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LeafNet: A proficient convolutional neural network for detecting seven prominent mango leaf diseases

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ABSTRACT

Fruit production plays a significant role in meeting nutritional needs and contributing to the lessening of the global food crisis. Plant diseases are quite a common phenomenon that hampers gross production and causes huge losses for farmers in tropical South Asian weather conditions. In context, early-stage detection of plant disease is essential for healthy production. This research develops LeafNet, a convolutional neural network (CNN)-based approach to detect seven of the most common diseases of mango using images of the leaves. This model is trained specially for the pattern of mango diseases in Bangladesh using a novel dataset of region-specific images and is classified for almost all highly available mango diseases. The performance of LeafNet is evaluated with an average accuracy, precision, recall, F-score, and specificity of 98.55%, 99.508%, 99.45%, 99.47%, and 99.878%, respectively, in a 5-fold cross-validation that is higher than the state-of-the-art models like AlexNet and VGG16. LeafNet can be helpful in the detection of early symptoms of diseases, ultimately leading to a higher production of mangoes and contributing to the national economy.

1. Introduction

Global food scarcity is evident because of the growing population and the consequences of climate change worldwide. The population is expected to grow by 22% over the next five years, and the pressing need for food will influence the environmental, political, and economic system. According to the annual report of the International Food and Agriculture Organization (FAO), 193 million people have already suffered due to acute food shortages in 2021 [1]. Grains and fruits play a significant role in food nutrition, and various fungal and bacterial diseases can impact the production of these crops. However, plant diseases have been considered a hindrance to producing healthy products since the beginning of civilization. They can negatively impact the quality and quantity of foods, and therefore, early detection of these diseases is one of the most useful ways to address these issues [2].

Bangladesh is an agriculture-based country in South Asia, with only 147,570 square kilometers and more than 166 million people are living in this area. Of many crops, mango is a vital fruit here to meet the nutritional needs of inhabitants. However, various common diseases like Anthracnose, Die Back, Gall Midge, Bacterial Canker, Cutting Weevil, Powdery Mildew, and Sooty Mould affect mango production severely and significantly impact the country's economy. The cultivation of mangoes faces many challenges to prevent these diseases. For instance, Anthracnose is a fungal disease more likely to occur in humid climates. Bacterial Canker primarily affects leaves but can also impact stems and branches. Cutting Weevil is a common insect in Bangladesh that cuts new leaves. Sooty mould is also a disease caused by insects such as mango hoppers and coccids. Die Back causes discoloration of leaves. The state of the leaves can indicate if a mango tree is diseased. Due to these diseases, farmers may face significant losses despite their efforts, which may go untreated due to a lack of knowledge or technical support. Many farmers in the Indian Subcontinent are not adequately trained to detect these diseases and primarily rely on their own visual experience, which may result in the production of low-quality mangoes despite significant

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investments [3].

For proper disease treatment, timely and accurate detection is necessary. In the past, this task was performed by agricultural experts, but it took time. So, farmers often avoided it due to inconvenience and cost. Artificial intelligence (AI) solutions and methods can classify leaves based on disease. For example, convolutional neural network (CNN) are frequently employed in this field. CNN is one of the most used deep learning methods for image-related tasks because it produces promising results with low computational complexity. It requires fewer neurons, shortens training time, and its feedforward network is highly efficient for image pattern recognition [4]. CNN can be trained on specific images for a particular purpose, extracting features and classifying image datasets. Therefore, by introducing the model with images, CNN is a viable option for detecting mango leaf diseases. Its hidden layers update the weights, and the final layer uses an activation function to classify images. These machines and deep learning techniques have numerous applications in agriculture. Plant disease detection is often ignored due to insufficient knowledge or proper identification [5]. Deep learning models can be trained on all types of region-specific diseases for highly accurate predictions, which may not be possible with the naked eye. Farmers can easily use this technology by taking pictures and quickly predicting the disease [6].

Based on geography, significant differences are found in the application of neural networks where the deep learning models can be trained using any dataset of mango leaves. This creates a new opportunity for disease detection through proper research. However, developing such models requires a large dataset, and obtaining a balanced dataset makes it tough to create models with bias-free parameters. Thus, a knowledge gap exists in this domain for evaluating state-of-the-art (SOTA) algorithms with applicable datasets. While some researchers have explored fungal diseases like Anthracnose, there is still a need for more research on machine and deep learning models for plant diseases [7]. The pattern of diseases varies by region, and machine and deep learning-based research for mango leaves in Bangladesh is limited due to the need for local datasets. LeafNet, trained on images of Bangladeshi trees from different orchards. Thus, the quality of the dataset has been ensured, making the model fit for use in locations with similar weather conditions.

However, this paper briefly compares the machine and deep learning-based models for disease detection in crops and fruit leaves. LeafNet, a deep learning-based architecture, is developed using a new dataset of Bangladeshi mango leaves that has yet to be used in any previous models. LeafNet can classify the condition of mango leaves for seven prevalent diseases, including Anthracnose, Powdery Mildew, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, and Sooty Mould. This dataset has been published by the same research group, and to the best of the author's knowledge, this is the first study of its kind to utilize this dataset with all state-of-the-art (SOTA) algorithms. The LeafNet performance is compared with other SOTA models to validate its effectiveness. This study can help researchers, agriculturalists, and farmers to produce more healthy mangoes by evaluating the performance of the model to detect the disease of mango leaves.

The prime contribution of this manuscript is summarized as follows.

- The research has been conducted on a new mango leaf imagery dataset collected from orchards in Bangladesh.
- The CNN-based model, LeafNet has been developed using this novel data set.
- The model deals with multiclass classification for a total of seven most prevalent mango diseases of Bangladesh as well as the Indian subcontinent.
- The LeafNet shows better performance in evaluation parameters like average accuracy, precision, recall, F-score, and specificity. It reduces the computational complexity compared to other SOTA models like AlexNet and VGG 16.

This literature is divided into several sections. Section 2 contains a discussion about CNN based mango-leaf disease detection methods. Section 3 described the methods of the experimental setup with the data processing and development of the algorithms. Sections 4 and 5 represent the observed results and the corresponding discussion. Finally, the conclusions of the study with limitations and the scope of future work about the research are presented in Section 6.

2. Literature review

Leaf and crop diseases are detected using direct methods in many studies. For example, Sankaran et al. [8] compared the benefits and limitations of various non-invasive techniques used for plant disease detection, such as PCR-based molecular techniques, spectroscopic and imaging techniques (e.g., fluorescence spectroscopy, fluorescence imaging), and volatile organic compounds profiling-based techniques (e.g., electronic nose, GC-MS-based volatile metabolite analysis) to identify plant diseases. Another study by Fang et al. [9] discussed the identification of plant disease and prevention methods to minimize crop damage, increase productivity, and ensure agricultural sustainability. They used direct methods in agriculture such as GC-MS, PCR, FCM, ELISA, IF, and FISH, as well as indirect methods like thermography, hyperspectral techniques, and fluorescence imaging. Furthermore, it provides an overview of biosensors that are related to bio-recognition components such as enzymes, antibodies, DNA/RNA, and bacteriophages as a new method for the prompt detection of plant diseases.

Undoubtedly those techniques are reliable and accurate but require expensive equipment, time-consuming and labor-intensive. There are also some indirect methods, such as using new automated non-destructive technologies that can detect diseases early and specifically in real-time in the field. For example, imaging techniques using deep learning architectures have been applied to image detection and classification for agricultural applications. The study done by Vishnoi et al. [10] examines the various aspects and techniques used in automated plant disease detection, including covers techniques for image acquisition, preprocessing, lesion segmentation, feature extraction, and classifiers. Similarly, research conducted by Aftab et al. [11] focuses on applying image processing methods to find plant illnesses early on. Raspberry PI is used to link a camera to a display device and transfer data to the cloud. As part of the procedure, leaves are photographed and then analyzed utilizing techniques including acquisition, pre-processing segmentation, and clustering. Two trained models—Faster RCNN and SSD Mobile net—were shown to be accurate enough to identify practically all plant diseases. This strategy seeks to decrease worker demand, expenses, and efforts to increase productivity in broad agricultural regions. The paper by Abdulridha et al. [12] presented a low-cost automated early disease detection technique for avocado trees using remote sensing. The technique can detect laurel wilt disease (Lw) and differentiate between healthy and unhealthy plants. To design their system they used two cameras, a Tetra camera, and a modified Canon camera along with two classification methods namely neural network multilayer perceptron (MLP) and K-nearest neighbors. The MLP classification method detected Lw with 99% accuracy. In another paper, Zang et al. [13] approach to detect a bacterial disease of citrus tree leaves, by using global and region based local features in leaf images collected in the field. Furthermore, an improved bi-level detection method using the AdaBoost algorithm is made to detect canker lesions. This work found an accuracy of 87.99% using image processing compared to the accuracy of 86.88% achieved by human experts.

