broader accuracy gap. Loss patterns across these datasets highlight the updated model's steady validation loss, indicating a more customised fit and reliable learning. To improve plant health, the research



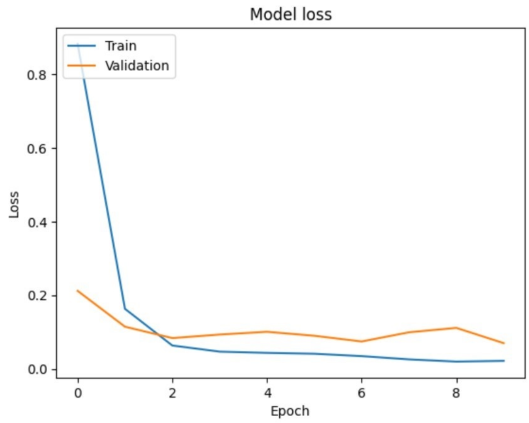
(a)



(b)



(c)



(d)

Figure 4: Training and validation loss and training and validation accuracy between the base model and modified model of chilli.

presents a novel deep-learning model that classifies and detects illnesses in chilli plants. The study modifies the MobileNet architecture to address computing costs and flexibility issues. It integrates an advanced optimisation model with feature extraction and augmentation techniques to improve learning from limited data. The modified MobileNet model demonstrates superior performance, as shown by detailed confusion matrices, high accuracy, and accurate solid positive rates across different plant species. The work highlights how deep learning, more significantly, CNN architectures like MobileNetV3, may improve measures for classifying plant diseases, including accuracy, precision, recall, and F1-score. Subsequent investigations should broaden the Dataset to encompass additional stages and manifestations of the ailment and investigate the model's utilisation in real-time precision agricultural monitoring systems.

5. Conclusion

This study offers a refined deep-learning model and a modified MobileNet architecture version for classifying plant diseases among different species. To overcome the high computational costs and restricted adaptability of earlier models, the study tackles significant concerns in agricultural health by combining cutting-edge computational approaches and reliable training strategies. The suggested model obtains a diagnostic accuracy of 97.18% in chilli plants, indicating its capacity to control complicated disease symptoms and lower the resources required for precise diagnosis. With a large leaf picture dataset and cutting-edge training techniques, including data augmentation and fine-tuning, the model shows promise as a valuable tool for agricultural real-time disease identification. The study also sets the stage for future research into tailoring AI models for different agricultural uses, potentially leading to significant advancements in precision farming. Despite the encouraging outcomes, the study recognises the necessity of high-quality image data and thorough training datasets and advocates for additional testing in diverse weather and environmental conditions. This study underscores the potential of AI-based diagnostic tools to transform agricultural methods, underscoring the significance of ongoing model improvement and dataset expansion to ensure strength and flexibility.

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