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RESEARCH ARTICLE

Plant Disease Classifier: Detection of Dual-Crop Diseases Using Lightweight 2D CNN Architecture

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ABSTRACT Tomatoes are the most widely grown crop in the world, and they may be found in a variety of forms in every kitchen, regardless of cuisine. It is, after potato and sweet potato, the most widely farmed crop on the planet. Cotton is another essential cash crop because most farmers grow it in huge quantities. However, many diseases reduce the quality and quantity of tomato and cotton crops, resulting in a significant loss in production and productivity. It is critical to detect these disorders at an early stage of diagnosis. The purpose of this work is to categorize 14 classes for both cotton and tomato crops, with 12 diseased classes and two healthy classes using a deep learning-based lightweight 2D CNN architecture and to implement the model in an android application named "Plant Disease Classifier" for smartphone-assisted plant disease diagnosis system, the results of the experiments reveal that the proposed model outperforms the pre-trained models VGG16, VGG19 and InceptionV3 despite having fewer parameters. With slightly larger parameters than MobileNet and MobileNetV2, proposed model also attains considerably larger accuracy than these models. The classification accuracy varies between 57% and 92% for these models, and the proposed model's average accuracy is 97.36%. Also, the precision, recall, F1-score of the proposed model is 97 % and Area Under Curve (AUC) score of the model is 99.9% which is an indicator of the very good performance of the model. Class activation maps were shown using the Gradient Weighted Class Activation Mapping (Grad-CAM) technique to visually explain the disease detected by the proposed model, and a heatmap was produced to indicate the responsible region for classification. The app works very impressively and classified the correct disease in a shorter period of time of about 4.84 ms due to the lightweight nature of the model.

INDEX TERMS Convolution neural network (CNN), lightweight 2D CNN, android application, plant disease diagnosis system, gradient weighted class activation mapping (Grad-CAM), tomato, cotton.

I. INTRODUCTION

Agriculture is a crucial term in many developing countries' economies, and the primary source of food and revenue. Agriculture supports approximately 60% of the world's population, as it is a vital aspect of many people's livelihood and subsistence [1]. Tomatoes and cotton are two of the most diverse and important commercial crops in Bangladesh, with the majority of people relying on agriculture for their income and survival. Tomato ranks as the fourth most widely cultivated vegetable in the nation. In Bangladesh, approximately 4.48 lakh tons of tomatoes were produced

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in 2021 [2]. Bangladesh's national economy gains significantly from tomato production, which has positive economic effects. Around one hundred million dollars in tomatoes were exported from Bangladesh in the year 2020 and also Millions of people are employed in this sector [3]. Cotton is also a major cash crop in Bangladesh. It is the second-largest cotton importer and the fourth-largest consumer in the world. In 2021, Bangladesh exported \$210 million in Raw Cotton, making it the 84th largest exporter of Raw Cotton in the world. In the same year, Raw Cotton was the 407th most exported product in Bangladesh [4]. In 2022, the country's domestic cotton production was around 0.2 million bales [5]. The Cotton Development Board of Bangladesh is taking the necessary steps to increase cotton production to meet the uprising cotton demand in Bangladesh as it is the second-largest apparel exporter in the world [6]. These statistics prove that cotton and tomato are significant crops in terms of the agricultural situation in Bangladesh. Plant diseases, on the other hand, have a negative impact on agricultural production. Organic agents such as fungi, bacteria, algae, and others cause plant diseases. Temperature imbalances, chemical toxicity, incorrect fertilizer, rainfall, nutrient inadequacy, and other nonliving variables, on the other hand, induce plant disorders [7].

Currently, these plant diseases are manually recognized with the naked eye, which is a time-consuming technique and frequently fails to effectively detect infections [8]. Farmers' incorrect diagnosis of diseases can result in the overuse or misuse of pesticides, which can harm plants and their yield. Plant disease classification is an important step that can help with the early diagnosis of pests and insects, disease treatment, and productivity increases, among other advantages. Disease symptoms are mostly visible on the leaves of cotton and tomato plants. For this, image processing techniques are applied to plant leaves in order to classify the diseases quickly, accurately, and appropriately. Consequently, utilizing deep learning to identify the pests and diseases in plants can dramatically speed up the detection process, reducing economic losses and saving time with even more accuracy.

A novel method using 2D CNN is proposed for identifying diseases in tomato and cotton crops after analyzing leaf photos in this research. Because 2D CNN outperforms other current methods in terms of localized feature extraction, efficiency, robustness, adaptability, and end-to-end learning capabilities, it is chosen for disease identification. These distinctive features place CNNs as the cutting-edge approach for image analysis and understanding and make them the superior option for a variety of computer vision jobs. Unquestionably, they have contributed to the field's advancement and encouraged innovation. The tomato and cotton leave images were collected from the publicly available PlantVillage dataset [9] and publicly available 'cotton-leaf-infection' dataset [39] for this experiment and classified using a lightweight 2D CNN model. The model's performance was evaluated using several metrics such as training accuracy, validation accuracy, precision, recall, F1-score, ROC curve, precision Vs recall curve and the number of trainable parameters.

The novel contributions of this work are:

(1) A novel lightweight 2D CNN model is constructed for extracting the most relevant features from the plant leaf images.

(2) Multiclass disease classification has been carried out for two different crops for an imbalanced large dataset using a 2D CNN architecture that has fewer parameters and is compared with other pre-trained models.

(3) The disease detection made by the trained model is visually explained by plotting class activation maps using the Grad-CAM technique and a heatmap was generated to identify and explain the characteristics region for the classification.

(4) An android application named "Plant Disease Classifier" has been developed using the trained lightweight 2D CNN model for exhibiting classified diseases and their information.

This technique will help farmers to identify plant diseases without having to rely on plant scientists and control the plant's disease in a timely manner, therefore enhancing the quality and quantity of the cotton and tomato crops produced and, as a result, providing economic benefits to the growers.

The paper has been organized as follows: Section II discusses findings from recent research on this topic. Section III detailed the proposed methodology of the model development. The results of the proposed model and a comparison with state-of-the-art (SOTA) models along with visualization using Grad-Cam and details of the developed Android application are presented in Section IV. Finally, the important conclusions from this study are provided in Section V.

II. RELATED WORKS

A detailed literature review has revealed that the automatic identification of plant diseases is carried out broadly by machine learning and deep learning-based methods. The following sections present a review of recent literature on this topic.

Basavaiah and Arlene Anthony [10] outlined an innovative strategy based on the extraction and concatenation of features to detect five classes of tomato leaf diseases for 500 images employing decision trees and Random Forest (RF) classifiers. The accuracy score for the suggested method was 94% for the RF classifier and 90% for the decision tree classifier. Chen et al. [11] proposed a method for detecting five tomato leaf diseases using a combination of the Artificial Bee Colony Algorithm-Binary Wavelet Transform combined with Retinex (ABCK-BWTR) and Both-channel Residual Attention Network (BARNet) models, with an overall detection accuracy of 89% for 5 classes and 8616 images from PlantVillage dataset. Agarwal et al. [12] utilized a CNN-based technique to detect and classify 9 tomato diseases and one healthy class and 91.2 % accuracy has been achieved for 10000 images of PlantVillage dataset. Cengil and Çınar [13] proposed a hybrid-based CNN model where feature extraction is done using AlexNet, ResNet50, and VGG16 and after the concatenation of the features, machine learning algorithms were used for classification, which gave 98.3% accuracy for the same PlantVillage dataset and 96.3% accuracy for a dataset having 6 classes and 4976 images. Khan and Narvekar [14] proposed a method for the automatic detection and classification of four classes of tomato diseases using superpixel-based optimized segmentation for the combined dataset of around 733 images and attained an average accuracy of 93.18%. Zhao et al. [15] proposed a tomato disease detection based on improved CNN by attention module which gave 96.81% accuracy for PlantVillage dataset having 10 classes and 4585 images and after enhancement 4 times the total resultant images were 22,925. Al-Gaashani et al. [16] proposed method for tomato disease detection where features from the images were extracted using pre-trained models and reduced using Kernel Principal Component Analysis (PCA) and multinomial logistic regression was used for classification which achieved an average accuracy of 97% for 1152 images from PlantVillage dataset for six classes. Wspanialy and Moussa [17] proposed a tomato disease detection & severity estimation method using ResNet & modified U-Net deep learning architecture which gave 97% accuracy for PlantVillage dataset having 10 classes. Chowdhury et al. [18] proposed a work in which classification is done on 18,162 images from PlantVillage dataset for ten classes where DenseNet201 achieved an accuracy of 98.05% for ten classes & 97.99% for six classes. For the same amount of data from PlantVillage dataset, Jasim et al. [19] proposed a method using CNN model and attained an average accuracy of 97.39% and Özbilge et al. [38] proposed a method using Compact CNN model and attained an average accuracy of 99.70% for ten classes. Chen et al. [20] proposed a method to implement the function of AlexNet modification architecture-based CNN on the Android platform to predict tomato diseases which gave 98% accuracy for a dataset having 10 classes and 22,930 images. Karthik et al. [21] proposed a method based on residual learning and attention mechanism using two different deep architectures to predict tomato diseases which gave 98% accuracy for a dataset having 4 classes and 120,000 images. Agarwal et al. [22] proposed a work in which eight hidden layers made up the compressed CNN model. For ten classes of tomato crops in the PlantVillage dataset, there are 14,529 training images and 3,631 validation images. The proposed work achieves an accuracy of 98.4%. Trivedi et al. [23] proposed a method where the classification of ten classes of tomato leaf diseases is done using CNN for 3000 images where the achieved average accuracy is 98.49%. Bhujel et al. [24] proposed a lightweight convolutional neural network by incorporating different attention modules for 11 classes of 19,510 tomato leaf images which is a combination of PlantVillage dataset and collected tomato leaf images from greenhouse and convolutional block attention module had attained the best accuracy of 99.34%. Indu and Priyadharsini [25] proposed an automatic tomato leaf disease identification system by using crossover-based wind-driven optimization (CROWDO) algorithm optimized Alexnet for 4 classes of 9584 tomato leaf images and attained 99.86% accuracy. But Alexnet has 60 million parameters which are very large and consumes very large disk space. Abbas et al. [26] proposed a deep learning-based method for tomato disease detection that utilizes the Conditional Generative Adversarial Network (C-GAN) to generate synthetic images of tomato plant leaves and DenseNet121 is used for the classification of 5 classes, 7 classes, and 10 classes and the achieved accuracy is 99.51%, 98.65%, and 97.11% respectively for PlantVillage dataset. In [27], the work proposed a method for the classification of ten classes of tomato diseases using GoogleNet for 18160 images and attained an average accuracy of 99.39%. For the same dataset, Tan et al. [28] proposed a method using ResNet34 where the achieved average accuracy is 99.7%. Nandhini and Ashokkumar [29] proposed a method for the classification of five classes of tomato leaf diseases using InceptionV3 and VGG16 utilizing the ICRMBO-CNN approach for optimization using PlantVillage dataset comprising 6208 images. But pre-trained networks have a very large number of parameters & the optimized VGG16 and Inception V3 provide a final classification accuracy of 99.98% and 99.94% respectively.