Besides, deep learning approaches were used to construct CNN models to detect plant diseases using leaf photos, which achieved higher success rates in detecting the corresponding [plant, illness] pair in many studies. For example, Vishnoi et al. [10] described a fast, cost-effective way to identify plant diseases using a transfer learning-based CNN model. They have used 87,867 images and classified them into 38 different classes. Popular transfer learning models like AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat, and VGG have some difficulties related to optimization, vanishing gradient, and degradation. This paper concluded that ResNet gave minimal losses and convergence time by showing an accuracy of about 99.90%. In another study conducted by Lu et al. [14] found that crops like rice disease can also be diagnosed using DCNNs techniques and 500 natural images of healthy and diseased rice leaves have been used. All these images were labeled into 10 individual classes based on the diseases and showed that CNN can successfully classify defective leaves using image processing. Their suggested approach performs better during training, faster propagation rate, and has higher recognition capabilities with an accuracy of 95.48% in comparison with other models. Similarly, Too et al. [15] provided the necessary analyses to prefer deep learning over machine learning and image processing in plant disease detection. They extended their research by analyzing models like VGG net, Inception V4, ResNet, and DenseNets. Apart from shallow networks VGG, all the other deeper models performed well. However, due to fewer parameters and reasonable computing time, they concluded that DenseNets would provide the best prediction to achieve state-of-the-art performance.

Conversely, Barbed et al. [16] found that deep learning in the field of plant pathology is impacted by various factors that need to be considered. These factors include a lack of sufficient data, issues with representing symptoms, changes in covariates, image backgrounds, conditions under which the images were captured, difficulty in segmenting symptoms, and disorders with identical symptoms. These factors were identified based on an experiment conducted on 50,000 images. In a similar study of disease detection, Golhani et al. [17] combined a neural network with a spectral disease index and compared it with a standard vegetation index to detect abnormalities in plants. Zhang et al. [18] proposed two improved models, GoogLeNet and Cifar, to identify maize leaf diseases. They classified their dataset of 500 images into 9 categories, with 8 categories representing diseased maize leaves and 1 category representing healthy leaves. Their research showed that the highest accuracy (98.8% and 98.9%) and efficiency can be achieved using these models, whereas conventional identification techniques like VGG and AlexNet structures require many model parameters and a long convergence period. Durmus et al. [19] performed a study to detect tomato leaf diseases using AlexNet and SqueezeNet deep learning structures. The images were taken from the Plant-Village database, which included 14 different crops. They only worked with tomato leaves, which were divided into 10 classes, and achieved a maximum accuracy of about 95% using AlexNet. However, in terms of model size and inference time, SqueezeNet performed better.

Additionally, Johannes et al. [20] worked with more than 3000 images of 38 different wheat plant varieties in a wild condition to identify three European endemic wheat diseases. They proposed a combination of a classic machine learning model with a statistical inference method, which consists of two stages: one for image preprocessing and normalization, and another for coupling the textural and color descriptors. However, the model's expressive capability was limited due to the color and texture descriptors, preventing it from becoming more generic. Picon et al. [21] updated the automated multi-disease detection technique demonstrated by Johannes et al. [20] for field acquisition settings. They used DCNN to detect early-stage diseases and simultaneous diseases, successfully validating the same three diseases on more than 8000 images and tested under real-field conditions. Juncheng Ma et al. [22] proposed using a DCNN to identify cucumber diseases using visible leaf symptom images. The model was created for symptom-wise categorization, enabling the identification of plant diseases without being influenced by multiple diseases present on a single leaf. The DCNN was trained using an image dataset that includes symptoms of cucumber disease namely anthracnose, powdery mildew, downy mildew, and target leaf spot. To compare the results, tests were performed using AlexNet and conventional models (Random Forest and Support Vector Machines), and the DCNN proved to be a reliable technique for identifying cucumber illnesses under field conditions, with a recognition accuracy of 93.4%.

In the disease detection of mango leaves, anthracnose is recognized as the most destructive fungal infection for a variety of tropical fruits including mango in recent times. A multilayer convolutional neural network (MCNN) has been proposed by Singh et al. [23] where they used 2200 images of different kinds of mango leaves. This deep learning model is appropriate for classifying infected mango leaves by the mentioned disease using several image datasets. The uniqueness of this model, compared to other state-of-the-art approaches, is that it can customize itself based on task-related findings. The structure of the model is inspired by the AlexNet architecture and showed an accuracy of 97.13%. Similarly, Rajbongshi et al. [24] used transfer learning techniques like DenseNet201, InceptionResNetV2, InceptionV3, ResNet50, ResNet152V2, and Xception to categorize and identify mango leaf diseases using CNN. The dataset of 1500 images of different varieties of mango leaves belonging to the diseased and healthy category was used to study several leaf diseases, including anthracnose, gall machi, red rust, and powdery mildew. The steps involved in disease detection include image acquisition, image segmentation, and feature extraction. Additionally, they assessed the performance matrices overall and discovered that DenseNet201 outperforms other models by achieving a maximum accuracy of 98%. Rao et al. [25] used a deep convolutional neural network (CNN) to detect and classify grape and mango leaf diseases using 8438 images of diseased and healthy leaves in the dataset. A well-established CNN architecture called AlexNet was used for feature extraction and their classification, achieving an accuracy rate of 99% for leaves of grape and 89% for that of mangoes. An application, "JIT CROPFIX" was developed to function the same on a smartphone with Android operating system. Limitations include a lack of diverse datasets, difficulty detecting small deformities, and challenges with varied lighting and occlusion.

A similar study was conducted by Merchant et al. [26] to detect the most common four nutritional deficiencies (Nitrogen, Iron, Potassium, and Copper) in mango. A popular unsupervised ML model, i.e., clustering technique, was used for finding the defective leaf by extracting the RGB values and texture indexes. Using digital image processing, healthy and unhealthy mango leaves can be distinguished by their deviation from the natural green color, which is dependent on the presence of water content. To detect the diseases of mango and potato plants, Arya et al. [27] collected approximately 3523 images with the help of two standard deep learning architectures: CNN and AlexNet. Although AlexNet took greater computational time to train than CNN, it outperformed by 98.33% in terms of accuracy. In contrast to conventional systems, the Neural Network Ensemble (NNE) for mango leaf disease detection (MLDR) presented in the research by Mia et al. [28] made disease identification simple and accurate. Support Vector Machines (SVMs) of NNE were employed in this study to identify four specific illnesses that affect mango leaves: Dag disease, Golmachi disease, Moricha disease, and Shutimold. According to their research, this approach was able to detect mango leaf diseases in 80% of cases. The authors proposed a machine-learning technique for the identification of pests in large mango fields using computer vision and deep learning. Their approach extended the VGG-16 model with a two-layer fully connected network, considering the real-world challenges faced by Indonesian farmers. The technique achieved an overall accuracy of 73% and 76% on the validation and testing data respectively representing an improvement of 13.43% in accuracy compared to the testing data. Another study by Militante et al. [29] offered an efficient solution for the detection of multiple diseases in various plant varieties, including apples, corn, grapes, potatoes, sugarcane, and tomatoes. The system was trained using both healthy and diseased leaves with 35,000 images and achieved 96.5% accuracy, with 100% accuracy for some cases. A model trained by Ferentinous et al. [30] using a convolutional neural network was applied to an open database of 87,848 images, resulting in a 99.53% accuracy rate in identifying plant diseases and healthy plants. To address crop health in remote regions of India, Jain et al. [31] developed a cloud-based system utilizing supervised learning and convolutional neural networks. They carried out the real-time classification of diseased plant images and compared algorithms to minimize the misclassification rate. Labeled data on plant diseases from India was collected for future reference and a dataset was made available. Table 1 presents a comparison of the literature studies on plant disease detection using deep learning and machine learning methods.

