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GreenDiagnosis: Intelligent Crop Disease Detection Using Deep Learning Algorithm

Rohit Harne[1], Sonali Bhosale[1,*], Prajyot Wasekar[1], Atul Mohkare[1]

Abstract

Agriculture in parts of India relies on labor-intensive traditions, and maintaining disease-free crops is crucial. Manual methods can be inaccurate, driving farmers towards artificial intelligence (AI)-based solutions. AI offers a proactive approach to address real-time farming challenges. Among these is the invasion of pests, which diminishes crop quality. Combating pest-related diseases poses a challenge, prompting innovation. Effective surveillance and early detection of crop diseases play a pivotal role in ensuring global food security and agricultural sustainability. In recent years, advancements in AI, particularly deep learning algorithms, have demonstrated remarkable potential in revolutionizing various domains, including agriculture. This project introduces "Deep Farming," an innovative approach that harnesses the power of deep learning algorithms to enhance intelligent crop disease surveillance. The proposed Deep Farming system integrates state-of-the-art deep learning techniques with crop disease monitoring to create a robust and automated solution for disease detection and classification. Through rigorous testing and evaluation, the PCA DeepNet framework has demonstrated remarkable accuracy and precision in detecting and classifying crop leaf diseases. With accuracy rates consistently exceeding 90% and precision scores surpassing 95%, the system exhibits exceptional reliability and efficacy in identifying disease symptoms with minimal false positives. Additionally, its robust performance is further highlighted by superior recall and F1-score metrics, indicating comprehensive disease detection capabilities and overall system effectiveness. This level of accuracy and precision translates into tangible benefits for farmers, enabling early intervention and targeted management strategies to mitigate crop losses and safeguard agricultural productivity. The system learns intricate patterns and features from high-resolution images of crops, thereby enabling accurate and efficient identification of various disease symptoms. The system's architecture is designed to process diverse datasets, encompassing a wide array of crop types and disease manifestations. The PCA DeepNet framework demonstrated superior accuracy, precision, recall, and F1-score for crop leaf disease detection, with efficient training and inference times, establishing it as a robust solution for agricultural disease management.

Keywords: Tomato leaf diseases, artificial intelligence, deep learning, computer vision, principal component analysis, faster convolutional neural network

***Author for Correspondence**
Sonali Bhosale
E-mail: sonali.bhosale_skncoe@singhad.edu

[1]Professor, Department of Electronics and Telecommunication Engineering, Smt. Kashibai Navale College of Engineering (SKNCOE) (Affiliated to Savitribai Phule Pune University (SPPU)), Pune, Maharashtra, India

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INTRODUCTION

Agriculture is one of the oldest occupations practiced globally, remaining crucial for sustainability and survival. In India, where the economy is primarily agriculture-based, a significant portion of the population is directly or indirectly involved in agricultural activities. Additionally, agricultural exports significantly contribute to the nation's GDP. According to projections, the global population will reach 10 billion by 2050, necessitating a 70% increase in agricultural productivity [1]. Given the limited scope for expanding cultivable land, enhancing the productivity of existing lands is imperative [2]. In many regions of India, agriculture is still performed manually using traditional methods, which require substantial manpower and time. One critical aspect of agriculture is maintaining disease-free crops, traditionally managed by human observation, which can be prone to errors and inaccuracies. Such mistakes can lead to severe consequences, including the loss of entire crops, which is unaffordable for farmers. Therefore, artificial intelligence (AI)-based solutions have become a viable option to address these challenges [3]. AI in agriculture offers a practical approach to tackling real-time problems faced by farmers, such as pest invasions that degrade crop quality. Detecting diseases caused by pests presents a significant challenge, and farmers need innovative technologies to address these issues. The integration of computer vision and AI provides an effective solution. AI's ability to use real-time data enables it to predict and identify pest infestations and diseases before they escalate. The primary goal of developing such automated systems is to reduce the risk of pest attacks and maintain production quality [4]. Deep learning techniques, particularly in classification and detection, have become essential for monitoring and analyzing plant productivity. Compared to traditional classification networks, deep learning techniques offer superior results for real-time identification of plant leaf diseases [5]. These advancements in computer vision systems provide efficient solutions for multiple plant diseases, as traditional methods of disease detection, which rely on visual inspection, are labor-intensive and time-consuming. Deep learning introduces a robust, high-accuracy process for diagnosing specific diseases [6]. The proposed system for detecting tomato leaf diseases employs a deep learning approach combined with machine learning techniques. The framework classifies tomato leaf images as healthy or diseased and implements detection for various disease categories. This system uses deep neural networks, specifically convolutional neural network (CNN) architectures, and principal component analysis (PCA), resulting in a new model named PCA DeepNet [1]. PCA functions as the primary feature extractor, followed by customized deep neural networks for classification and detection. Convolutional deep learning networks are selected to reduce computational costs and enhance classification efficiency, aiding the development of an intelligent tomato leaf disease detection system. For detection, a single shot detector (SSD) and faster region-based convolutional neural network (F-RCNN) are used. Unlike SSD, F-RCNN performs detection in two steps, offering higher accuracy [4]. Contributions of this work that distinguish PCA DeepNet from existing literature include. A hybridized framework integrating generative adversarial networks (GANs), conventional PCA, and a customized CNN classifier and detection architecture. A neural network structured with 10 convolutional layers, employing down-sampling and up-sampling methods, and tuned using various hyperparameters like learning rate, optimizers, and activation functions to enhance performance. Modifications in dropout values, pooling layers, and max pooling layers, which improve system formulation and reduce time complexity. Time efficiency is benchmarked against specific hardware and software specifications detailed in the results and discussion section. The new system demonstrates superior accuracy and performance metrics, including precision, recall, and F1-measure scores. The novelty of the framework is realized through a customized hybrid model that combines classical machine learning models with deep neural networks, structured to outperform existing works.