Based on the literature, the following gaps have been identified.

1. Using conventional image processing methods, it is difficult to locate and extract important information from tomato leaves that can help distinguish between the characteristics of various diseases. Since the features of these diseases vary greatly, it is necessary to thoroughly investigate their patterns using a variety of datasets in an automated manner.

2. The characteristics of the manually chosen, handcrafted features are the only factors that affect how well the machine learning-based models perform. Therefore, feature extraction needs to be automated in order to choose and learn the best collection of features for classification.

3. Some deep learning models make use of widely used and tested architectures, such as VGG16, GoogleNet, ResNet34 etc. As a result, it uses millions of parameters for classification. The computational complexity and accuracy must be balanced in order to deploy these models in real time.

4. Disease detection for the combination of two types of crops can be done using models having fewer parameters than disease detection for one type of crop.

5. Additionally, a high number of samples must be used to train the deep learning network in order to ensure improved feature generalization.

III. MATERIALS AND METHODS

A. PROPOSED METHODOLOGY

With the application of 2D CNN, a complete overview of the overall detection methodology of tomato & cotton leaf diseases is provided in this study. 2D CNN has been chosen because traditional approaches call for handcrafted features, whereas 2D CNN learns hierarchical representations over numerous layers, which enables it to capture increasingly complicated and abstract characteristics. The ability to extract hierarchical features improves the accuracy with which visual data can be understood and interpreted. Additionally, parameter sharing is used by CNNs, which greatly reduces the number of trainable parameters. As a result, CNNs are more effective than other techniques at handling enormous datasets and challenging tasks. Because of their resistance to changes in object position and translation invariance, CNNs are very good at tasks like object localization and detection. The benefit of CNNs is end-to-end learning, where the model gains knowledge directly from the input data. CNNs can identify complex patterns and connections that might not be visible using conventional techniques since they automatically learn features and representations. Following the mentioned reasons, two datasets (tomato and cotton) are merged and a large number of data are used, which influenced the authors to choose 2D CNN over the other conventional methods as it is suitable for detecting tomato and cotton leaf diseases. A flowchart depicting the workflow of the whole study is displayed in Fig. 1. The conducted approach is outlined step by step in the following subsections.

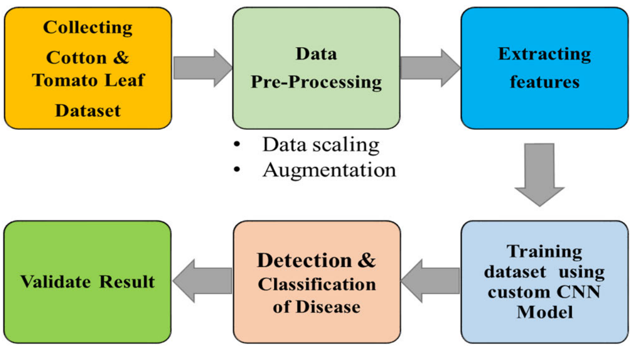

FIGURE 1. Overall research methodology overview.

B. DATASET DESCRIPTION

The dataset is at the heart of deep learning research. Tomato and cotton leaf images represent different types of plant diseases as well as healthy leaf images. Tomato dataset was obtained from the publicly available 'PlantVillage' dataset [9] and cotton dataset was obtained from publicly available 'cotton-leaf-infection' dataset [39]. The PlantVillage dataset has become a key tool in the field of agricultural computer Vision. It has sparked studies and innovation in the automated identification and diagnosis of plant diseases due to its large collection of marked photos, related metadata, and various plant species and diseases. As the cotton leaf dataset is not included in the PlantVillage dataset, it was collected separately, and merged for this research work. The merged tomato and cotton datasets contain a total of 11,366 training and 1,327 testing images organized into 14 classes. Therefore, the split ratio of the training and testing dataset is approximately 9:1. Fig. 2 depicts example images from all the classes of the dataset.

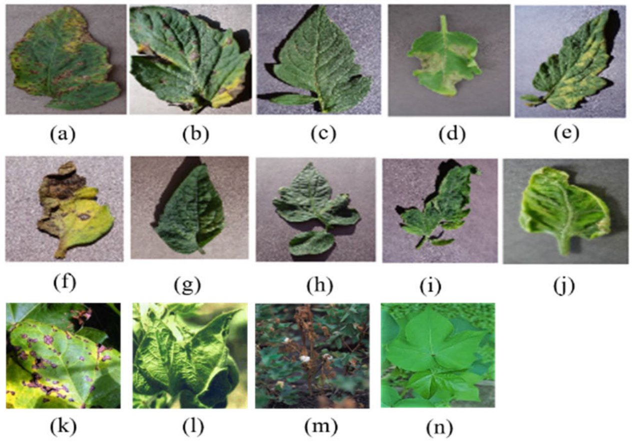

FIGURE 2. Sample leaf images from the dataset representing 14 plant disease classes: (a) Bacterial Spot, (b) Early Blight, (c) Healthy (Tomato), (d) Late Blight, (e) Leaf Mold (f) Septoria Leaf Spot, (g) Spider Mites, (h) Target Spot, (i) Mosaic Virus (j) Yellow Leaf Curl Virus, (k) Bacterial Blight, (l) Curl Virus,(m) Fussarium Wilt, (n) Healthy (Cotton).

TABLE 1. Dataset details.

Plant	Disease Type	Training	Testing
Tomato	Bacterial Spot	1000	100
	Early Blight	1000	100
	Healthy (Tomato)	1000	100
	Late Blight	1000	100
	Leaf Mold	1000	100
	Septoria Leaf Spot	1000	100
	Spider Mites	1000	100
	Target Spot	1000	100
	Mosaic Virus	1000	100
	Yellow Leaf Curl Virus	1000	100
Cotton	Bacterial Blight	358	90
	Curl Virus	335	84
	Fussarium Wilt	336	84
	Healthy (Cotton)	341	85
	Total	11,366	1,327

Table 1 displays the class-wise dataset's details for both training and testing.

C. DATA PRE-PROCESSING

Image preprocessing of the diseased tomato leaves is a crucial step before classification as the quality of images has a considerable impact on the classification outcomes. It is done in the following steps:

1) DATA SCALING/RESIZING

When dealing with 2D CNN, data scaling is a recommended stage of pre-processing. The technique equalizes all of the images in the datasets and transforms the image size to fit the model developed. The data resizing would minimize the memory to be used when the images are loaded into the training stage. For the proposed model, the image data was resized 150 × 150 and for transfer learning models the image data size was 224 × 224. as it is the default image size for implementing transfer learning models.

2) IMAGE AUGMENTATION

Image augmentation is a technique for artificially extending the number of training images in a dataset. This strategy aids in the model's performance enhancement capability and reduces overfitting issues [21]. This approach can manipulate the training images in a variety of ways, including zooming, rotating, shifting, and flipping. In this case, six types of augmentations were applied e.g., rotation, width shifting, height shifting, shearing, zooming and horizontal flipping as shown in Fig. 3. The value of the rotation range parameter was set to 40 degrees. As a result, randomly rotated images with a rotation range of 1 degree to 40 degrees were obtained. Similarly, the parameters for width shifting, height shifting, shearing and zooming were set to 0.2. By setting the horizontal flip parameter to true, horizontally flipped images were obtained. Image augmentation was only applied to the training images. The total amount of training images was 11,366. After augmentation, the images were 6 times greater than they were before. As a result, a total of 68,196 training images were attained.