3. Methodology

This section will describe the methodology of the study with a brief discussion of the data collection and processing techniques. Then, the deep learning model AlexNet, VGGNet and the proposed CNN model, LeafNet architecture are described. All the architectures were implemented in Python using Tensorflow and Keras [33]. The experiments were conducted in a 64-bit machine having Ubuntu 20.04.4 LTS operating system, AMD @ Ryzen 9 5900x 12 Core Processor × 24, 128 GB RAM, Nvidia RTX 3080 Graphical Processing Unit (GPU). Fig. 1 illustrates the total workflow that has been used in this research.

3.1. Dataset description

The dataset, MangoleafBD [34] is used in this paper, in which the image data was collected from various regions of Bangladesh. It is a well-balanced dataset that contains images of seven different diseases of mango, including Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, and Sooty Mould, as well as images of healthy mango leaves, making a total of 8 classes. The dataset is ideal for proposing a deep-learning model for Bangladesh because the diseases of mango can vary regionally. The dataset consists of 1800 images of individual mango leaves captured using mobile phone cameras from four orchards in Bangladesh. As the background of the images of diseased leaves can cause bias and error in the training of the model, this dataset provides images with a white background. Additionally, the images were augmented with zoom and rotation to improve their size and scalability, resulting in a final dataset comprised of 4000 mango leaf instances from 8 categories, each with 500 images. The architectures used and proposed in this research aim to classify the eight categories of mango leaves. The eight categories of leaves are classified based on the disease they represent. First, there is anthracnose, which is a fungal disease caused by Colletotrichum gloeosporioides. This disease is characterized by dark, sunken lesions on the fruit and twigs, as well as brown spots on the leaves. It is most common in humid and damp conditions, and the leaves of infected plants will display a “shot hole” structure. In the final stages, the disease may affect the flowers, leading to their death. It is particularly prevalent in rainy and misty weather with 95% humidity around the plant. Next, there is bacterial canker, which is caused by Xanthomonas campestris pv. Mangiferaeindicae bacteria. The symptoms of this disease include sunken, water-soaked lesions on the stem, branches, and leaves. Tiny irregular stellate lesions can be seen on the mango leaves, the light-yellow lesions gradually turn yellow with necrotic cankerous patterns and brown patches on the lower side of the leaves. The halos on younger leaves are larger in shape compared to those on older leaves, and the severity of the disease can cause the leaves

Table 1
Literature comparison of the machine and deep learning methods applied in various plant disease detection.

Ref	Author(s)	Plant	Disease Name	Methods/ Techniques	Dataset Source	Dataset (No. of Images)	Accuracy/Auc
[31]	Jain et al.	Firecracker and pomegranate	Multiple	CNN	Self	1030	93.4%
[14]	Lu et al.	Rice	RB, RFS, RBS, RBD, RSHB, RSR, RBLB, RBSR, RSEB, BW	DCNN	Agricultural pest and insect pests picture database	500	95.48%
[20]	Johannes et al.	Wheat	Septoria, rust and tan spot	Image processing technique	Self-Captured	3000	0.8 (Auc)
[19]	Durmus et al.	Tomato leaves	Bacterial spot, late blight, leaf mould, septoria leaf spot, mosaic virus, yellow leaf curl virus and spider mites	SqueezeNet	Plant Village	54,309	94%
[15]	Too et al.	Plant leaves	Multiple	DenseNets	ImageNet	1.2 m	99.75%
[30]	K. Ferentinos	Multiple	Multiple	CNN	PlantVillage	87,848	99.53%
[16]	Barbed et al.	Multiple	Multiple	GoogLeNet	Digipathos		80.75%
[18]	Zhang et al.	Maize leaf	Curvularia leaf spot, dwarf mosaic, northern leaf blight, gray leaf spot, brown spot, round spot, rust, and southern leaf blight	GoogLeNet and Cifar	Plant Village and Google	500	98.8% and 98.9%
[21]	Picon et al.	Wheat	Septoria, rust and tan spot	DCNN Deep residual neural network	Imagenet ILSVRC15 dataset	8178	0.96 (Auc) 84%
[22]	J. Ma et al.	Cucumber leaves	Downy mildew powdery mildew and target leaf spots	DCNN	PlantVillage	14208	93.4%
[26]	Merchant et al.	Mango Leaves	Discoloring of leaves	ML clustering model	Self-Captured	-	-
[27]	Arya et al.	Potato and mango leaf	Early blight(potato) Anthracnose(mango)	CNN and AlexNet	PlantVillage	4004	98.33% (AlexNet 90.85% (CNN)
[23]	Singh et al.	Mango Leaves	Anthracnose	MCNN	PlantVillage	2200	97.13%
[29]	Militante et al.	Tomato, grape, apple, corn, suger-cane	Multiple	CNN	PlantVillage,	35000	96.5%
[28]	Mia et al.	Mango leaf	Dag disease, Golmachi, Moricha, and Shutimold disease	SVM of NNE	Self -Captured	-	80%
[32]	Kusrini et al.	Mango leaves	Multiple	SVM	PlantVillage, Self	510	76%
[10]	Kumar et al.	Mango Leaves	Anthracnose	ResNet	Self-captured, Plant Village	87867	99.90%
[24]	Rajbongshi et al.	Mango Leaves	Anthracnose, gall machi, powdery mildew, and red rust	DenseNet201	Self-Captured	1500	98.00%
[25]	Rao et al.	grape and mango leaf	Mango (BacteriaCanker disease, Powdery Mildew, Scab) and Grape (Black Measles, Black rot, Blight)	Transfer Learning using AlexNe	PlantVillage	8438	99% (grape) 89%(mango)

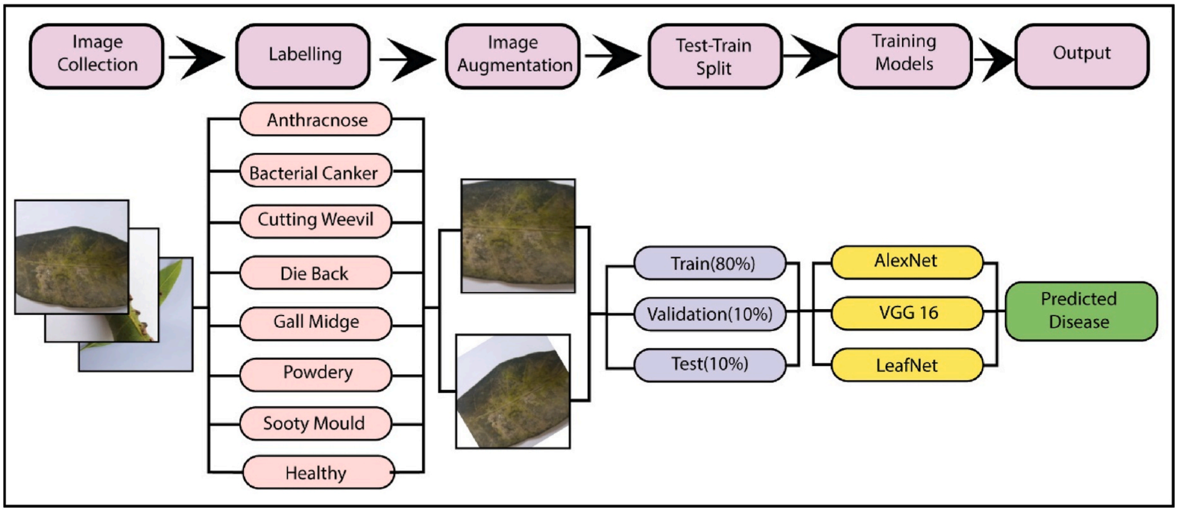

Fig. 1. Proposed workflow.

to fall off. Table 2 provides a detailed description of the mango leaves dataset. On the other hand, Fig. 2 provides a snapshot of the dataset and lists the corresponding class names for each category.