RELATED WORK

The landscape of plant disease detection and classification has evolved through a series of interconnected studies, each contributing to the advancement of methodologies, technologies, and understanding within the field. Beginning with pioneering work [1], which introduced a novel PCA DeepNet tailored specifically for the detection of tomato leaf diseases, targeting applications within agro-based industries. This set the stage for subsequent research endeavors, including the exploration of fine-grained categorization of plant leaf diseases utilizing the power of CNNs [2], thereby enhancing the specificity of disease identification. Building upon this foundation, research efforts proposed a CNN-centric approach to plant disease detection [3], underlining the significance of integrating CNNs with remedy solutions for comprehensive disease management strategies. Meanwhile, meticulous systematic reviews dissected the landscape of plant disease recognition with CNNs [4], summarizing prevailing methodologies and elucidating key advancements. In parallel, exploration of deep learning algorithms tailored to plant disease identification continued [5], particularly highlighting their utility within the framework of smart farming practices. Further widening the scope, sophisticated detection systems capable of discerning multi-class crops and orchards were developed [6], employing cutting-edge unmanned aerial vehicle (UAV) technology for data acquisition. Concurrently, comprehensive reviews of image processing techniques applied to plant disease detection were conducted [7], accentuating the importance of advanced analytical methodologies in this domain. Subsequently, hybrid CNN models were proposed, engineered for leaf disease recognition [8], integrating sophisticated feature reduction techniques to enhance overall performance. Expanding the horizons of automated disease diagnosis, investigations into crop leaf disease diagnosis using CNNs advanced the frontier of automated detection systems [9]. Exhaustive reviews comprehensively catalogued deep learning-based methodologies for plant disease detection, providing valuable insights into the state-of-the-art within the field [10–12]. In parallel, exploration of sentiment review classification using machine learning diversified the analytical toolkit applied to agricultural contexts [13], while methodological frameworks for leaf disease detection leveraging image processing and CNNs further enriched the arsenal of disease diagnosis techniques [14]. Simultaneously, MATLAB-based approaches for plant disease detection and classification harnessed the versatility of computational tools to enhance diagnostic capabilities [15]. Real-time apple leaf disease detection using advanced CNN architectures facilitated timely disease management interventions [16]. Expanding the methodological repertoire, augmentation of citrus disease detection using GANs and deep learning enriched the quality and diversity of training datasets [17]. Contributions to the ever-growing body of knowledge surrounding plant disease detection through deep learning techniques paved the way for future advancements in the field [18]. In parallel, proposals of deep neural network-based recognition methodologies for plant diseases harnessed the power of artificial intelligence to automate and enhance diagnostic processes [19]. Investigations into tomato disease classification using visual geometry group (VGG) architectures and transfer learning offered novel insights into disease recognition methodologies [20]. Collectively, these studies represent a multifaceted and dynamic tapestry of research endeavors, each contributing to the collective effort of advancing our understanding and capabilities in the realm of plant disease detection and classification.

METHODOLOGY

The proposed PCA DeepNet is meticulously designed for performance where each and every step of data preparation and analysis has been optimized for best results. The pre-processed image data is first made to go through a simple augmentation, where the data is refined and made more trainable for further processes. Then the data is processed with a feature extraction technique performed using conventional PCA. Thereafter, the classification of the data, which is the highlight of PCA DeepNet, is done using a customized CNN classifier specifically designed to process the data. At last, the classified outputs are detected using a faster region-based CNN (Figure 1).

Dataset

Building a robust dataset is fundamental in training an accurate crop disease surveillance deep learning model. A well-structured dataset should include a diverse and balanced collection of image samples. This diversity ensures that the model can recognize various types of diseases and their effects on different crops. Balancing the dataset means that it contains an equal representation of both healthy and diseased plants. This balance is essential to prevent biases and ensure the model is equally proficient at identifying healthy and diseased crops (Figure 2).