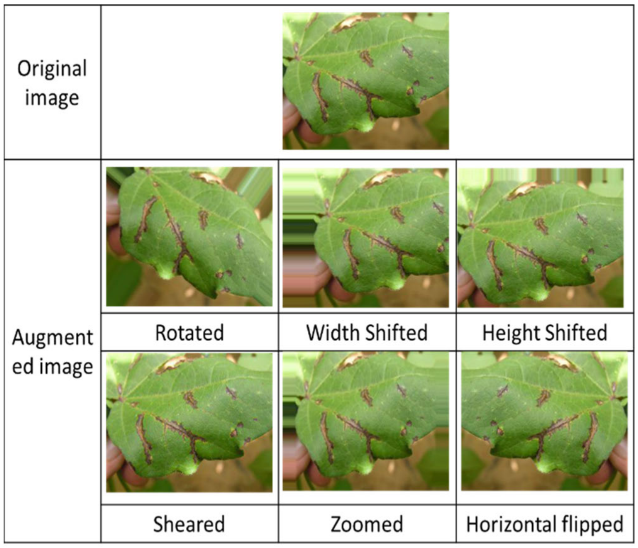

FIGURE 3. Sample augmented images from original input tomato leaf image.

TABLE 2. Summary of proposed simple 2D CNN model.

Layer (Type)	Output Shape	Params
Input Layer	(150,150,3)	
L1 (Conv2D)	(None, 148, 148, 16)	448
max_pooling2d_15 (MaxPooling)	(None, 74, 74, 16)	0
L2 (Conv2D)	(None, 72, 72, 32)	4640
max_pooling2d_16 (MaxPooling)	(None, 36, 36, 32)	0
L3 (Conv2D)	(None, 34, 34, 64)	18496
max_pooling2d_17 (MaxPooling)	(None, 17, 17, 64)	0
flatten_5 (Flatten)	(None, 18496)	0
dense1 (Dense)	(None, 512)	9470464
batch_normalization_4 (Batch)	(None, 512)	2048
dropout_6 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 14)	7182
Total params: 9,503,278 Trainable params: 9,502,254 Non-trainable params: 1,024		

D. MODEL BUILDING

A simple 2D CNN has been proposed in this part to extract the most important features. If the relevant distinctive features between the various leaf diseases are retrieved, the model's classification performance will improve. These extracted attributes can be effectively used to classify leaf diseases. The proposed 2D CNN model architecture is represented in Fig. 4. Three convolution and max-pooling layers were included in the proposed 2D CNN design. A max-pooling layer was incorporated after each convolutional layer. Batch normalization was used since it accelerated and improved the model's performance by re-centering and re-scaling the layers' inputs [30]. The most significant features were extracted using max-polling, which was utilized to select the largest value from each cluster's whole neuron. The next step is to flatten the pooled featured map once it has been acquired. The entire pooled feature map matrix is flattened into a single column, which is then provided to the neural network for processing. In this scenario, dropout was used to reduce overfitting by frequently skipping training all nodes in each layer during the training phase, resulting in a significant increase in training speed [20].

The proposed 2D CNN model is described in Table 2 and the values of the hyperparameters of the models (2D CNN, VGG-16, VGG-19, Inception-V3, MobileNet and MobileNetV2) used in this work are shown in Table 3. After numerous training attempts, the values of the other model's hyperparameters was kept identical to have the best

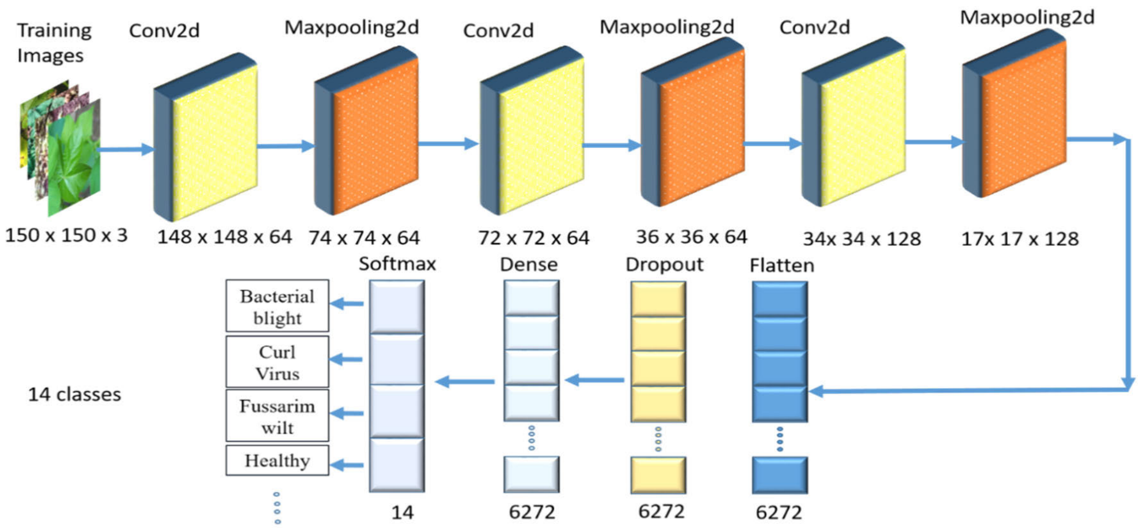

FIGURE 4. Lightweight 2D CNN architecture for tomato leaf disease classification.

optimized model. The proposed model contained a total number of 9,503,278 trainable parameters and 1,024 non-trainable parameters. Categorical cross-entropy was used as a loss function as multiclass data need to be detected. Adam optimizer was used to ensure reliable performance for the bigger dataset used [31].

TABLE 3. Hyperparameters used for the models.

Parameter Name	Attribute
Learning rate	0.001
Activation function	ReLU
Batch size	32
Loss function	Categorical cross-entropy
Optimizer	Adam

IV. EXPERIMENTS AND RESULTS

A. EXPERIMENTAL RESULTS & PERFORMANCE METRICS

The experiment was carried out on Kaggle platform (www.Kaggle.com) in order to take advantage of its available Nvidia P100GPU. Specification of the GPU is: GPU Memory: 16 GB, GPU Memory Clock: 1.32 GHz, Performance: 9.3 TFLOPS.

Several assessment metrics have been utilized such as accuracy (ACC), precision (P), recall (R), F1-score, and area under the curve (AUC), to quantitatively assess the performances of the developed model. The percentage of accurately detected images among all the images is known as accuracy (ACC). It represented the degree to which the classification method was successful in identifying leaf diseases. True positive (TP) means a disease-infected leaf is detected as infected, true negative (TN) means a non-diseased leaf is detected as non-infected, false positive (FP) means a non-diseased leaf was incorrectly detected as infected leaf was incorrectly detected as non-diseased [32]. disease-infected, and false negative (FN) means a disease Equation 1 to Equation 4 defines various performance measure metrics.

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \quad (1)$$

$$Precision = \frac{T_P}{T_P + F_P} \quad (2)$$

$$Recall = \frac{T_P}{T_P + F_N} \quad (3)$$

$$F1\_score = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (4)$$

B. MULTICLASS CLASSIFICATION RESULTS

1) ACCURACY GRAPHS

The efficacy of the models was validated in a series of studies using healthy and infected tomato and cotton leaf images using VGG-16, VGG-19, Inception-V3, MobileNet, MobileNetV2 and Proposed 2D CNN. The training and validation accuracy graphs for VGG-16, VGG-19, Inception-V3, MobileNet, MobileNetV2 and Proposed 2D CNN are shown in Fig. 5(a), Fig. 5(b), Fig. 5(c), Fig. 5(d), Fig. 5(e) and Fig. 5(f) respectively.

From Table 4, it can be seen that the average validation accuracy for VGG-16, VGG-19, Inception-V3, MobileNet, MobileNetV2 and proposed model are 81.39%, 82.97%, 92.31%, 83.65%, 57.50% and 97.36% respectively. Therefore, it is evident that the evaluation metrics accuracy, precision, recall and F1-score of the proposed model is significantly higher than the transfer learning models which is a very good indicator on the reliability of the proposed model's performance in classifying 14 categories of plant leaf diseases from a huge dataset.