The Cutting Weevil, a type of beetle known as Sternochetus mangiferae, is a severe pest of mango trees. It affects young trees by cutting the bark of shoots and branches, causing wilting and death. The weevil also lays eggs in the cuts and the larvae feed on the sapwood of the branches, causing additional damage. Symptoms of cutting weevil damage include wilting leaves and shoots, as well as small, round holes in the bark and frass near the holes. Dieback, a disease of mango, is caused by various pathogens such as bacteria and fungi.

Dieback disease in mango trees can cause the wilting and death of branches, twigs, and leaves and, if not treated promptly, can eventually affect the entire tree. The specific reason for dieback may vary based on location and conditions, including Phytophthora spp, Fusarium spp, and Ceratocystis fimbriata. Environmental factors like waterlogged soil, high humidity, and high temperatures can also contribute to the disease. The dieback symptoms include wilting and discoloration of leaves and branches, followed by death of twigs, branches, and the entire tree.

Table 2
Description of dataset [34].

Subject	Agriculture
Specific subject area	The problem of classifying mango leaves using ML-based techniques
Data type	Digital image
Data description	The authors selected four mango orchards in different locations in Bangladesh to collect mango image data based on the variety of trees and size. They considered the frequently occurring seven mango leaf diseases. The images were captured a few days before the winter of 2021. The dataset contained around 1800 unique images. There were in total seven categories of diseased leaves and one category of healthy leaves. Each -category contained 500 images, making a total of 4000 images. After collecting the 1800 unique leaves, they were pictured after zooming in different scales along with rotating in different orientations to include different real-life scenarios in the dataset
Data format	Analyzed and filtered.
Data source location	Selected mango orchard locations in Bangladesh data collection: Sher-e-Bangla Agricultural University mango garden, Dhaka, Jahangir Nagar University Garden, Savar, Udaypur village mango garden, Rajbari Itakhola village mango garden, Nilphamari
Data accessibility	Repository name: Mendeley data Data identification number:10.17632/hxsnvwty3r.1 Direct URL to data: https://data.mendeley.com/datasets/hxsnvwty3r/1

Affected branches show yellowing and drying of leaves along with dark and sunken bark. Powdery mildew is a fungal disease caused by the fungus Oidium mangiferae that affects the leaves, twigs, and fruits of mango trees, causing significant damage if left untreated. Symptoms include smaller, poor-quality fruit, curled and distorted leaves in addition to a powdery white fungal growth on leaves, twigs, and fruit. As the disease progresses, affected leaves may turn yellow and fall off prematurely. Sooty mould is a fungal disease caused by various species of fungi in the genus Capnodium, which leads to the development of a black, sooty growth on leaves and fruit. As a result, the leaves start to twist, and the black fragments produce sticky substances on the surface. The fungus primarily attacks the flowers and may cause young fruits to fall off. It is more prevalent in poorly managed orchards.

3.2. *State-of-the-art algorithms*

In this section, the architecture of three state-of-the-Art algorithms AlexNet and VGGNet will be discussed with the proposed CNN based model LeafNet to detect the disease of the above mango leaf dataset.

3.2.1. *AlexNet architecture*

The architecture of AlexNet [35] is presented to properly understand the layers, feature maps, activation functions, and parameters in Fig. 3 and Table 3. At first, the architecture expands the number of channels, then it gradually shrinks the number of channels or filters. There are mainly five convolutional blocks and two fully connected dense layers (FC). Except for one, each convolutional block consists of one convolutional layer (CONV) and one max pooling layer (Max Pool). A three-channel colored image in RGB sample space is fed to the architecture and eight class labels are predicted. For simplicity, max-pooling layers are mostly omitted and only the important feature maps are shown. The image is generated using a deep-learning layer drawing tool [36].

3.2.2. *VGGNet architecture (VGG16)*

The architecture of VGG16 is described to understand its parameters and flow of information in Table 4 and Fig. 4. VGG16 belongs to the category of generic VGG architectures and is known for its depth and complexity in terms of layers and parameters. Here, instead of a single convolution, multiple convolution layers are used one after another, and then the resultant feature map is passed through a max pooling layer (Max Pool) before sending to the following set of convolutional layers (CONV). This architecture also uses two fully connected layers (FC) and a SoftMax layer for the prediction of the concerned 8 classes. The input is

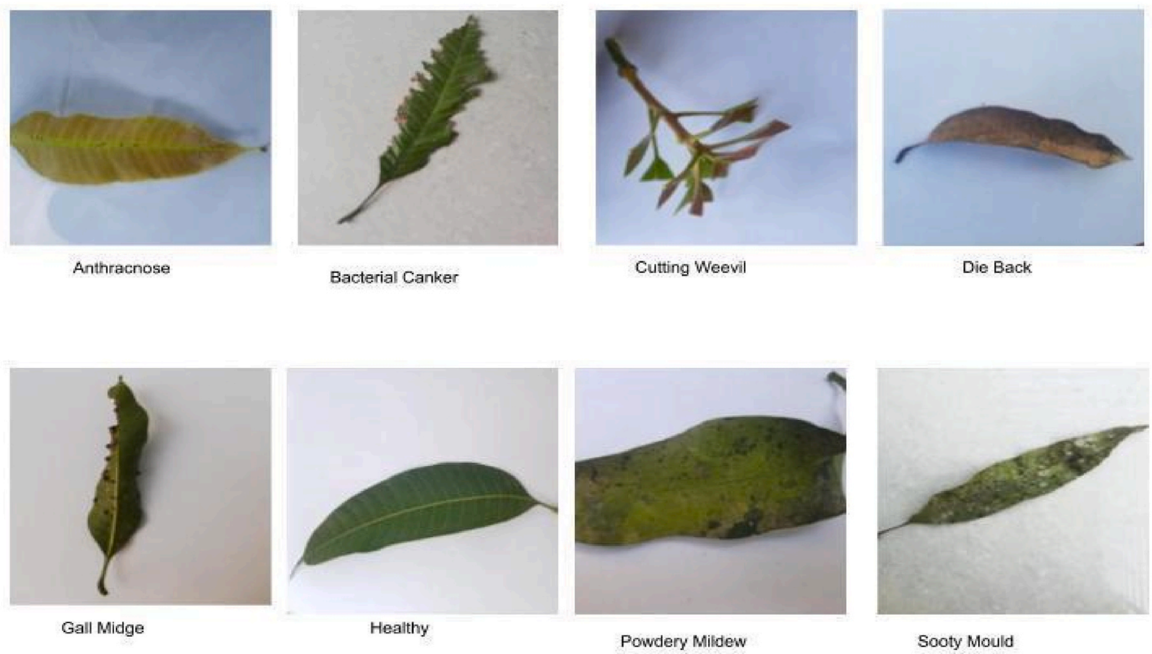

Fig. 2. Sample dataset of mango diseases.