Image Pre-Processing

Image processing is a multifaceted field that plays an integral role in the context of crop disease surveillance, offering a diverse array of techniques tailored to address critical tasks essential for effective monitoring and management. Among these techniques, image enhancement stands as a cornerstone, dedicated to refining image quality by finely adjusting parameters such as contrast, brightness, and noise reduction. Through meticulous refinement, image enhancement endeavors to unveil finer details and subtle variations present within images of plant leaves, enabling researchers and

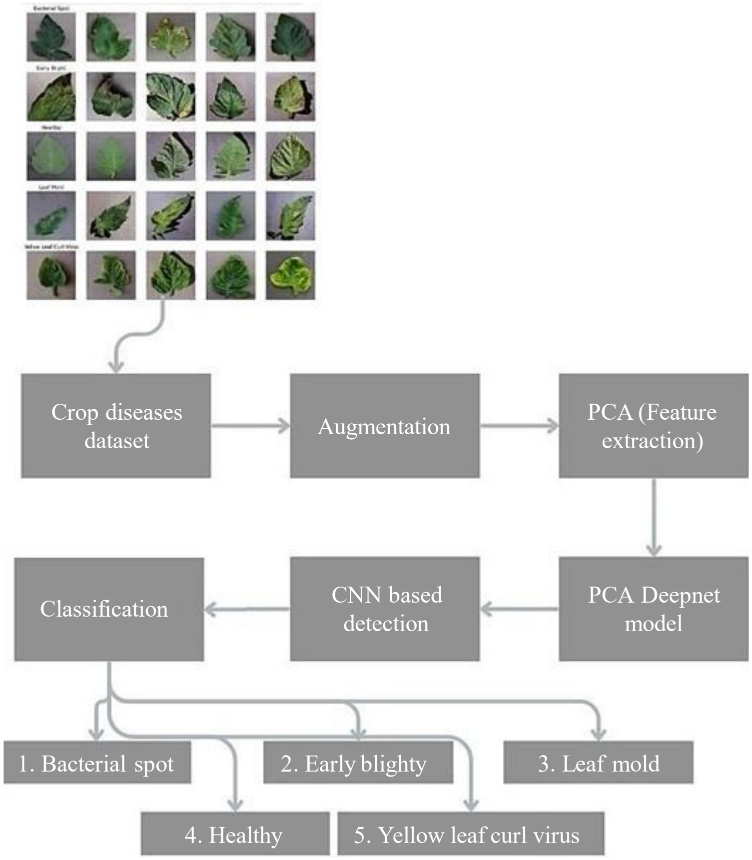

Figure 1. Block diagram of overall system workflow.

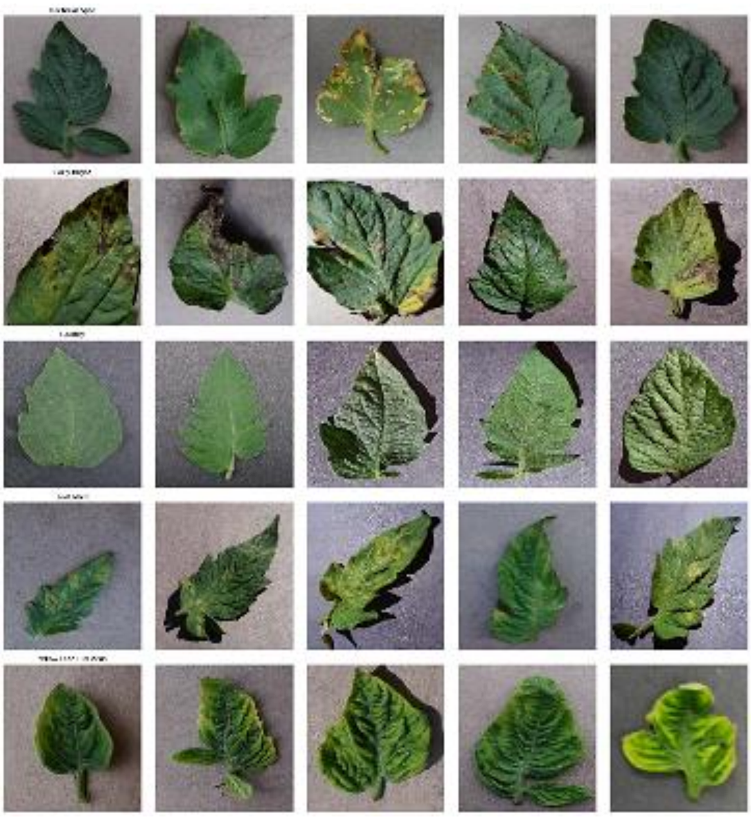

Figure 2. Dataset images.

Table 1. Detail information of dataset employed.