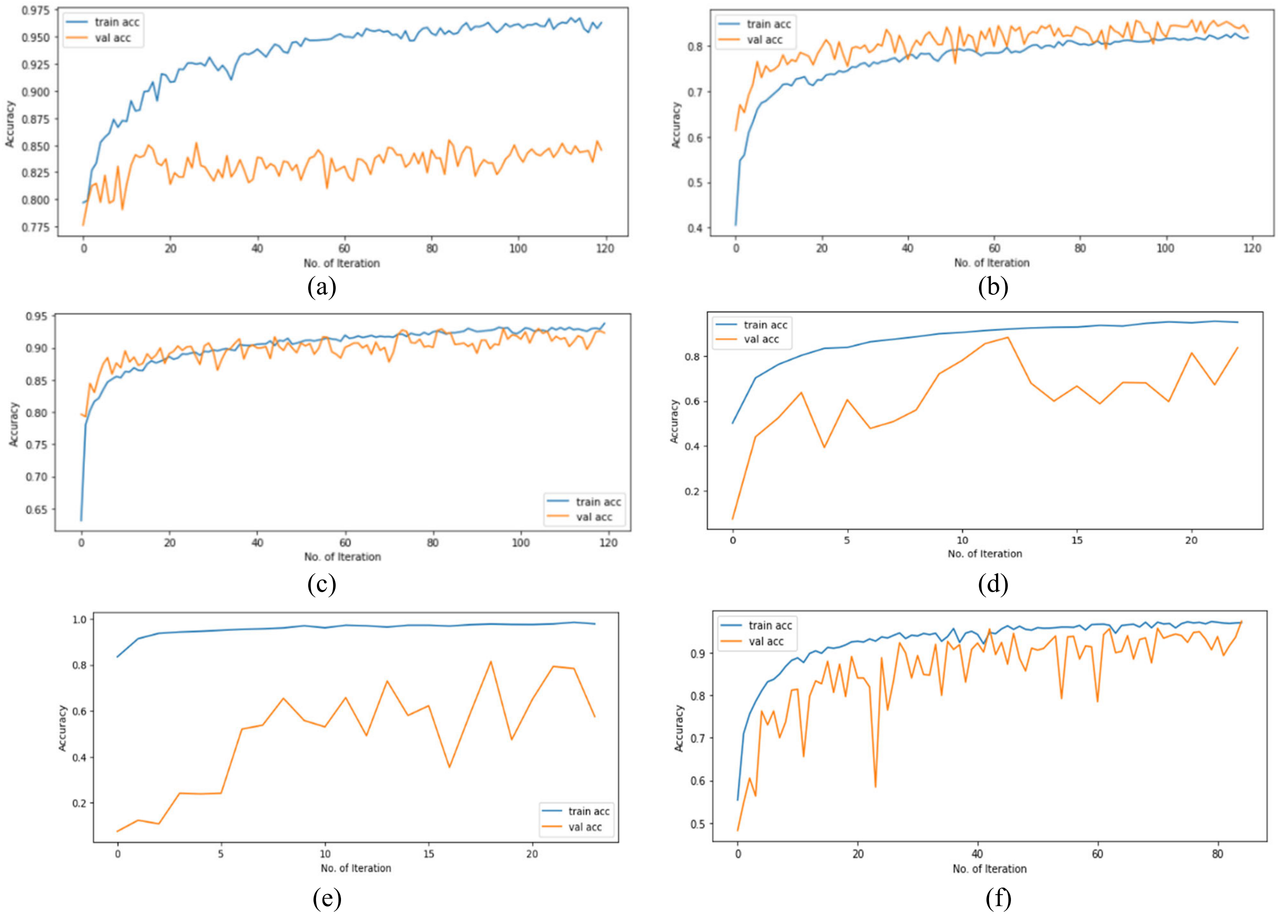

FIGURE 5. Accuracy graphs for training and validation accuracy for (a) VGG16 model, (b) VGG19 model, (c) InceptionV3 model, (d) MobileNet model, (e) MobileNetV2 model and (f) Proposed model.

TABLE 4. Evaluation metrics comparison with transfer learning models.

Models	Accuracy	Precision	Recall	F1-Score
VGG16	81.39%	86%	85%	85%
VGG19	82.97%	86%	83%	82%
Inception V3	92.31%	93%	92%	92%
MobileNet	83.65%	90%	88%	88%
MobileNetV2	57.50%	86%	81%	82%
Proposed CNN model	97.36%	97%	97%	97%

2) CONFUSION MATRIX

The confusion matrix, which is important in determining the performance of architectures, is also taken into account in this research as shown in Fig. 6. It displays the degree to which the classification method is successful in identifying the diseases in plant leaf images. This study considered a 14-class problem, which consisted of 2 healthy classes of cotton and tomato leaves and 12 different unhealthy classes of the both cotton and tomato leaves. It is noticed that out of 1327 images, 98, 242, 118, 156, 246 and 51 images were misclassified for VGG16, VGG19, Inception V3, MobileNet, MobileNetV2 and the proposed model respectively. So, it is clear that the proposed model can classify 14 numbers of classes accurately rather than the existing transfer learning models with a lightweight structure.

3) ROC CURVES

From Table 5 it is noticeable that the AUC score for the proposed model is almost nearly one and also it has surpassed the other transfer learning model's AUC.ROC curve is a metric for assessing and fine-tuning the performance of a deep learning model and ROC curves for different models are presented in Fig. 7. The precision vs. recall curves for the four models are shown in Fig. 8.

The precision-recall curve shows the trade-off between precision and recall for different thresholds. A low false positive rate is associated with good precision, whereas

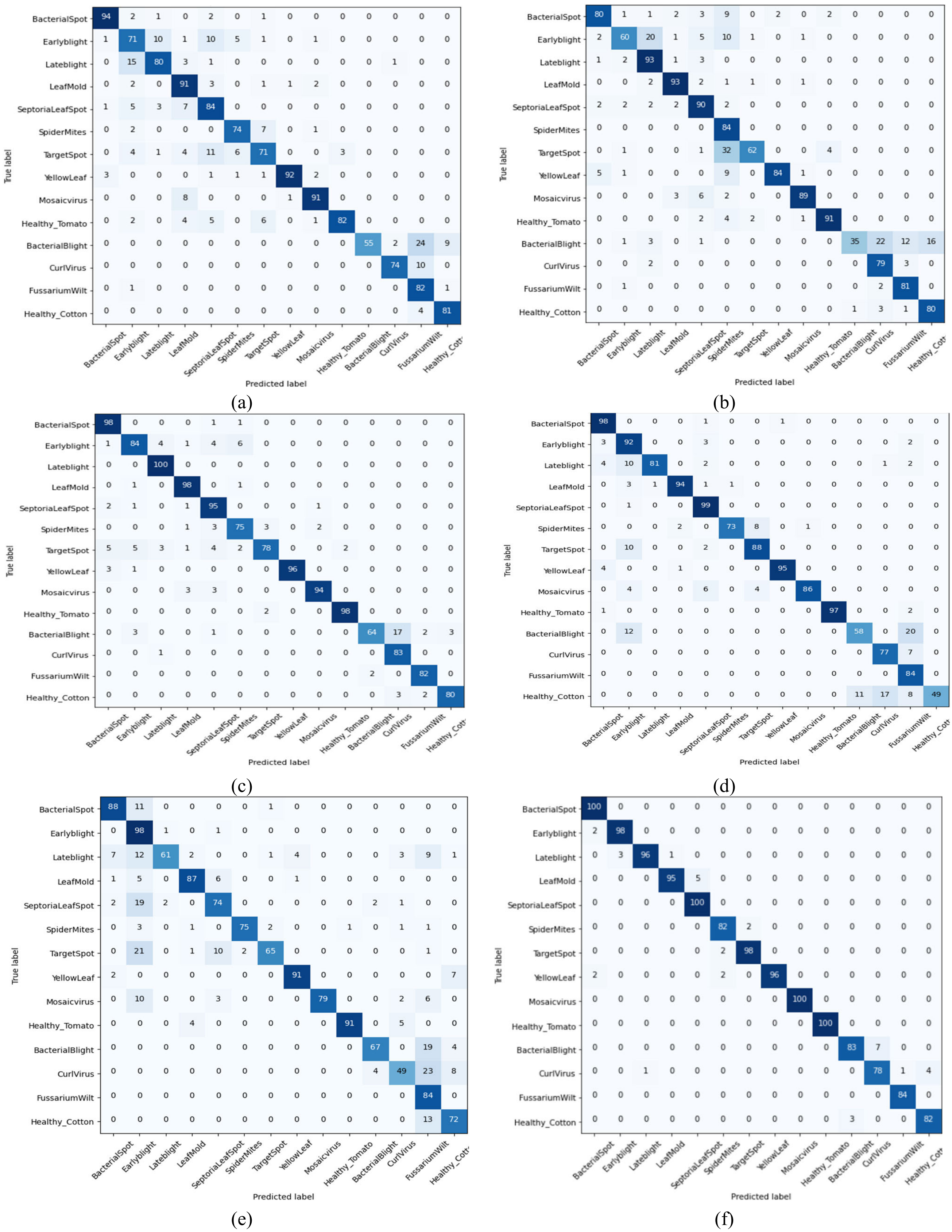

FIGURE 6. **Confusion matrix for (a) VGG16 model, (b) VGG19 model, (c) InceptionV3 model, (d) MobileNet model, (e) MobileNetV2 model and. (f) Proposed model.**