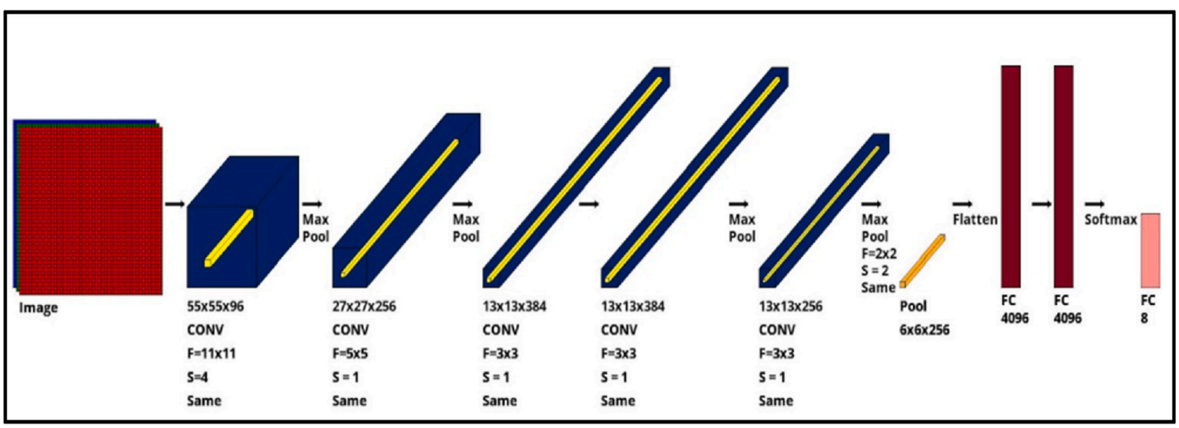

Fig. 3. AlexNet architecture.

a three-channel colored image having dimensions of (227 x 227 x 3) [37].

3.2.3. *Proposed convolutional neural network architecture (LeafNet)*

The proposed architecture also follows AlexNet's convention of first expanding and then decreasing the number of filters or channels during the feature map extraction. Though this architecture is lightweight and has lesser number of channels, similar to AlexNet, each convolutional block contains one convolutional (CONV) layer and a max pooling layer (Max Pool) except one. It also includes two fully connected dense layers (FC) and a softmax layer to generate predictions. Various regularizations like batch normalization and dropout layers are added to reduce the probability of overfitting. Here, Table 5 presents the description of the proposed architecture, and Fig. 5 contains a pictorial representation of LeafNet.

4. Hyperparameters, training, and testing strategies

The cross-validation technique is used to validate each cross, as there were no separate testing instances. A total of 5-folds based on random seeding is used. For each fold, 80% of data instances were in the training dataset, the remaining 10% were used for validation and the remaining 10% was considered as the testing dataset. The validation dataset was used to validate the performance after each epoch. The testing dataset was evaluated after the training had stopped and used the best state or weights observed over the validation dataset. In the following Table 6, the summary of the hyperparameters along with other relevant concerns presented that were used during training the architectures. For patience value, 60 was chosen because it falls between [1100], the standard practice, and a moderately significant value to capture sudden abrupt changes in the loss. A maximum Epoch 300 was chosen, but in most of the cases, due to the early stopping callback, all the architectures' training stopped prior. On the other hand, Table 7 shows that due to being a lightweight model LeafNet takes the least amount of time in training, whereas being the most heavyweight model, VGG16 takes the most amount of time.

5. Result and analysis

The following section describes the result of the study in terms of loss

Table 3
Summarized information of the feature maps of AlexNet.

Layer	#Filters/Neurons	Filter Size (F)	Stride (S)	Size of Feature Map	Activation Function
Image				227 227 3*	
CONV	96	11 11	4	55 55 96	ReLU
Batch Normalization				55 55 96	
Max Pool	-	3 3	2	27 27 96	
CONV	256	5 5	1	27 27 256	ReLU
Batch Normalization				27 27 256	
Max Pool	-	3 3	2	13 13 256	
CONV	384	3 3	1	13 13 384	ReLU
Batch Normalization				13 13 384	
CONV	384	3 3	1	13 13 384	ReLU
Batch Normalization				13 13 384	
CONV	256	3 3	1	13 13 256	ReLU
Batch Normalization				13 13 256	
Max Pool	-	3 3	2	6 6256	
FC				4096	ReLU
Dropout	rate = 0.5			4096	
FC				4096	ReLU
Dropout	rate = 0.5			4096	
FC				8*	Softmax

Table 4
Summarized information on the feature maps of VGG16.

Layer	#Filters/ Neurons	Filter Size (F)	Stride (S)	Size of Feature Map	Activation Function
Image				227 × 227 × 3*	
2 * CONV	64	3 3	1	227 × 227 × 64	ReLU
Max Pool		2 2	2	113 113 64	
2 * CONV	128	3 3	1	113 113 128	ReLU
Max Pool		3 3	2	56 56 128	
3 * CONV	256	3 3	1	56 56 256	ReLU
Max Pool		2 2	2	28 28 256	
3 * CONV	512	3 3	1	28 18 512	ReLU
Max Pool		2 2	2	14 14 512	
3 * CONV	512	3 3	1	14 14 512	ReLU
Max Pool		2 2	2	7 7512	
FC	25088			4096	ReLU
Dropout	rate = 0.5			4096	
FC	4096			4096	ReLU
Dropout	rate = 0.5			4096	
FC	4096			8*	Softmax

and accuracy training in each fold, comparison of the number of parameters, and accuracy over the testing datasets.

5.1. Loss and accuracy during training in each fold

This section discusses the observed changes in loss and accuracy over training and validation datasets across different epochs. A trial in a single fold is selected for discussion and records the changes in accuracy and loss over epochs. From the analysis, it is observed that the characteristics or patterns in changing are almost identical across different folds for a particular architecture. So, the analysis is presented over a single fold.

From the above Fig. 6, slowly LeafNet converges, minimizing the loss and increasing the accuracy in the fold. Some small spikes can be seen, which occur due to the abrupt gradient change, but mostly the variation becomes quite stable in both loss and accuracy.

Like LeafNet, Fig. 7 shows that AlexNet also behaves accordingly and slowly converges minimizing the loss and increasing the accuracy. However, the number of abrupt changes is comparatively higher in AlexNet than LeafNet which states that based on stability in variation, LeafNet provides improved performance.

Fig. 8 illustrates that, due to a large number of parameters, VGG16 fails to properly converge and starts to overfit. It can be observed that, in the training dataset, the loss gets minimized, and accuracy has increased significantly. But in the validation dataset, the performance could be better leading to an overall degradation in accuracy in the testing dataset.

5.2. Comparison between the number of parameters

Deep learning models can bring benefits such as faster training times, lower memory requirements, better generalization to unseen data, and ease of interpretation if the number of parameters is less. Table 8 illustrates that LeafNet needs fewer parameters than VGG16 and AlexNet. But to ensure the quality of a model, it is important to consider not just the number of parameters but also the model architecture and training process. AlexNet network is specifically designed for image classification and consists of multiple convolutional layers. The network can extract a rich set of features from input images with a substantial number of filters. To accurately capture and predict these features, the network requires many parameters, which necessitates using a large dataset during training. Compared to AlexNet, VGG16 uses multiple convolutional layers with fewer filters in each layer. As a result, the depth of the network increases, which makes it more capable of capturing fine-grained features from the input images. However, using the VGG16 model requires a trade-off, as a deeper network means more parameters but also a higher capacity to learn complex representations of the input data. Finally, in the case of LeafNet, a combination of hand-crafted and learned features have been utilized to effectively classify plant species. The network includes several convolutional layers to learn local features from the leaf images, as well as pooling layers to reduce the spatial dimensions of the feature maps. The final feature representation is then fed into a fully connected layer for classification. This specialized architecture reduces the number of parameters compared to larger networks, making it computationally efficient and well-suited for small datasets.

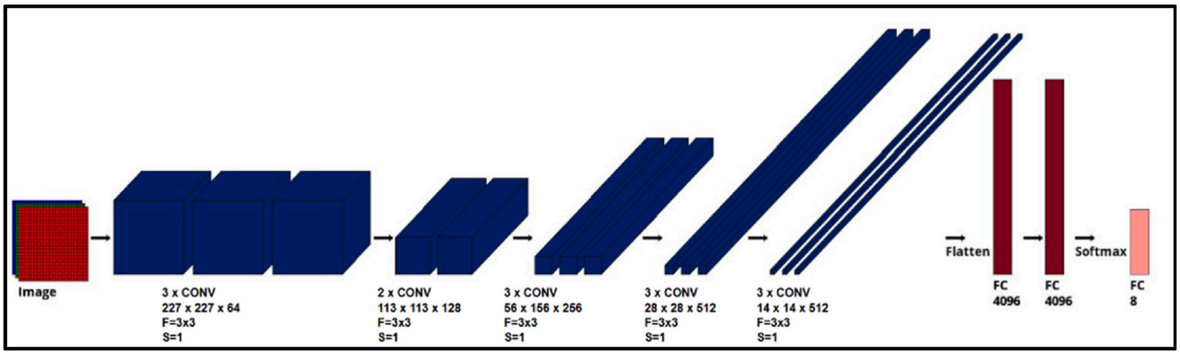

Fig. 4. VGG16 architecture.

