CNN-Based Mango Leaf Disease Detection: Deep Learning Approach for Precision Agriculture

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***Abstract*—Mango plays a crucial role in Bangladesh's agricultural landscape due to its significant economic importance. Nonetheless, it faces considerable hurdles, primarily in the form of diseases that can severely diminish yield outcomes. Traditional disease detection methods often rely on visual inspections, which can be time-consuming and prone to biases. In this research, we leverage advanced computer vision techniques and deep learning models, specifically Convolutional Neural Networks (CNNs), to automate the detection and classification of mango leaf diseases. We used the "MangoLeafBD" dataset, comprising various disease categories and healthy leaf images, totaling 4,000 samples. The proposed CNN architecture includes preprocessing, data augmentation, and multiple convolutional layers, demonstrating remarkable results. Through a 30-epoch training process, the model achieves a test accuracy of 98.18%, showcasing its proficiency in mango leaf disease identification. This research contributes to the automation of disease diagnosis in agriculture, offering potential benefits for crop management and yield improvement.**

***Index Terms*—Deep Learning, Convolutional Neural Network, Mango Leaf Disease, Computer Vision**

I. Introduction

Agriculture stands as the economic backbone of nations, with Bangladesh exemplifying this reliance on crop cultivation. Mango (Mangifera indica), a globally renowned fruit, occupies a significant position in Bangladesh agriculture. Despite the advancements in modern agricultural technologies, the sector faces challenges, including a surge in leaf diseases and the escalating use of pesticides, adversely impacting crop yields [1]. The mango crop faces numerous challenges such as pathological disorders, serious diseases, and the extensive use of pesticides, all of which can significantly impact its yields. Diseases in mango plant leaves can be caused by adverse climatic conditions, parasites, fungus, viruses, and bacteria. The common diseases of mango plant includes gall midge, cutting weevil, die back, powdery mildew, anthracnose, bacterial canker, sooty mould etc. These maladies not only deteriorate mango quality but also detrimentally affect production, incurring substantial losses for stakeholders. Currently, disease detection primarily relies on visual inspections conducted by agricultural experts, an approach often fraught with biases and inaccuracies and inefficient for vast agricultural fields [2]. A variety of advanced computer-aided techniques, deep learning techniques, artificial intelligence technologies, and machine learning approaches with optimization algorithms have been used for categorization of mango leaf disease. These solutions provide a significant platform for mango plant enhancement, maintenance, management, disease identification, and productivity improvement [3].

This research paper incorporates a cutting-edge approach that employs a deep learning-based convolutional neural network (CNN) technique for the precise identification and classification of mango leaf diseases based on images. In this study, we leverage the "MangoLeafBD" dataset as our primary resource [19].

II. Related Work

Over the past few decades, leaf disease detection has been a prominent area of research. To enhance the accuracy of disease diagnosis, scientists have explored various methodologies involving machine learning and pattern recognition. These approaches encompass a range of techniques, including Convolutional Neural Networks (CNNs) [4], Artificial Neural Networks [5], Back Propagation Neural Networks [6], Support Vector Machines (SVMs) [7], and various image processing methods [8], [9].

Ferentinos in [10] has proposed a VGG convolutional neural network for the identification and classification of the plant leaves. The proposed method classifies the given images between healthy and diseased. The result was validated on a large dataset shows the accuracy of the deep learning approach. Kaur et al. in [11] have presented a study of the computer vision concepts and methods adopted for the detection and classification of the plant leaves. The advantages and disadvantages of the several studies have been discussed separately. Too et al. in [12] have used four different deep convolutional network architectures including VGG 16, Inception V4, ResNet and DenseNets for the classification of disease from an image. The images were taken from the plant Village dataset consists of 38 diseased classes and 14 healthy classes. The DenseNets network achieves higher classification accuracy and lesser computational time when compared with other architectures. GoogLeNet and Cifar10 network have been presented by Zhang et al. in [13] for the classification of diseases from the maize leaf images. The proposed models achieve higher accuracy when compared with other networks like VGG and AlexNet for classifying nine different types of maize leaves.