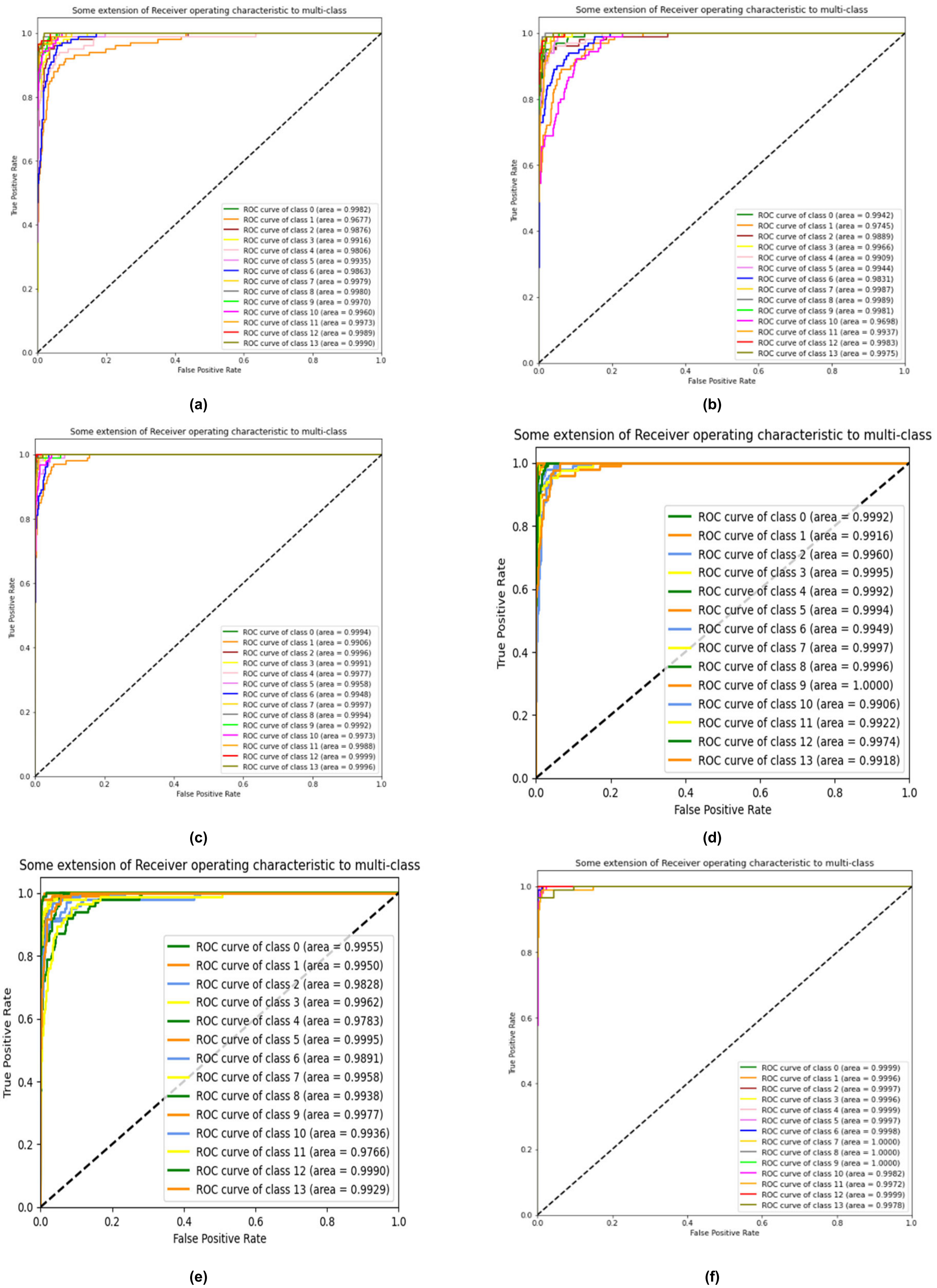

FIGURE 7. **ROC Curve for (a) VGG16 model, (b) VGG19 model, (c) InceptionV3 model, (d) MobileNet model, (e) MobileNetV2 model and (f) Proposed model.**

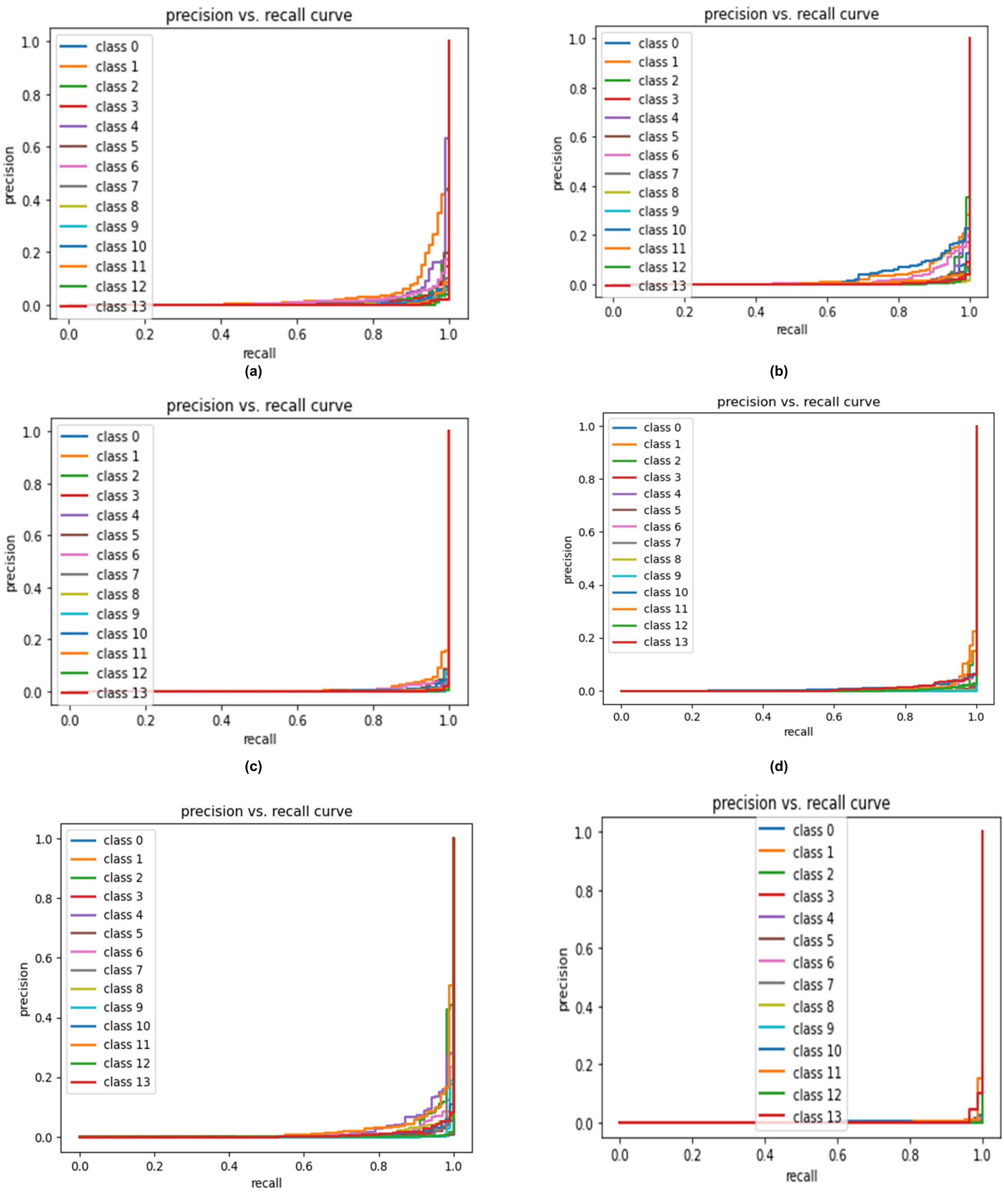

FIGURE 8. Precision Vs Recall Curves for (a) VGG16 model, (b) VGG19 model, (c) InceptionV3 model, (d) MobileNet model, (e) MobileNetV2 model and (f) Proposed model.

TABLE 5. AUC score comparison with transfer learning models.

Models	AUC SCORE
VGG16	99.23%
VGG19	99.12%
Inception V3	99.79%
MobileNet	99.63%
MobileNetV2	99.18%
Proposed 2D CNN model	99.93%

a low false negative rate is associated with strong recall. Great recall and high precision is both indicated by a high area under the curve. The precision-recall curve is utilized because ROC curves are appropriate for datasets that have a uniform distribution of observations across classes, whereas precision-recall curves are appropriate for imbalanced datasets that have been used in this experiment. So the evidence of the enhanced performance of the proposed model is clearly visible from this comparison.

4) COMPARATIVE ANALYSIS

The proposed model is said to be lightweight because it contained significantly less trainable and non-trainable parameters than the transfer learning models. From Table 6, the lightweightness of the proposed CNN model has been proved against some existing transfer learning models. Compared to the popular pretrained models such as VGG16, VGG19 and InceptionV3, the proposed 2D CNN has comparably much lower architectural complexity and parameter count. From Table 6, it is clear that size of the proposed model appeared almost 3 times smaller than VGG16 and VGG19 and almost 4 times smaller than Inception V3. In future, smartphones and portable devices with higher computation power will further normalize the issue. The proposed model's size on the disk is greater than the size of the MobileNet & MobileNetV2 models, but in terms of accuracy, the proposed 2D CNN model has outperformed the mentioned lightweight MobileNet family. The training time and epochs required for the proposed model is also lesser compared to the heavyweight transfer learning models (VGG16, VGG19 and Inception V3). Transfer learning models have more trained weights and it is trained on millions of images. It can perform better for very high number of classes, but in this research, the compared transfer learning models failed to impress against the proposed 2D CNN model. The 2D CNN model has worked better for an imbalanced dataset with a very small number of parameters than the existing transfer learning models.