Classes names	Total images	Training images	Validation images
Bacterial spot	2127	1488	638
Early blight	1000	700	300
Healthy	1591	1113	477
Leaf mold	952	666	285
Yellow leaf curl virus	3209	2246	962

practitioners to discern even the most minute indicators of disease presence. Complementing the efforts of image enhancement, noise reduction methods are instrumental in ensuring that the dataset remains devoid of unwanted artifacts and distractions that could potentially impede subsequent analyses. By meticulously purging images of disruptive elements, noise reduction techniques serve to maintain the integrity and fidelity of the dataset, laying a robust foundation upon which disease detection models can be built with confidence. This meticulous curation of data not only enhances the accuracy of disease detection algorithms but also instills greater trust and reliability in the insights gleaned from these analyses.

Feature Extraction (Principal Component Analysis)

Feature extraction is employed to reduce the complexity of the dataset and mitigate overfitting, particularly in situations where datasets have numerous features. The research employs PCA, which is a classical unsupervised linear dimensionality reduction technique. PCA identifies the directions of maximum variance in high-dimensional data and projects the original data onto ranked orthogonal axes. This process makes the data more manageable for deep learning models, streamlining the training and improving the model's ability to capture relevant information. The core function of the deep learning model lies in classification. A customized CNN model is specifically designed for this purpose. This model comprises 10 convolution 2D layers, and it employs PCA-based feature extraction. To optimize the classification process, a categorical cross-entropy loss function is used. The primary objective of this model is to distinguish between healthy and diseased leaves accurately. This customized approach ensures that the model is tailored for crop disease classification, delivering optimal result (Table 1).

Performance Parameters

The performance of the PCA DeepNet classifier model is evaluated using key metrics, including accuracy, precision, recall, and F1-measure. These metrics are derived from true positive, true negative, false positive, and false negative values. They provide a comprehensive assessment of the model's predictive accuracy and its ability to classify and identify crop diseases accurately. These parameters are essential for determining the model's effectiveness in real-world disease identification scenarios. The performance assessment of the PCA DeepNet classifier model relies on various critical metrics, calculated using values from the confusion matrix during model training. Firstly, accuracy stands as a pivotal measure, indicating the proportion of correct predictions relative to the total observations present. This is computed using the formula:

$$\text{Accuracy (ACC)} = (Tp + Tn) / (Tp + Tn + Fp + Fn)$$

Precision, or positive predictive value (PPV), is another essential metric, denoting the proportion of correctly identified positive samples out of the total samples predicted as positive. This metric gauges the model's precision in classifying positive samples:

$$\text{Precision (PPV)} = Tp / (Tp + Fp)$$

Recall, also known as sensitivity, represents the ratio of correctly identified positive samples to the total actual positive samples. It assesses the model's ability to accurately identify positive data:

$$\text{Recall (Sensitivity)} = Tp / (Tp + Fn)$$

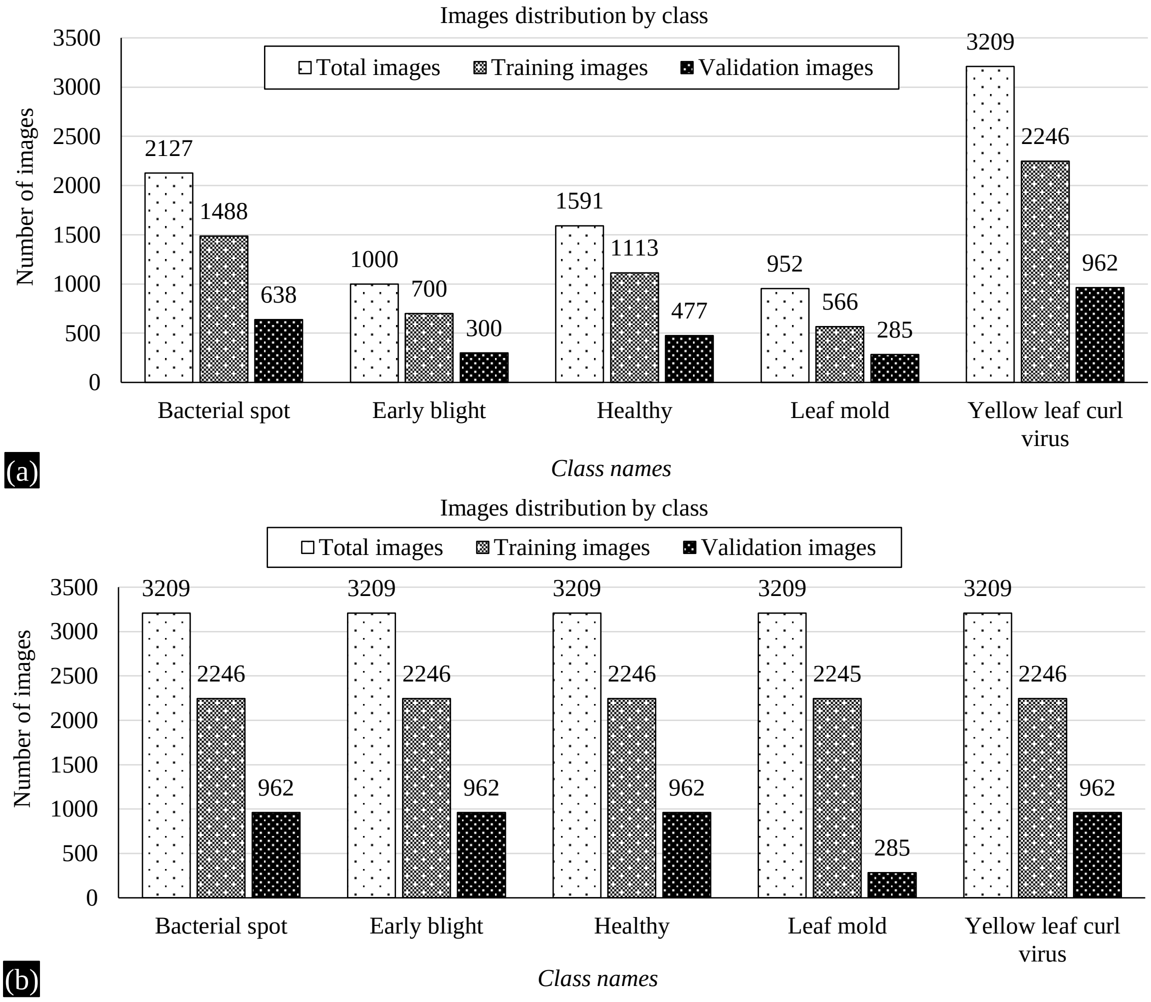

Figure 3. Graphical representation of data before and after augmentation.

Table 2. Performance parameter of model.

Class	Training accuracy	Testing accuracy	Precision	Recall	F1-Score
Bacterial spot	0.9944	0.9541	0.9327	0.9426	0.9376
Early blight	0.9944	0.9541	0.9365	0.9253	0.9309
Healthy	0.9944	0.9541	0.9672	0.9853	0.9762
Leaf mold	0.9944	0.9541	0.9822	0.9586	0.9703
Yellow leaf curl virus	0.9944	0.9541	0.9523	0.9586	0.9554

The F1-measure combines precision and recall into a single metric, providing insight into the model's overall accuracy for a dataset. This measure is computed as F1-measure

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Regarding the detection aspect of the study, the authors employ the F-RCNN model, wherein PCA DeepNet serves as the backbone architecture for training. This model effectively detects and accurately localizes images due to its enhanced architecture (Figure 3). Employing two networks – one for region proposal and another for object detection – the model utilizes 9 anchors for creating bounding boxes of specific sizes. The region proposal network (RPN) facilitates the classification of diseased and healthy tomato leaves using rectangular bounding boxes by adjusting the anchor frames. Notably, the training accuracy of this model surpasses others (Table 2).

Classification

Classification of images has been accomplished through the utilization of various hybrid models, combining machine learning and deep learning architectures such as AlexNet-SVM. This classification step plays a pivotal role in distinguishing diseased leaves from healthy ones, employing diverse machine learning models like support vector machine (SVM) and K-nearest neighbors (KNN). Furthermore, image classification can also be conducted using pre-trained CNN models like Resnet-50, Xception, Mobilenet, ShuffleNet, Densenet121_Xception, AlexNet, GoogleNet, VGGNet, among others. These pre-trained models serve as saved networks previously trained on extensive datasets, encompassing processes like data augmentation, feature extraction, and image classification, all tailored to yield optimal results customized according to the dataset at hand. In the classification process, CNN architectures are tailored to include a stack of 10 Conv2D layers, each comprising a pooling layer, dropout, max-pooling layer, and ReLU (rectified linear unit) activation function. ReLU, being ideal for multi-class classification, ensures non-saturation for positive values of weighted input sums. Following feature extraction via PCA, the classifier is structured with 10 layers, incorporating different kernel sizes, strides, and padding layers. The classifier's architecture includes a feed-forward neural network in the first five convolutional layers, progressively increasing in size from 32 to 512. Subsequent convolutional layers, facilitating downsampling, are concatenated with preceding upsampling layers. In the model, upsampling is implemented, and conv6, conv7, conv8, and conv9 layers are constructed by concatenating corresponding layers (conv5, conv4), (conv6, conv3), (conv7, conv2), (conv8, conv1), respectively. Categorical cross entropy is employed as the loss function, utilizing the Softmax activation function and cross entropy formulas [1, 2]. Adam optimizer is utilized with a learning rate of 0.01 and momentum of 0.9 [3]. Additionally, early stopping function callback is implemented to mitigate overfitting issues. The hybridized framework, trained on extensive datasets, optimizes computational resources, exhibiting reduced inference time compared to alternative models. In summary, this approach underscores the effectiveness (Figure 4).