Table 5
Summarized information of the feature maps of the proposed LeafNet architecture.

Layer	#Filters/Neurons	Filter Size (F)	Stride (S)	Size of Feature Map	Activation Function
Image				227 227 3*	
CONV	50	11 11	3	73 73 50	ReLU
Batch Normalization				73 73 50	
Max Pool	-	2 2	2	36 36 50	
CONV	100	11 11	1	36 36 100	ReLU
Batch Normalization				36 36 100	
Max Pool		2 2	2	18 18 100	
CONV	150	5 5	1	18 18 150	ReLU
Batch Normalization				18 18 150	
CONV	100	5 5	1	18 18 100	ReLU
Batch Normalization				18 18 100	
Max Pool		2 2	2	9 9 100	
CONV	90	3 3	1	9 9 90	ReLU
Batch Normalization				9 9 90	
Max Pool		2 2	2	4 4 90	
Flatten				1440	
FC	800			800	ReLU
Dropout	rate = 0.5				
FC	800			800	ReLU
Dropout	rate = 0.5				
FC	8				Softmax

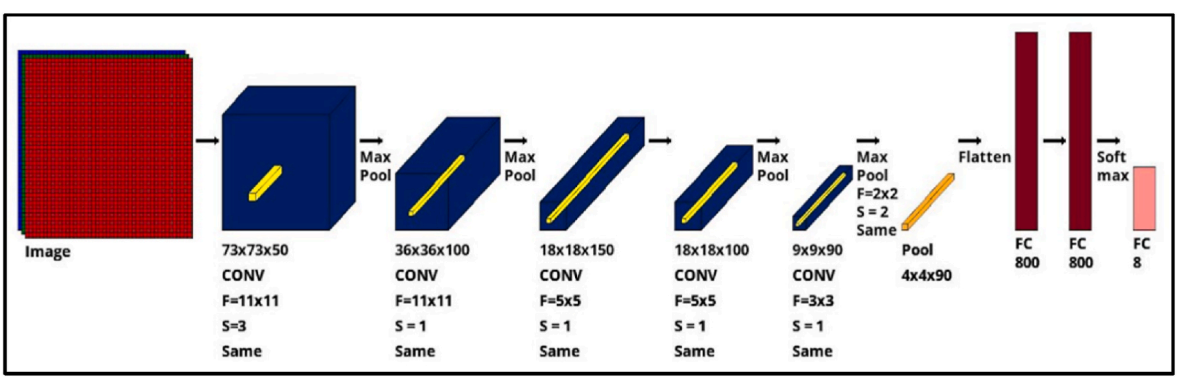

Fig. 5. LeafNet architecture.

5.3. Size of the saved weights for each architecture

Table 9 presents the average size of the weight files for all architectures that were found after training in different folds. It can be observed that the proposed architecture is the most lightweight compared to the other two. This is one of the main contributions of this manuscript, where LeafNet architecture provides a decent performance in accuracy over the collected dataset compared to the widely used AlexNet architecture, even after being around 36 times lighter. Also, as the problem lies mostly in real-life practical applications and not in exactly sensitive life-centric medical scenarios, slight degradation in performance should be acceptable.

5.4. Evaluation matrices

The evaluation matrices used for this research are average accuracy, precision, recall, F score, and specificity are shown by equations (1)–(5) respectively. In each fold, each architecture was run multiple times,

Table 6
Information about batch size, maximum epoch, loss function, optimizer, learning rate, and early stopping callback used during training across different architectures.

Loss function	Categorical cross-entropy
Optimizer	Stochastic Gradient Descent (SGD)
Learning Rate	0.001
Early stopping	Monitor metric = validation loss patience = 60
Batch Size	10
Maximum Epochs to run	300

Table 7
Comparison of the average training time in milliseconds.

	Average Training Time			
	Per Batch (CPU)	Per Batc (GPU)	Per Epoch (CPU)	Per Epoch (GPU)
LeafNet	2000 ms/step	6 ms/step	609000 ms	2000 ms
AlexNe	2010 ms/step	11 ms/step	651000 ms	3000 ms
VGG16	21000 ms/step	50 ms/step	6729000 ms	15000 ms

accuracy was recorded in each trial, and the average is presented in Table 10.

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

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

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

$$F - score = \frac{2 * (Recall + Precision)}{(Recall + Precision)} \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

Here, TP = True Positives, FP = False Positives, and FN = False Negatives.

The main objective here is to find the robustness and remove the bias in the performance of each architecture and to focus more on the average behavior. Table 10 shows the average accuracy, precision, recall, F score, specificity, and observed from the testing dataset in each fold for the three architectures. It has been observed that LeafNet provides excellent performance across all 5 folds. In most of the folds, LeafNet provides almost similar performance like AlexNet even after

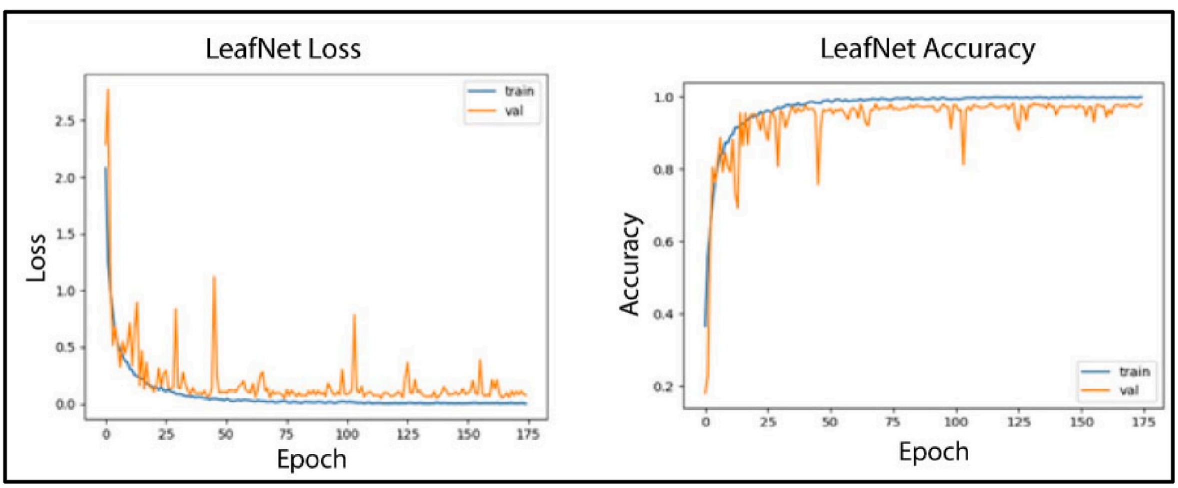

Fig. 6. Change in loss and accuracy of LeafNet in fold-5 over training and validation datasets.