The lightweightness of the proposed 2D CNN model has also been analyzed against the existing research works mentioned in Table 7. By looking at some of the previous works, it was noticed that some methods proposed in references [19], [20], [22] and [23] used very lightweight CNN models that have very similar accuracies and parameter count is lower than that of the proposed model. However, they are incapable of classifying 14 different classes with high accuracy and precision unlike the proposed method. Even though, 9.5 million+ parameter count may sound like a contradictory proposition for this method, the model has the capability to classify 14 different classes unlike most of the literatures in Table 7. Besides, the proposed 2D CNN only requires high computational power for training purposes, but model evaluation or sample prediction time is comparably still low as demonstrated. One common trend of most of the mentioned literatures in this field is that many methods can show testing accuracies greater than 97% in 2- or 3- class predictions, but then gradually decrease to around 90% as the classes start to increase [12], [33]. The reason behind this issue could be due to a comparably higher parameter count (9.5M+) in the proposed 2D CNN model, it can extract feature maps at higher resolution scales in the Conv2D layers. Because it comprised much less trainable and non-trainable parameters than the transfer learning models, the suggested model is referred to as being a lightweight model.

From Table 7, the performance of the proposed model has also been compared with existing works in terms of evaluation metrics like accuracy, precision, recall, F1 – score and number of classes. It is clear that the proposed model has better results in these evaluation metrics than the existing works for two types of crops and 14 classes whereas most of the existing compared works are based on one type of crop (Tomato). Among the mentioned works, the highest number of classes is 10 for the tomato plant whereas in the proposed work, these 10 classes are merged with 4 cotton classes to form the merged dataset with a view to forming a multi-crop disease dataset. During training, various types of image augmentation techniques are applied to this dataset to increase the dataset for better training.

In [13], transfer learning architectures AlexNet, ResNet50, and VGG16 are employed for the extraction of features which has more layers than the proposed model as well as more parameters.

In [16] accuracy and precision are less than the proposed work. This work deals with 6 classes which is two times fewer than the classes used in the proposed work.

In [17], the work utilizes Modified UNET and ResNet used to have larger parameters [35] for the detection of tomato leaf diseases and attained an average accuracy of 97% for 10 classes of the PlantVillage dataset.

In [18], DenseNet201 was used to achieve the best accuracy, but this architecture has 20.2M parameters which is very large and consume very large disk space.

In [23], the attained accuracy is 98.49% for 10 classes of tomato diseases and the training dataset contains 3000 images. Here accuracy is a bit higher than the proposed model but training has been done on a lesser number of training data.

TABLE 6. Parameter comparison with transfer learning models.

Models	Total Params	Trainable Params	Non-Trainable Params	Size (MB)	Time Required (s)
VGG16	41,469,774	26,755,086	14,714,688	362	17184.55
VGG19	46,779,470	26,755,086	20,024,384	382	18257.30
Inception V3	47,525,806	38,550,542	8,975,264	476	10464.20
MobileNet	3,254,158	3,232,270	21,888	37	4153.15
MobileNetV2	2,275,918	17,934	2,257,984	26	4555.46
Proposed 2D CNN model	9,503,278	9,502,254	1,024	108	6840.23

TABLE 7. Performance comparison with previous works.

Ref. No.	Method	Accuracy	Precision	Recall	AUC	F1-score	Classes	Plant
[12]	CNN	91.2%	90%	92%	-	91%	10	Tomato
[13]	Hybrid-based CNN	96.3%	-	-	-	-	6	Tomato
		98.3%	-	-	-	-	10	
[15]	CNN with attention mechanism	96.81%	96.77%	96.81%	-	96.79%	10	Tomato
[16]	Transfer learning with features concatenation	97%	96.5%	97.33%	-	98.16%	6	Tomato
[17]	ResNet	97%	-	-	-	-	10	Tomato
[18]	InceptionV3	97.99%	97.99%	97.99%	-	97.98%	6	Tomato
	DenseNet201	98.05%	98.03%	98.03%	-	98.03%	10	
[19]	CNN	97.39%	-	-	-	-	10	Tomato
[20]	AlexNet modification architecture-based CNN	96%	98%	95%	-	97%	10	Tomato
[22]	CNN	98.4%	-	-	100%	92.59%	10	Tomato
[23]	CNN	98.49%	-	-	-	-	10	Tomato
[26]	DenseNet121	97.11%	97%	97%	-	97%	10	Tomato
[27]	GoogleNet	99.39%	99.29%	99.12%	99.72%	99.20%	10	Tomato
[28]	ResNet34	99.7%	99.6%	99.7%	100%	99.7%	10	Tomato
[33]	Neural network classifier	92.5%	-	-	-	-	4	Cotton & Tomato
[34]	ResNet	97.28%	-	-	-	-	8	Tomato
Proposed Model	Lightweight 2D CNN Model	97.36%	97%	97%	99.93%	97%	14	Cotton & Tomato

In [26], DenseNet121 was used which has 8.1M parameters which is less compared to the proposed model but the attained accuracy and other evaluation metrics are less than the proposed model.

In [27], the attained accuracy was good using GoogleNet and this network has seven million parameters but this network is much deeper and wider, with 22 total layers. The processing time for the classification is 133.15 minute which is very time consuming than the proposed work's processing time (114 minute). This work had an AUC of 99.72% which is lesser then the AUC of the proposed work. Similarly, in [28] ResNet34 has almost 60.5M parameters which is very large and can consume more space and processing time.

From Table 8, the classwise accuracy comparison has been demonstrated with two of the existing works. In [13], though the average classification accuracy is higher (98.3%) than the proposed model (97.3%), the proposed model has higher classification accuracy (100%) for classes named healthy, septoria leaf spot. In [17], the individual classification accuracy for spider mites and target spot is 78.8% and 77.4% whereas in the proposed work classification accuracy for these two classes is 97.61% and 98%, so the probability of

TABLE 8. Classwise accuracy comparison with existing works.

Disease Class Names for tomato leaves	Accuracy (%)		
	[13]	[17]	Proposed Model
Bacterial Spot	99.9	99.4	100
Early Blight	99.2	99.7	98
Healthy (Tomato)	99.6	-	100
Late Blight	99.9	96.1	96
Leaf Mold	99.8	99.7	95
Septoria Leaf Spot	99.6	99.7	100
Spider Mites	99.9	78.8	82
Target Spot	100	77.4	98
Mosaic Virus	99.9	99.7	100
Yellow Leaf Curl Virus	100	99.8	96

misclassification for the mentioned classes is clearly less in the proposed model.

So, it is worth mentioning that the proposed work deals with multiclass classification for two different crops for an imbalanced dataset with large diversity instead the existing works deal with a dataset of tomato plant disease only, which has less diversity than two merged datasets. Also, most of the existing models have greater parameters. The superiority of the proposed model is that it can detect multiple crop diseases with fewer parameters and comparable accuracy to the existing models. Moreover, in this work, the model is implemented on an Android application for disease detection purposes which hasn't been done for all the works except the work in [20].

To the best of our knowledge, the combination of cotton and tomato crops is not too much used. Work is found for this combination [33] which classifies only 4 classes and attained an accuracy of 92.5% for less amount of data which is smaller than the proposed work's accuracy of 97.36% for the comparatively large number of classes.

C. EXPLAINING THE MODEL USING GRAD-CAM

To make deep learning more comprehensible and explainable, a lot of effort is being done. It is critical to make the deep learning model more interpretive in various deep learning applications connected to plant disease imaging. The Gradient Weighted Class Activation Mapping (Grad-CAM) approach, developed by Selvaraju et al. [36], provides an explainable view of the deep learning models. Grad-CAM creates an observable explanation for any deeply linked Neural Network, which aids in understanding more about the model while executing detection or prediction tasks.

Grad-CAM has been used in this study to evaluate whether the leaf sections in the input image have a significant impact on the diagnosis or to see the evidence of diagnosis visually. To determine the degree of importance of each map, the Grad-CAM calculates a gradient of the target class on each feature map and averages them. Calculating a weighted sum of each

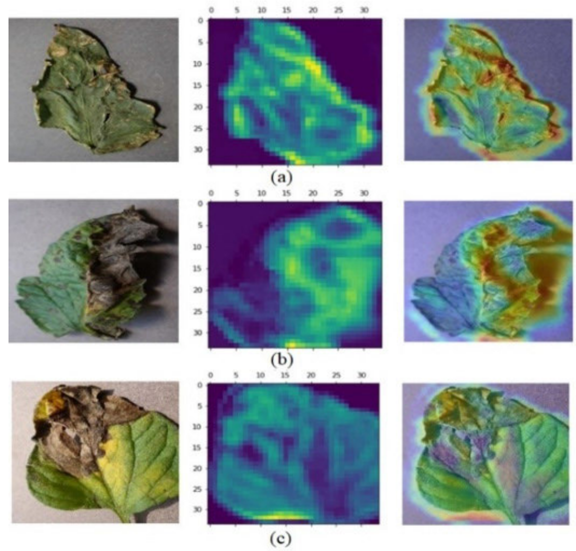

FIGURE 9. Input, Heatmap and superimposed image on input images of (a) Bacterial Spot, (b) Early Blight, (c) Late Blight.