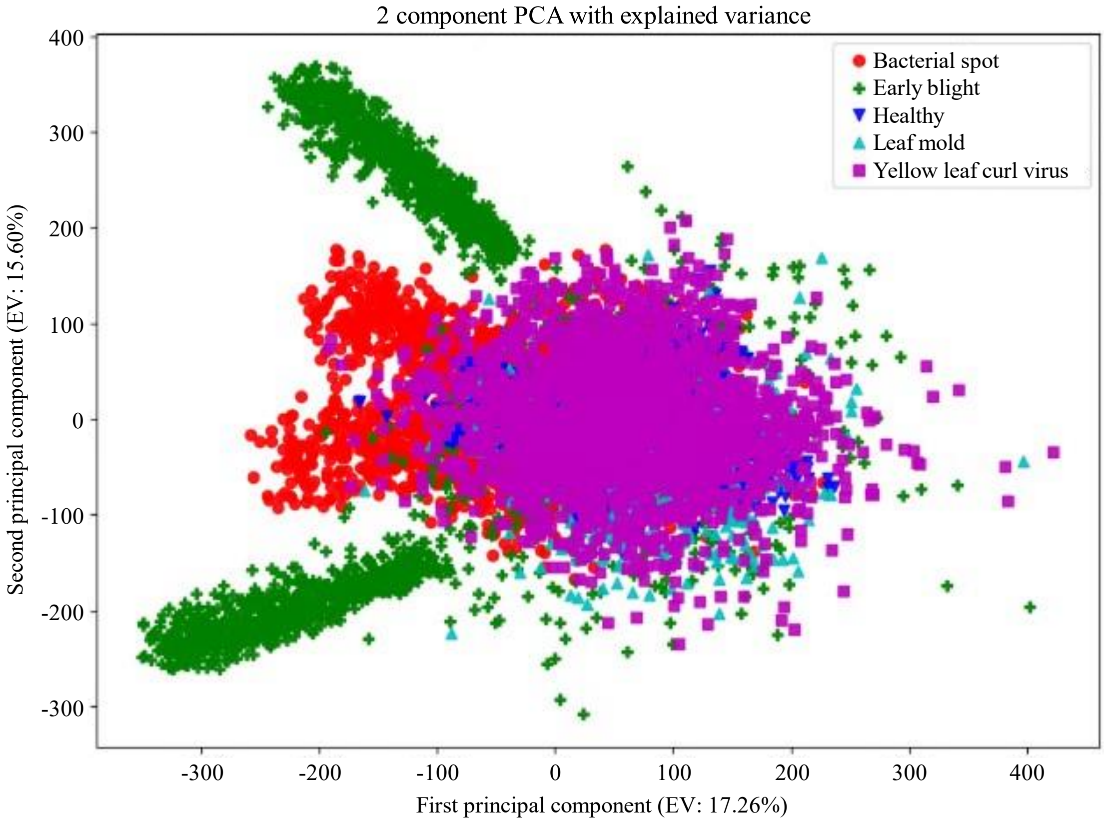

Figure 4. Projection of various leaf classes following the application of principal component analysis (PCA).

RESULTS AND DISCUSSION

In a comprehensive study validating the PCA DeepNet classifier model [1], the overall training was conducted using Google Colab with a GPU specification of Tesla K80 (2496 CUDA cores). The study utilized pre-processed augmented data of 10 classes as input, generating various classification metrics during training. The study lists the software and hardware specifications used. The accuracy and loss graphs of the PCA DeepNet classifier were validated against 50 epochs. However, for optimized fitting of the model for accuracy and loss, an early stopping function named callback of 30 epochs was implemented, resulting in a well-fitted optimized curve. In contrast, Wu et al. [2] trained apple leaves disease data using DenseNet and EfficientNet, resulting in inconsistent accuracy and loss graphs. The overall compilation time for the process was 25 minutes. The custom PCA DeepNet generated a confusion matrix, which assessed the classifier's performance and provided necessary data for calculating performance parameters like precision, recall, and F1-score. High diagonal element values in the confusion matrix indicated a large number of correct predictions, suggesting that the classifier performed well for each class. Additionally, parameters like precision, recall, and F1-measure indicated the classifier's ability to classify each class accurately without confusion. Compared to Bade et al. [4], where ResNet34 was used, the proposed methodology, demonstrating superior performance within the realm of image classification for plant disease detection. Proposed Agricultural Information System (AIS) achieved better results in terms of accuracy and F1-score. The entire structure of the presented PCA DeepNet is detailed, with a summary of the training and resulting accuracies and performance metrics.