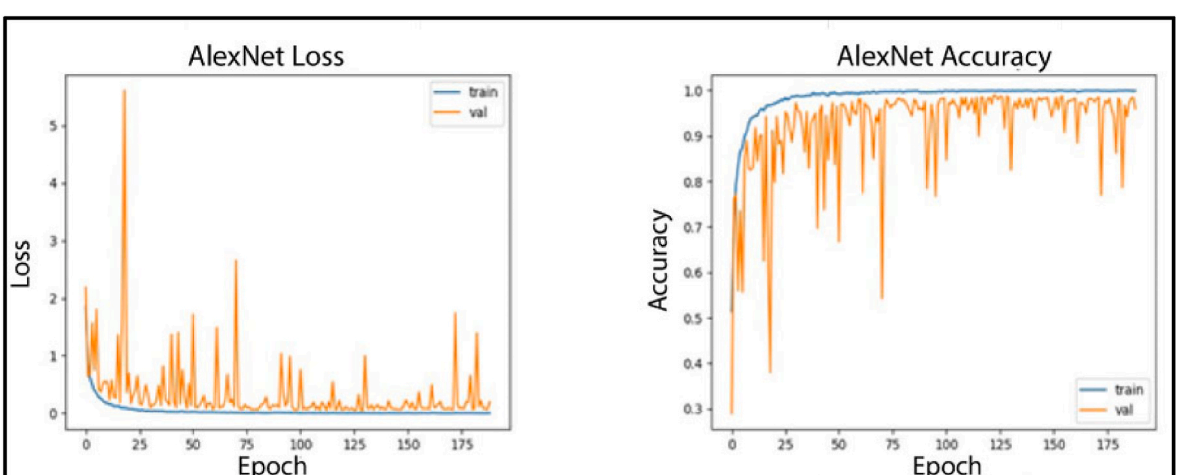

Fig. 7. Change in loss and accuracy of AlexNet in fold-5 over training and validation datasets.

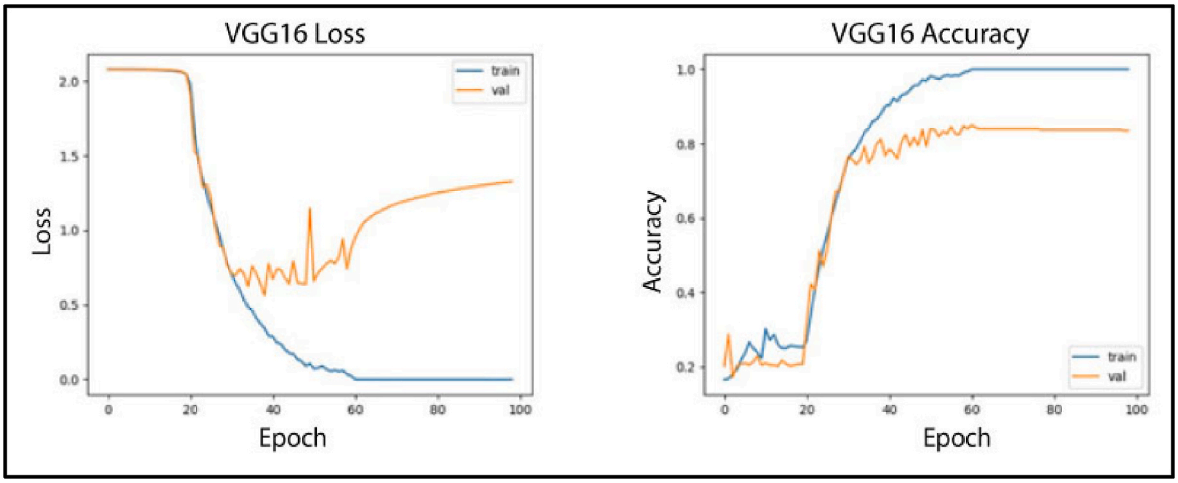

Fig. 8. Change in loss and accuracy of VGG16 in Fold-5 over training and validation datasets.

Table 8
Comparison of total parameters and no. of trainable parameters.

Architecture Name	Total No of parameters	Total No of trainable parameters
LeafNet	3,256,608	3,255,628
AlexNet	58,319,624	58,316,872
VGG16	134,293,320	134,293,320

Table 9
Size of the saved weight files for all the architectures found in hdf5 format.

Architecture Name	Size in Megabytes (MB) of the saved weights
LeafNet	13.1
AlexNet	466.6
VGG16	537.2

Table 10
The average results observed by multiple trials in each fold of cross-validation over testing datasets across different architectures.

	Accuracy	Precision	Recall	F-Score	Specificity
AlexNet	99.25	99.254	99.086	99.054	99.852
VGG16	78.4	80.84	80.68	80.46	97.248
LeafNet	99.55	99.508	99.45	99.47	99.878

being a much lighter model. Although the parameters of evaluation stay within 0.5% proximity, the results fall slightly behind in some folds compared to the others. VGG16 shows poor performance in all the folds. Moreover, this study suggests that the sample size and dataset variations were insufficient to train the 134 million parameters (approximately).

Across the 5 folds, Fig. 9 illustrates that LeafNet's accuracy varied from 99% to 100% showing the model is not over-fit and each fold produces similar results. Furthermore, the other parameters such as precision, varied from 98.91% to 100%, and recall varied from 98.84% to 99.69%. Since these metrics are closely related to the accuracy measures, the pattern aligns with the earlier discussion. LeafNet gives a very close performance with AlexNet, whereas VGG16 falls behind with a good margin in all the folds.

As seen in Fig. 10, the confusion matrix is depicted for all the folds. The confusion matrix is the parameter used to observe the class-wise prediction of the model. The diagonal data of a confusion matrix shows how accurately the model predicts accurate positive data. It is clear from the oblique data that LeafNet outperforms in the majority of the 8 classes as all the data is close to 1. VGG16 also falls behind by a small margin across all individual classes, despite the size of the model. It is evident that AlexNet and LeafNet perform similarly according to class-wise data in the confusion matrix.

Another parameter of evaluation used in this research is the ROC values for each class which also shows the perfect true positive to false positive rate as shown in equations (6) and (7) respectively. The ROC values for each class have been recorded in Table 11. The values show the ability of the models to classify with a varied threshold providing a tradeoff between sensitivity and specificity. It can be observed that for most of the classes the value is 1 or nearly 1 which makes LeafNet fit for the classification problem.

$$True\ Positive\ \text{Rate} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

$$\text{True Negative}\ Rate = \frac{TN}{TN + FP} \tag{7}$$

6. Discussion

Datasets are the foundation for training deep learning models and having a well-balanced image dataset for accurate prediction of mango leaf diseases is essential. To ensure the quality and diversity of the images in the dataset, completely new and recent pictures were collected from various parts of Bangladesh and different mango orchards. This has a direct impact on the model's ability to identify and classify different disease symptoms accurately. The dataset was then used to classify the diseases using several deep learning models such as VGG16, AlexNet, and proposed LeafNet. While all of these are state-of-the-art models known for their unique architectures and strengths, LeafNet stands out by providing faster and more efficient training, along with better performance on the target dataset. Research showed that LeafNet had the highest average accuracy of 98.55%, while AlexNet had an accuracy of 98.25%. LeafNet has also outperformed the other two models in almost all the parameters of evaluation that has been used in this research. It can be inferred that VGG16 has not performed up to the mark, but AlexNet and LeafNet had similar results. To compare these two models, other criteria such as average training time and number of trainable parameters must also be considered. LeafNet outperforms in both evaluations and is a powerful tool for diagnosing these diseases. As the most lightweight model, LeafNet can achieve the highest accuracy with only 32 million trainable parameters, compared to 58 million for AlexNet and 134 million for VGG16. The lower number of parameters makes a model more interpretable, easier to debug, less prone to overfitting and requires fewer computational resources. However, it's important to note that the impact of the number of parameters on the performance of a deep learning model varies based on the task and dataset. Through

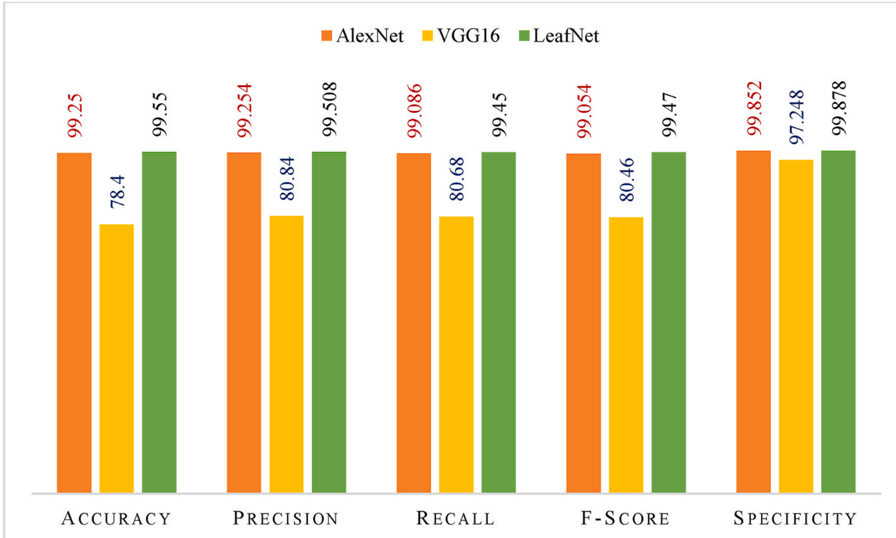

Fig. 9. Overall average performance of each fold of cross validation.