Gandhi et al. [14] have worked with Generative Adversarial Networks (GANs) and CNN for the identification of diseases from the plant leaf images using a mobile application. Iqbal et al. in [15] have presented the number of studies for the identification and classification of the citrus plant leaves diseases. In this review work, the authors have discussed almost all the methodologies associated with detecting the disease, including concepts of image processing, techniques, challenges, advantages, and disadvantages etc. Barbedo [16] have presented a study of the deep learning in the plant pathology. The author in this work has presented various issues and parameters that affect the efficiency of the network. Finally, the results verified the performance of the convolutional neural network on the images taken from the Digipathos repository. In [17] Picon et al. have used DCNN for the classification of three fungal diseases found in the wheat plant. The images in the proposed work were collected in the real-time environment at two locations for about three consecutive years. AlexNet and then SqueezeNet deep learning network has been used by Durmus et al. in [18] for the classification of plant leaf diseases. The images are taken from the plantVillage database for the tomato plant leaf images in ten different classes.

III. Methodology

This section presents the details of the dataset, proposed methodology and implemented model.

A. Dataset Description

The dataset 'MangoLeafBD' was collected for the study. The dataset comprises seven different classes of mango leaf diseases and one healthy leaf image. The dataset contains leaf images infected with powdery mildew, anthracnose, dieback, cutting weevil, bacterial canker, gall midge, sooty mould, and healthy leaf. The dataset comprises 500 images in each class, totaling 4,000 images consisting of both infected and healthy leaves. Each image has width of 320 pixels and height of 240 pixels.

B. Convolutional Neural Network Architecture

The model layout has three levels as described below.

- The first level is the preprocessing and augmentation level. At first, the images are resized to 240X240 and then rescaled. After the preprocessing, the image dataset is enhanced using various types of argumentation operations such as flipping, rotation, zooming and contrasting.
- The second level covers the stacking of various convolutional neural network layers with sub layers such as Conv2D, MaxPooling2D, BatchNormalization, Dropout, and Dense layers. The detail of the neural network is given in the next subsection.
- The third level uses a machine learning model which apply classification on the aggregated outcome of all the deep learning models and finally predict the disease in plant leaf.

1) Preprocessing and Augmentation: The preprocessing and augmentation procedures applied to the raw image dataset to prepare it for training and testing is discussed below.

- Image Resizing: Initially, all images in the dataset are resized to a uniform dimension of 240x240 pixels. This resizing step standardizes the input size, ensuring consistency across the dataset.
- Image Rescaling: Following resizing, the pixel values of the images are rescaled to a common range, typically [0, 1]. This normalization process helps in stabilizing training by preventing the neural network from being sensitive to variations in pixel intensity.
- Data Augmentation: To enrich the dataset and enhance its diversity, we employ various data augmentation techniques. Flipping increases the dataset's variability by presenting mirror images to the model. Rotation simulates variations in object orientation and viewpoint. Zooming mimics changes in camera distance and viewpoint. Contrasting introduces variations in brightness and enhances the model's robustness to different lighting conditions.

2) CNN Layers: The model is trained with the data extracted in the previous level. In the CNN, the image dataset is processed in different layers, and each layer has the following sub-layers:

- Convolutional Layer: Convolutional layers in CNNs use learnable filters to scan input data like images, extracting spatial patterns and features through convolution. This process creates hierarchical representations, enabling the network to detect complex features in the data.
- Pooling Layer: Pooling layers are crucial in CNNs as they reduce the spatial dimensions of feature maps through downsampling, using methods like max-pooling or average-pooling. This preserves important information while simplifying computations, enhancing the network's robustness to variations.
- Fully Connected Layer: This layer connects to both preceding and subsequent layers, a common CNN practice that demands significant computational resources. The main challenge is the high number of weights, which can be addressed by reducing nodes, links, and dimensions. Dropout is an effective method for trimming nodes and connections.
- Dropout Layer: Dropout is a regularization technique in neural networks, including CNNs, where a fraction of neurons is randomly turned off during training. This promotes the learning of robust and general features, reducing overfitting and improving performance on new data.
- Batch Normalization Layer: Applied to intermediate layers, batch normalization standardizes activations within mini-batches, enhancing training stability and convergence while mitigating gradient issues.