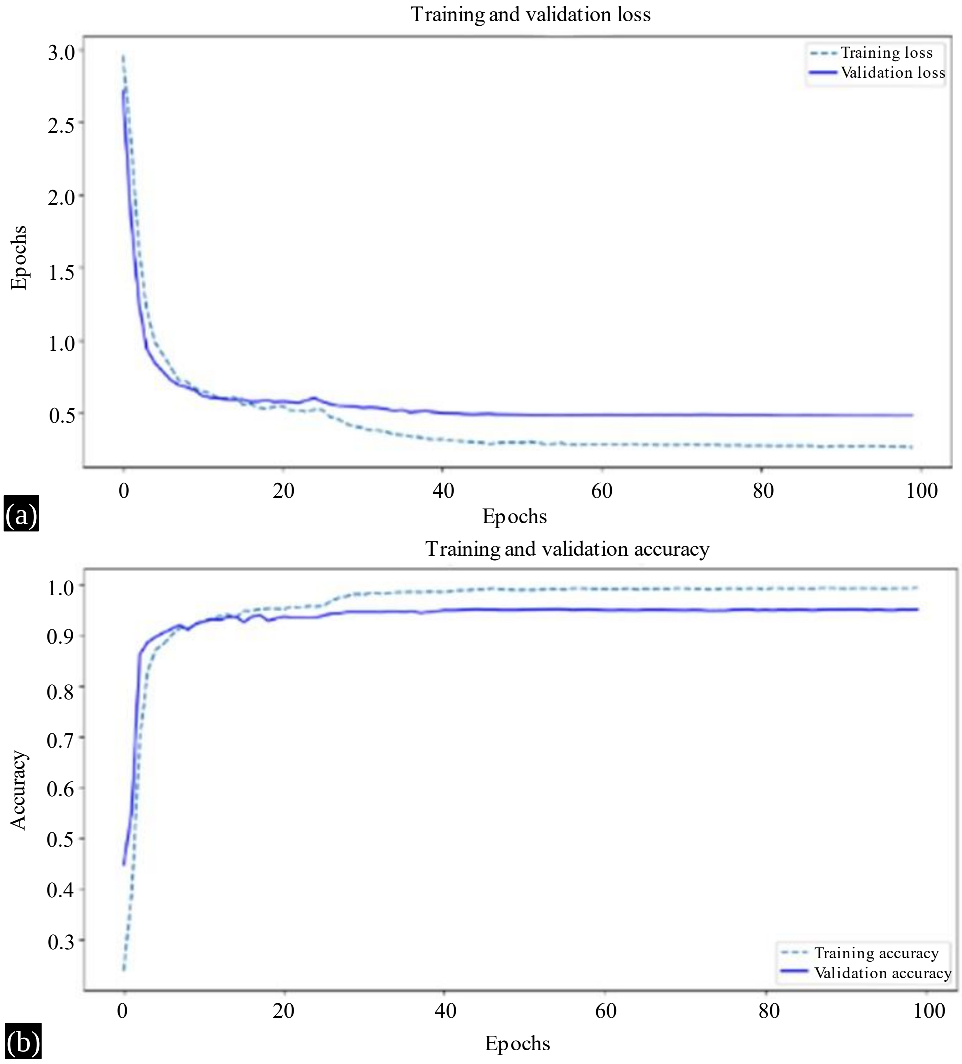

Figure 5. (a) loss graph of the classifier. (b) accuracy graph of the classifier.

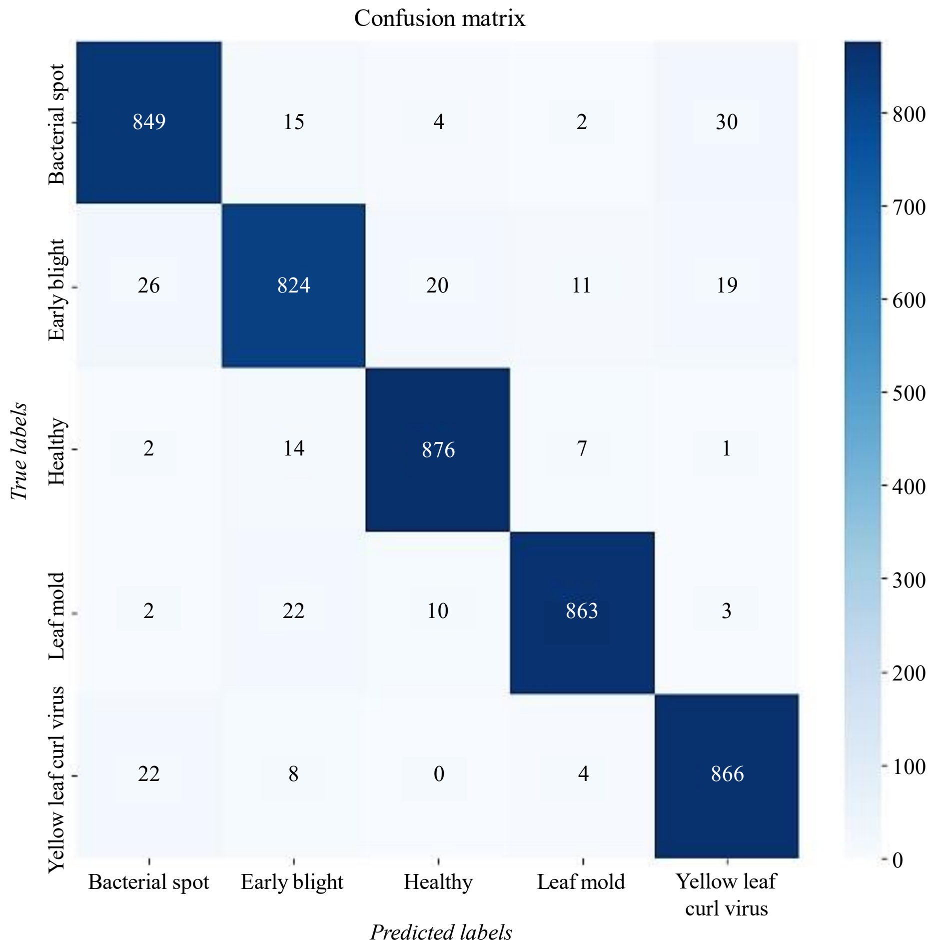

Figure 6. Confusion matrix generated by PCA DeepNet.