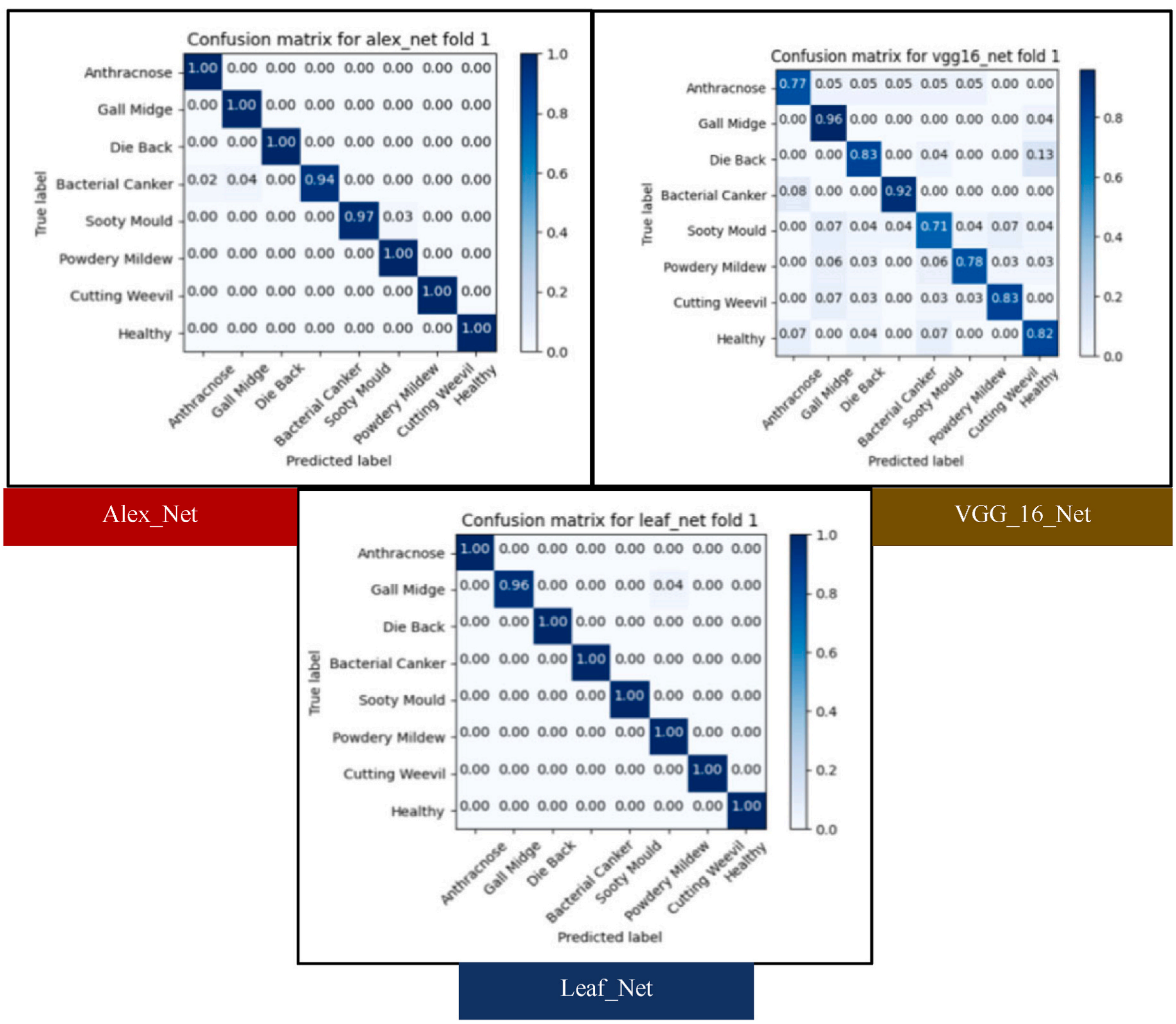

Fig. 10. Confusion matrix for second fold.

experimentation with different architectures and parameter settings, LeafNet was the optimal model for the given task. To further evaluate LeafNet, precision, recall, F score, specificity, confusion matrix, and ROC values have been recorded where it has been seen that LeafNet had ideal values for these parameters. So, it can be mentioned that based on most of the parameters, LeafNet and AlexNet performed alike other than

Table 11
The ROC values observed in Fold 2 of cross-validation over testing datasets across different architectures.

	Class 0	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
AlexNet	1	0.98	0.99	1	1	1	1	0.97
VGG16	0.91	0.91	0.91	0.90	0.86	0.91	0.88	0.9
LeafNet	1	1	1	1	1	1	1	0.97

training time and model complexity which makes LeafNet a good choice for use in devices with low configurations. Thus, a fast and light model, LeafNet can be a perfect fit for the farmers of Bangladesh as well as other parts of the world to use their smartphones making them aware of the diseases of plants at the lowest possible cost.

One of the challenges in developing deep learning models is avoiding overfitting. To detect overfitting, models are commonly tested with different variations of data. To overcome this problem, the model used two methods: K-fold cross-validation and early stopping. During K-fold cross-validation, the dataset was divided into 5 training and validation sets, allowing the model to be trained and tested on different patterns of data. While 300 epochs were chosen for training, early stopping prevented overfitting. This approach allowed the model's performance to be evaluated on all variations of the data, ensuring it generalizes well to new, unseen data.

7. Conclusion

The automation of the agricultural industry is a necessity and developing countries like Bangladesh lag the current standards by a considerable margin. The use of AI in plant disease diagnosis has gained significance in recent years, as it offers an integrated system that can work in real-world situations, supporting non-experts, non-botanists, and non-pathologists. In this study, the objective of the LeafNet architecture is to develop a custom CNN model that can identify 7 different types of diseases in mango leaves, mostly prevalent in the Indian subcontinent specially in Bangladesh. A dataset of 4000 images depicting infected leaves was collected from Bangladesh and manually classified into 7 diseased classes and 1 healthy class. The images were 3-channel colored, with a size of 227x227x3, to enable the mapping of features and suit them for input into LeafNet and other state-of-the-art CNN models. The proposed LeafNet model consists of five conv-pool pairs and two fully connected dense layers with dropouts, resulting in 32 million trainable parameters. The model is designed to maintain accuracy while reducing computational complexity, as shown by its average accuracy of 98.55%. The performance of the model on unseen data was validated through 5-fold cross-validation. This model is considered a benchmark for evaluating other complex deep learning architectures. When evaluated with chosen parameters, LeafNet displayed better performance in comparison to other state-of-the-art models. Furthermore, LeafNet is efficient in terms of not only accuracy or precision but also considerable reduction of computation time and complexity having much lower trainable parameters. The potential applications of the CNN architecture in plant disease diagnosis are numerous, and the proposed CNN model can be an excellent addition to image processing functions to improve its ability to handle images of varying quality. In addition to that, such a lightweight model can be integrated into any kind of smart phone which does not have high configurations making it suitable to use for farmers. Other deep learning models such as EfficientNet, EfficientDet, ResNet etc. can also be used to evaluate the performance of the dataset. However, as LeafNet is a custom CNN model, it can always be fine-tuned by adjusting hyperparameters such as the activation function and optimizer, to further improve accuracy and reduce loss along with computational complexity.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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