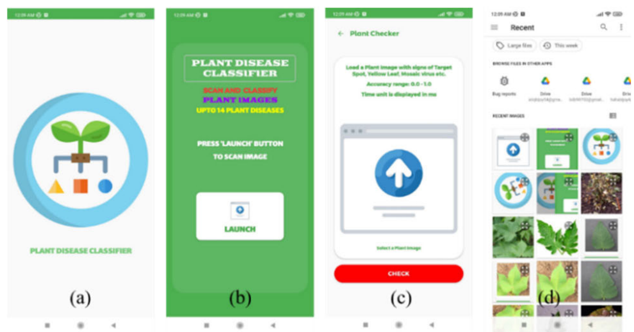

FIGURE 10. Images of the android application activities (a) Opening activity, (b) Launching Activity, (c) Checking Activity, (d) Gallery Images.

feature map activation with the significance corresponding to the input image yields visualization. Grad-CAM is a suitable approach that does not sacrifice execution speed because it does not require extra specially designed components [37]. As shown in Fig. 9, a simple image was taken as an input by the Grad-CAM and applied detection techniques using the proposed model. In most cases, the last convolution layer was the one that will be utilized to apply the Grad-CAM. Grad-CAM utilizes the gradients of the target of the final convolutional layer and creates a heat map that highlights the key areas of an image. When this heatmap is superimposed on the original image, the regions based on which classification is done can be identified.

D. ANDROID APPLICATION

To demonstrate the implementation of the established model in a practical application, a serviceable prototype of an Android App was built and developed. The trained 2D CNN model was translated to TFLite model format in order to create the Android app with a user interface (UI) for classifying

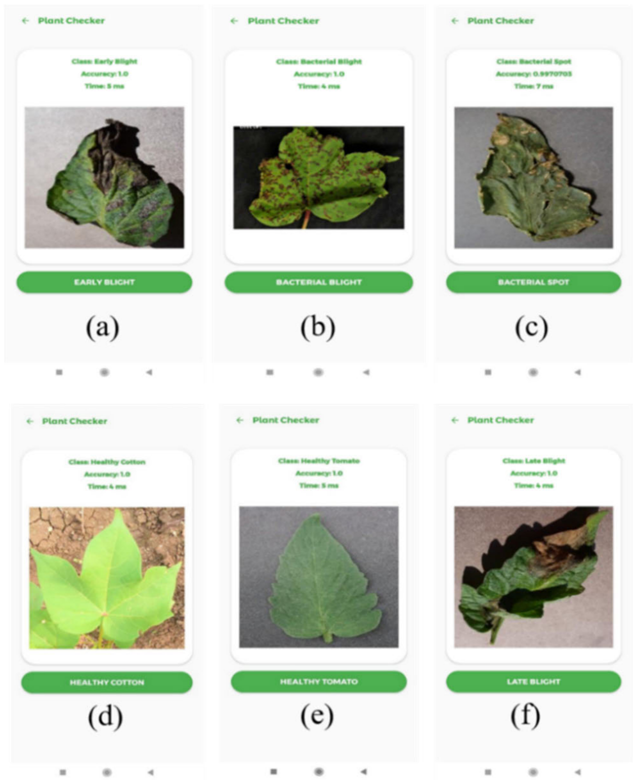

FIGURE 11. **Sample Images of Android application TFLite based image classification of (a) Early Blight (Tomato), (b) Bacterial Blight (Cotton), (c) Bacterial Spot (Tomato), (d) Healthy (Cotton), (e) Healthy (Tomato), (f) Late Blight (Tomato).**

the diseased leaf images on an Android device (Fig. 10). The Android app first loaded the model into memory before allocating tensors and creating a TFLite Interpreter depending on the loaded model. The Interpreter then imported the input leaf image into the input tensor, which was scaled to 150 $\times$ 150 pixels and normalized by using TFLite Image Processor API. The Interpreter then performed inference and output categorization outcomes into the output tensor. The TFLite model can identify a total of 12 disease classes as well as two healthy classes. Fig. 11 depicts the test accuracy and inference runtime outputs. All of the tests were ran using GPU acceleration and required between 4 to 7 milliseconds to run inference on the example leaf images and to diagnose cotton and tomato leaf diseases with great accuracy and faster than a plant diseases specialist. GPU acceleration though was not compulsory to classify an image. All testing were carried out using a Xiaomi Poco F3 with Android 11 and a Qualcomm SM8250-AC Snapdragon 870 5G (7 nm). The Android app is able to detect 14 different forms of plant leaf diseases. The Android app would take considerably less time (4 ms to 7 ms) to diagnose cotton and tomato leaf diseases with great accuracy than a plant doctor. The average detection accuracy is approximately 4.84 ms which can be considered almost real-time disease detection. From the test images, it is observable that the detection accuracy is pretty excellent in the application and the range is between 0.997-1.0 for the mentioned classes. This is a very good aspect of this research. This detection time can be further lessened by using a smartphone that has a processor greater than the mobile's processor used in this research.

As a result, when several plant leaf images have to be examined one after another, this app can save a huge amount of time. Furthermore, the android application will be a guiding tool for the farmers who have no idea about the disease but accurately detecting the disease can lead them to take further steps against the disease and can help them economically. By collecting new leaf photos for different cropping, the model's number of disease classes and accuracy can be increased in the future. The application is now only available for Android devices, although an iOS version could be created in the future.

V. CONCLUSION

In the proposed work, a 2D CNN-based model has been constructed to detect the 12 classes of diseases and two healthy classes in tomato and cotton crops. The proposed 2D CNN-based architecture has three convolutional and three max-pooling layers, which are followed by two fully connected layers. Due to this type of shallow structure, the suggested model has fewer parameters and less storage space consumption than transfer learning models. The average testing accuracy of the model is 97.3%, which has surpassed heavy-weight transfer learning architectures (VGG16, VGG19 and Inception V3) and lightweight transfer learning architectures (MobileNet and MobileNetV2) which are having an average accuracy range from 57% to 92%. The model's performance has also been evaluated using the confusion matrix, ROC curve, and AUC score with the transfer learning models. From the result, it can be revealed that the model has attained an excellent performance that can help the farmers as well as plant doctors to precisely detect various cotton and tomato plant diseases, which can save money for the farmers and aid plant doctors to take accurate measures against the disease. Moreover, this can help the country's economy. The storage space needed by the proposed model is approximately 3 and 4 times lesser than the transfer learning models as the model has very lesser parameters. This lightweight structure can help this model to be implemented on mobile and other devices conveniently. To utilize this research work practically, the model has been implemented in an Android application named "Plant Disease Classifier" for a smartphone-aided plant disease diagnosis system. The average disease detection time is 4.84 ms for the Android application which can be considered almost real-time. To visualize the detection achieved by the trained model, class activation maps were created using the Grad-CAM technique, and a heatmap was created to represent the responsible region for categorization. Nevertheless, deploying a model in practical settings can present various challenges and limitations. One major factor to be mentioned is the computational requirements. The proposed 2D CNN model is fairly lightweight for an Intel/AMD-based computational system. However, for mobile devices, it may require significant computational resources, such as large RAM, CPU/GPU processing power, and fast UFS/NVMe storage. As per several tests, it has been observed that devices that have these types of specifications has very less amount of disease detection time and the detection can be considered almost real-time whereas for devices without such high-quality specifications, the detection can't be considered as real-time. Still, the app's performance and responsiveness are very little affected due to the mobile device's low specification and the diseases can be detected accurately. Collecting continuous image data to keep the model updated is another challenging task because data will be greatly varied due to the environmental or regional variations in cotton and tomato species, diseases prevalent, lighting conditions, and other factors. As new cotton and tomato leaf diseases emerge or the existing ones evolve, the app's average detection accuracy may decrease from 97.3% and inference runtime may increase over 4.84 ms. Also, managing future Plant Disease Classifier model updates and delivering them to end-users can be complex, due to the lack of a system for model versioning, deployment, and maintenance. Regardless of the challenges, the proposed model has outperformed the previous works in terms of precision, recall and F1- score despite having more classes.

In the future, authors have intended to modify the model with a greater number of images with some other crops. Moreover, the accuracy of the model will be improved, and the number of parameters will be reduced to decrease the model's size on the disk.

REFERENCES

[1] T. T. Mim, M. H. Sheikh, R. A. Shampa, M. S. Reza, and M. S. Islam, "Leaves diseases detection of tomato using image processing," in *Proc. 8th Int. Conf. Syst. Model. Advancement Res. Trends (SMART)*, 2019, pp. 244–249.