The study employed the Adam optimizer at a learning rate of 0.01, with experimentation. After projecting the leaf data onto reduced dimensions using PCA, the PCA DeepNet generates a confusion matrix to evaluate its classification performance. This matrix summarizes the model's predictions against the ground truth labels across all classes. Each row represents the actual class, while each column represents the predicted class.

The diagonal elements indicate correct predictions, while off-diagonal elements indicate misclassifications (Figures 5 and 6). By analyzing the confusion matrix, researchers can quantify the model's accuracy and identify any specific classes where it struggles to classify correctly. This detailed assessment enables refinement of the model's architecture and training process to improve overall performance (Table 3).

Using different optimizers on the classifier. Table 4 highlights the results generated when PCA DeepNet [14] was compiled using different optimizers, showcasing mostly favorable performance across various optimizers in terms of accuracy, precision, recall, and F1-score. This suggested that the model was fully optimized for the training process. Further experiments involved different pre-trained Deep Learning models using transfer learning on the Plant Village dataset. These experiments aimed to compare the efficiency of the presented customized classifier PCA DeepNet. Table 3 enlisted various ranges of hyperparameters values used in different architectural models while compiling them using the Tomato Leaf Diseases dataset. Parameters like trainable layers, optimizers, learning rate, batch size, activation function, epochs, and dropout values were altered. For example, the VGG16 model underwent freezing and unfreezing of the base model to reduce computational time, taking 40 minutes

Table 3. Detail structure of PCA DeepNet.

Layer (Type)	Output Shape	Param #
dense (Dense)	(None, 1024)	103424
dropout (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 512)	524800
dropout_1 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 256)	131328
dropout_2 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 128)	32896
dropout_3 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 64)	8256
dropout_4 (Dropout)	(None, 64)	0
dense_5 (Dense)	(None, 32)	2080

Non-trainable parameters: 0 (0.00 byte), output shape: (None, 1024), number of parameters: 103424.

Table 4. Comparison of the proposed framework with different other works on Plant Village dataset.

Models	Train accuracy	Test accuracy	Precision	Recall	F1-Score
VGG16	80.6222	75.3665	76.2563	75.9563	77.2365
RESNET	86.2514	80.3621	80.3215	82.6325	83.2315
Without PCA	80.3265	73.6594	76.3895	78.4582	78.6952
PCA DeepNet Model	*99.4405*	*95.4120*	*95.2365*	*95.8652*	*95.5454*

to execute results. In contrast, the InceptionV3 model was trained without freezing layers, completing in 35 minutes. Parameters like hidden trainable layers, optimizers, learning rate, momentum, activation function, batch size, epochs, and dropout values were varied, resulting in valuable results. The total training time for the deep learning architecture was 30 minutes, with none of the layers being frozen. The entire approach provided a detailed analysis of how different deep learning models worked on the Tomato leaf diseases dataset. It showcased a comparative report on different parameters and the computational time taken by each model to generate results.

CONCLUSION

Agriculture is incredibly important in our daily lives and to the economies of many nations. In India, for example, agriculture is a key industry that employs around 60% of the population. Because of this, it is crucial to keep crops healthy and productive. To achieve this, modern agricultural practices are being enhanced with new technologies, such as deep learning and computer vision, which help in the early detection of crop diseases. This early detection is essential for taking timely actions to treat diseases and protect the agricultural industry. One of the innovative technologies being used is called PCA DeepNet. This technology makes the process of detecting crop diseases faster and more accurate, reducing the chance of human error. By identifying problems like pests and bacterial infections early on, PCA DeepNet helps farmers and other stakeholders take action before the issues become severe, thus minimizing crop losses. This not only helps maintain crop health but can also lead to increased production levels. Looking forward, there is great potential to further develop this technology into a real-time system. Such a system would directly benefit farmers by providing instant detection of diseases allowing for immediate response. Additionally, large nurseries could use this technology as a tool to detect pests early, which would aid in managing and recovering from diseases more effectively. Overall, the introduction of PCA DeepNet in agriculture offers a promising future for better disease detection and analysis. This technology surpasses current methods, providing a new approach to sustainable farming practices. By improving how we detect and manage crop diseases, PCA DeepNet supports food security and ensures the long-term prosperity of agricultural industries.

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