3) Output Layer: The output layer of neural networks often utilizes the softmax function to transform raw scores into probability distributions over classes. The softmax is defined by the below function:

$$P(y_i = 1|x) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (1)$$

$P(y_i = 1 \,|\, x)$ denotes the probability of class i. z_i represents the raw score for class i. K is the total number of classes.

C. Model Description

The dataset consists of total 4000, 320x240 pixel images of both diseased and healthy leaves. The proposed CNN consists of input layer, hidden layers, and output layer. The layer implementation is described in Table-1.

TABLE I
LAYER DETAILS OF CNN

Layer	**Filter Size**	**Output Size**
Input Layer		(320, 240, 3)
Resize & Rescale		(240, 240, 3)
Data Augmentation		(240, 240, 3)
Conv. Layer 1	(16, 16)	(115, 115, 16)
Max Pool Layer 1		(57, 57, 16)
Batch Norm. Layer 1		(57, 57, 16)
Conv. Layer 2	(32, 32)	(51, 51, 32)
Conv. Layer 3	(32, 32)	(51, 51, 32)
Max Pool Layer 2		(25, 25, 32)
Batch Norm. Layer 2		(25, 25, 32)
Conv. Layer 4	(32, 32)	(19, 19, 32)
Conv. Layer 5	(64, 64)	(19, 19, 64)
Max Pool Layer 3		(9, 9, 64)
Batch Norm. Layer 3		(9, 9, 64)
Flatten		5184
Dropout		5184
FC Layer		128
Batch Norm. Layer 3		128
Output		8

Initially, the input images, resized to 240x240 pixels with three color channels, are processed through a convolutional layer featuring 16 filters of size 11x11. This layer uses the Rectified Linear Unit (ReLU) activation function and produces an output volume of 115x115x16. Subsequently, a max-pooling layer reduces the spatial dimensions to 57x57x16, followed by batch normalization to enhance training stability.

The network then proceeds through two more convolutional layers, each equipped with 32 filters of size 7x7 and ReLU activation. These layers maintain the output size at 51x51x32. A second max-pooling layer further reduces the dimensions to 25x25x32, and batch normalization is applied once more for normalization purposes. Moving forward, two additional convolutional layers are introduced. The fourth layer employs 32 filters of size 7x7, without specifying an activation function, resulting in an output size of 19x19x32. The fifth layer employs 64 filters of size 5x5, utilizing the ReLU activation function and yielding an output size of 19x19x64.

Following these convolutional layers, a final max-pooling layer is employed, reducing the spatial dimensions to 9x9x64, and batch normalization is applied again. Subsequently, the output is flattened to a one-dimensional vector, and dropout regularization is introduced to reduce overfitting. The network continues with two fully connected layers, comprising 128 and 8 units, respectively, where the final layer employs the softmax activation function for classification, producing output probabilities for the different classes of the problem.

IV. RESULT DISCUSSION

In this study, we trained a deep learning model for diseased mango leaf classification over 30 epochs, incorporating advanced techniques such as early stopping and learning rate scheduling to optimize its performance. The model's training progress is reflected in the training and validation loss and accuracy metrics. The accuracy and loss comparison is shown in Figure-1 & Figure-2.