[2] D. Roy and J. Chakma. (Feb. 20, 2023). "Tomato farmers face peak season plight," The Daily Star. Accessed: Jun. 25, 2023. [Online]. Available: https://www.thedailystar.net/business/economy/news/tomato-farmers-face-peak-season-plight-3252416

[3] *Bangladesh Bureau of Statistics-Government of the People's Republic of Bangladesh*. Accessed: Jun. 25, 2023. [Online]. Available: https://www.bbs.gov.bd/

[4] OEC—The Observatory of Economic Complexity. (2021). *Raw Cotton in Bangladesh | OEC*. [Online]. Available: https://oec.world/en/profile/bilateral-product/raw-cotton/reporter/bgd

[5] *Cotton Development Board*. Accessed: Jun. 25, 2023. [Online]. Available: https://www.cdb.gov.bd/

[6] (Jun. 2013). *Current scenario of Bangladesh Textiles Industry | Scenario of Bangladesh Textiles*. [Online]. Available: https://www.fibre2fashion.com

[7] S. S. Chouhan, A. Kaul, U. P. Singh, and S. Jain, "Bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards plant pathology," *IEEE Access*, vol. 6, pp. 8852–8863, 2018.

[8] J. Shijie, J. Peiyi, and H. Siping, "Automatic detection of tomato diseases and pests based on leaf images," in *Proc. Chin. Autom. Congr. (CAC)*, 2017, pp. 2510–2537.

[9] *PlantVillage Dataset*. Accessed: Aug. 17, 2023. [Online]. Available: https://www.kaggle.com/datasets/emmarex/plantdisease

[10] J. Basavaiah and A. A. Anthony, "Tomato leaf disease classification using multiple feature extraction techniques," *Wireless Pers. Commun.*, vol. 115, no. 1, pp. 633–651, Nov. 2020.

[11] X. Chen, G. Zhou, A. Chen, J. Yi, W. Zhang, and Y. Hu, "Identification of tomato leaf diseases based on combination of ABCK-BWTR and B-ARNet," *Comput. Electron. Agricult.*, vol. 178, Nov. 2020, Art. no. 105730.

[12] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, "ToLeD: Tomato leaf disease detection using convolution neural network," *Proc. Comput. Sci.*, vol. 167, pp. 293–301, 2020.

[13] E. Cengil and A. Çınar, "Hybrid convolutional neural network based classification of bacterial, viral, and fungal diseases on tomato leaf images," *Concurrency Comput., Pract. Exper.*, vol. 34, no. 4, p. e6617, Feb. 2022.

[14] S. Khan and M. Narvekar, "Novel fusion of color balancing and superpixel based approach for detection of tomato plant diseases in natural complex environment," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 34, no. 6, pp. 3506–3516, Jun. 2022.

[15] S. Zhao, Y. Peng, J. Liu, and S. Wu, "Tomato leaf disease diagnosis based on improved convolution neural network by attention module," *Agriculture*, vol. 11, no. 7, p. 651, Jul. 2021.

[16] M. S. Al-Gaashani, F. Shang, M. S. A. Muthanna, M. Khayyat, and A. A. A. El-Latif, "Tomato leaf disease classification by exploiting transfer learning and feature concatenation," *IET Image Process.*, vol. 16, no. 3, pp. 913–925, Feb. 2022.

[17] P. Wspanialy and M. Moussa, "A detection and severity estimation system for generic diseases of tomato greenhouse plants," *Comput. Electron. Agricult.*, vol. 178, Nov. 2020, Art. no. 105701.

[18] M. E. H. Chowdhury, "Tomato leaf diseases detection using deep learning technique," in *Technology in Agriculture*, F. Ahmad and M. Sultan, Eds. London, U.K.: IntechOpen, 2021.

[19] Y. A. Jasim, "High-performance deep learning to detection and tracking tomato plant leaf predict disease and expert systems," *Adv. Distrib. Comput. Artif. Intell. J.*, vol. 10, no. 2, pp. 97–122, Feb. 2021.

[20] H.-C. Chen, A. M. Widodo, A. Wisnujati, M. Rahaman, J. C.-W. Lin, L. Chen, and C.-E. Weng, "AlexNet convolutional neural network for disease detection and classification of tomato leaf," *Electronics*, vol. 11, no. 6, p. 951, Mar. 2022.

[21] R. Karthik, M. Hariharan, S. Anand, P. Mathikshara, A. Johnson, and R. Menaka, "Attention embedded residual CNN for disease detection in tomato leaves," *Appl. Soft Comput.*, vol. 86, Jan. 2020, Art. no. 105933.

[22] M. Agarwal, S. K. Gupta, and K. K. Biswas, "Development of efficient CNN model for tomato crop disease identification," *Sustain. Comput., Informat. Syst.*, vol. 28, Dec. 2020, Art. no. 100407.

[23] N. K. Trivedi, V. Gautam, A. Anand, H. M. Aljahdali, S. G. Villar, D. Anand, N. Goyal, and S. Kadry, "Early detection and classification of tomato leaf disease using high-performance deep neural network," *Sensors*, vol. 21, no. 23, p. 7987, Nov. 2021.

[24] A. Bhujel, N.-E. Kim, E. Arulmozhi, J. K. Basak, and H.-T. Kim, "A lightweight attention-based convolutional neural networks for tomato leaf disease classification," *Agriculture*, vol. 12, no. 2, p. 228, Feb. 2022.

[25] V. T. Indu and S. S. Priyadharsini, "Crossover-based wind-driven optimized convolutional neural network model for tomato leaf disease classification," *J. Plant Diseases Protection*, vol. 129, no. 3, pp. 559–578, Jun. 2022.

[26] A. Abbas, S. Jain, M. Gour, and S. Vankudothu, "Tomato plant disease detection using transfer learning with C-GAN synthetic images," *Comput. Electron. Agricult.*, vol. 187, Aug. 2021, Art. no. 106279.

[27] V. Maeda-Gutiérrez, C. E. Galván-Tejada, L. A. Zanella-Calzada, J. M. Celaya-Padilla, J. I. Galván-Tejada, H. Gamboa-Rosales, H. Luna-García, R. Magallanes-Quintanar, C. A. G. Méndez, and C. A. Olvera-Olvera, "Comparison of convolutional neural network architectures for classification of tomato plant diseases," *Appl. Sci.*, vol. 10, no. 4, p. 1245, Feb. 2020.

[28] L. Tan, J. Lu, and H. Jiang, "Tomato leaf diseases classification based on leaf images: A comparison between classical machine learning and deep learning methods," *AgriEngineering*, vol. 3, no. 3, pp. 542–558, Jul. 2021.

[29] S. Nandhini and K. Ashokkumar, "Improved crossover based monarch butterfly optimization for tomato leaf disease classification using convolutional neural network," *Multimedia Tools Appl.*, vol. 80, no. 12, pp. 18583–18610, May 2021.

[30] S. Santurkar, D. Tsipras, A. Ilyas, and A. Ma, "How does batch normalization help optimization?" in *Proc. 32nd Conf. Neural Inf. Process. Syst. (NeurIPS)*, 2018, pp. 1–12.

[31] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," 2014, *arXiv:1412.6980*.

[32] H. I. Peyal, S. M. Shahriar, A. Sultana, I. Jahan, and M. H. Mondol, ''Detection of tomato leaf diseases using transfer learning architectures: A comparative analysis,'' in *Proc. Int. Conf. Automat., Control Mechtron. Ind. 4.0 (ACMI)*, 2021, pp. 1–6.
[33] C. U. Kumari, S. J. Prasad, and G. Mounika, ''Leaf disease detection: Feature extraction with K-means clustering and classification with ANN,'' in *Proc. 3rd Int. Conf. Comput. Methodologies Commun. (ICCMC)*, 2019, pp. 1095–1098.
[34] K. Zhang, Q. Wu, A. Liu, and X. Meng, ''Can deep learning identify tomato leaf disease?'' *Adv. Multimedia*, vol. 2018, pp. 1–10, Sep. 2018.
[35] Ö. Çiçek, A. Abdulkadir, S. S. Lienkamp, T. Brox, and O. Ronneberger, ''3D U-Net: Learning dense, volumetric segmentation from sparse annotation,'' in *Medical Image Computing and Computer-Assisted Intervention—MICCAI 2016*, vol. 9901, S. Ourselin, L. Joskowicz, M. R. Sabuncu, G. Unal, and W. Wells, Eds. Cham, Switzerland: Springer, 2016, pp. 424–432.
[36] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, ''Grad-CAM: Visual explanations from deep networks via gradient-based localization,'' in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Oct. 2017, pp. 618–626.
[37] E. Fujita, H. Uga, S. Kagiwada, and H. Iyatomi, ''A practical plant diagnosis system for field leaf images and feature visualization,'' *Int. J. Eng. Technol.*, vol. 7, nos. 4–11, pp. 49–54, Oct. 2018.
[38] E. Özbilge, M. K. Ulukök, Ö. Toygar, and E. Ozbilge, ''Tomato disease recognition using a compact convolutional neural network,'' *IEEE Access*, vol. 10, pp. 77213–77224, 2022.
[39] *Cotton-Leaf-Infection*. Accessed: Apr. 24, 2022. [Online]. Available: https://www.kaggle.com/raaavan/cottonleafinfection

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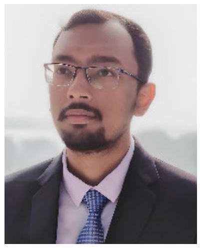

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