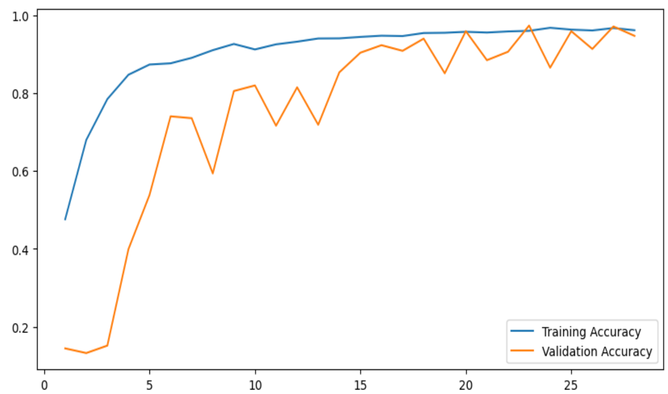

Fig. 1. Training and Validation Accuracy

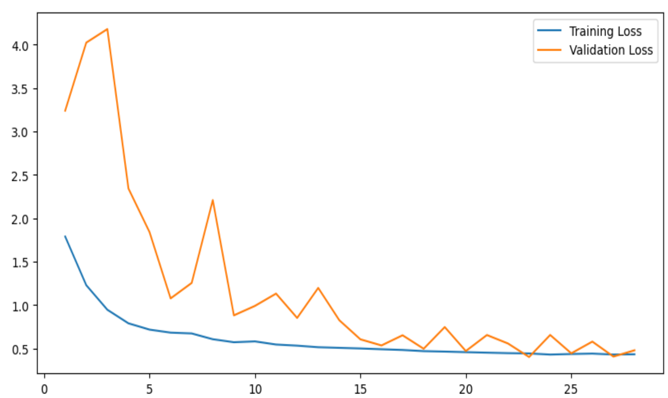

Fig. 2. Training and Validation Loss

At the beginning of the training process, the model exhibited an accuracy of approximately 47.59% on the training data, indicating limited discriminative power, while the validation accuracy lagged significantly behind at 14.42%. This initial performance gap between training and validation accuracy hinted at a potential overfitting issue.

However, as training progressed, the model's accuracy on the training data steadily improved, reaching an impressive 98.18% by the end of the training phase. This substantial enhancement underscores the model's capacity to learn and adapt to the training data. Notably, the validation dataset also saw improvements over time, with the highest accuracy reaching 95.91% by the training's conclusion. This demonstrates that the model not only learned from the training data but also displayed a high level of generalization to unseen data, affirming its effectiveness in image classification.

Concerning loss, the training loss consistently decreased throughout the epochs, indicating the model's convergence. Nevertheless, the validation loss exhibited fluctuations, potentially attributed to dataset complexity or model architecture intricacies. Further investigation to minimize the gap between training and validation loss may be a promising avenue for future research.

Our deep learning model achieved an outstanding test accuracy of 98.18%, attesting to its proficiency in this image classification task. The incorporation of advanced techniques, notably early stopping and learning rate scheduling, played a pivotal role in optimizing the model's performance. While fluctuations in validation loss and the initial performance gap between training and validation accuracy suggest room for model refinement, these results unequivocally highlight the model's potential for achieving high accuracy in image classification, holding promise for diverse real-world applications.

V. Conclusion

In this study, we've used deep learning techniques for detecting and classifying mango leaf diseases. Mango cultivation is vital in Bangladesh, but disease challenges can severely affect yields. Traditional diagnostic methods rely on time-consuming visual inspections, often prone to biases and unsuitable for large fields. To overcome these limitations, we used the "MangoLeafBD" dataset, featuring 4000 mango leaf images. Our deep learning approach, based on Convolutional Neural Networks (CNNs), automates disease detection and classification. The CNN architecture includes preprocessing, data augmentation, and multiple layers. With rigorous training over 30 epochs and advanced techniques like early stopping and learning rate scheduling, our model achieved an outstanding 98.18% accuracy. The impact of this research on precision agriculture is significant. Automated disease detection in mango crops can revolutionize crop management, enabling quicker, more accurate diagnoses, reducing yield losses, and promoting sustainable practices. Future work may explore optimization techniques, and adapt the model for real-world agricultural deployment. Overall, this research advances precision agriculture, enhancing crop yields and food security.

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