International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(8s) 2026 pp. 615-626
https://doi.org/10.70917/ijcisim-2026-3300
Article

Comparative Evaluation of Hybrid Deep Learning Models for Multiclass Capsicum Leaf Disease Detection

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Abstract: In modern agriculture early and accurate disease diagnosis is vital for increasing crop productivity and minimizing economic losses in plant leaf diseases. Capsicum (Capsicum annuum L.) is a high-value vegetable crop that is very vulnerable to several fungal diseases of leaves and timely disease diagnosis is important to achieve successful crop management. This study proposes an image processing system for recognizing the multi-classes capsicum leaf diseases by using hybrid deep learning methods. The dataset consisted of 7,735 images of leaves from the Mendeley Pepper Bell Disease dataset and images of leaves taken from the field in Ahilyanagar district of Maharashtra, India. There are six types of leaf diseases: Cercospora Leaf Spot, Bacterial Spot, Leaf Curl, Nutrition Deficiency, Powdery Mildew, & Healthy leaves. Before the development of the models, all of the images were preprocessed by resizing, normalization, and augmentation of the data. The models of the Convolutional Neural Network (CNN), CNN-Support Vector Machine (CNN-SVM), and CNN-Long Short-Term memory (CNN-LSTM) were designed and tested under the same training, validation, and testing conditions. The accuracy, recall, specificity, precision, F1 score & multiclass confusion matrix analysis were used to evaluate the results of the model. The CNN-LSTM model performed between 98.9% classification accuracy, which is higher compared to CNN-SVM (96.7%) and conventional CNN (95.3%) models. The results prove that hybrid deep learning architectures can offer better feature learning and classification accuracy to detect capsicum leaf diseases, which can be applied for the development of intelligent decision support systems in precision agriculture.
Keywords: Capsicum leaf disease detection, Image processing, Hybrid deep learning, Convolutional Neural Network (CNN), CNN-LSTM, CNN-SVM, Precision agriculture.

1. Introduction:

Globally, agriculture holds a key position in food security and in the economic development. Capsicum (Capsicum annuum L.) is one of the most important and nutritious horticultural crops. Bacterial Spot, Cercospora Leaf Spot, Leaf Curl and Powdery Mildew are the most important foliar diseases affecting the productivity and quality of capsicum crops, as is nutrient deficiency[11]. Proper diagnosis is crucial to getting a better yield, healthier crops, and lower use of pesticides, as incorrect or late diagnoses may lead to all these. Thus, an efficient and automated disease detection system is crucial for timely action and sustainable crop management [15], [16].

In the last twenty years there has been a drastic growth in plant disease diagnosis, with the introduction of image processing, computer vision and deep learning, whereby an automatic analysis of leaf images has been obtained. While visual inspection requires expertise and may be subjective, disease detection systems based on images are fast, objective, and scalable. Convolutional Neural Networks (CNNs) have shown great success in hierarchical image feature extraction & classification of plant diseases using deep learning models[4], [8], [11]. However, the effectiveness of the standalone CNN model can appear to decrease when the disease symptoms have high visual similarity, or when images are taken under different environmental conditions [2], [10].

To address these drawbacks, researchers have suggested combining CNNs with other machine learning or sequential learning methods to create hybrid deep learning architectures. CNN-SVM and CNN-LSTM are two hybrid models that utilize the ability of CNN for powerful feature extraction and SVM/LSTM for advanced decision making, achieving better classification accuracy[3], [5]. CNN-SVM adopts convolutional layers for feature extraction, and an

SVM classifier for the enhancement of class separation. Likewise, CNN-LSTM fuses spatial feature extraction and sequential feature learning, which brings the model to integrate complex feature relationship and enhance classification accuracy[9], [17].

In this study, a comprehensive dataset of 7,735 capsicum leaf images was prepared by combining the data from Mendeley Pepper Bell Leaf Disease Dataset with the images collected from real-time farms in the agriculture field in Ahilyanagar District, Maharashtra, India. The data consists of 6 classes: Cercospora Leaf Spot, Bacterial Spot, Leaf Curl, Nutrition Deficiency, Powdery Mildew, & Healthy leaves. Before feeding the images into the model, they underwent pre-processing tasks, such as resizing and normalization, to improve the quality of the data and generate the model. This data set was then divided into three sets: training set, validation set, & test set, to test the performance.

The main aim of this work is to compare three deep learning models CNN, CNN-SVM and CNN-LSTM for the multiclass classification of capsicum leaf diseases. Performance of models are assessed based on the conventional performance indicators such as accuracy, recall, precision, specificity, F1 score & Multi class confusion matrix analysis. The experimental results show that CNN-LSTM model has the best accuracy rate of 98.9% in the classification process, which is higher than CNN-SVM model (96.7%) and traditional CNN model (95.3%). The results show that the hybrid deep learning methods outperform other methods in both feature representation and classification for automated capsicum leaf disease detection.

The major contributions of this research are summarized as follows:

1. Designing a multiclass capsicum leaf disease detection system using image processing and hybrid deep learning.

2. Development of a comprehensive data set of 7735 leaf images – using both benchmark and real-time field data.

3. Comparative evaluation of CNN, CNN-SVM and CNN-LSTM models with the same experimental settings.

4. Fully comprehensive evaluation by accuracy, recall, precision, specificity, F1 score and confusion matrix analysis.

5. Successful application of the CNN-LSTM model for accurate and reliable diagnosis of capsicum leaf diseases, which will aid precision agriculture applications.

2. Literature Survey:

Image processing, computer vision and deep learning are an important development in recent years that can significantly facilitate the automatic detection of plant disease from the images taken of the leaves [6]. The traditional method of disease diagnosis is visual diagnosis by agricultural experts, but this is not suitable for large-scale farming and takes time and is subjective. As a result, machine learning and deep learning methods are gaining in popularity for creating an intelligent disease diagnosis system that will accurately diagnose the plant diseases based on digital images[16].

In the existing work, most of the researchers used traditional machine learning algorithms, which involved handcrafting features from leaf images such as color, texture, shape and edge to classify the leaf images with the help of algorithms like Support Vector Machine (SVM), Random Forest, & Artificial Neural Network (ANN) [22]. While these methods were able to perform well in controlled settings, they required a great amount of feature engineering and generally failed to perform as well when images were shot in different environments[29], [30].

With the advent of Convolutional Neural Networks (CNNs), the need for manual feature extraction was removed and CNN learns hierarchical feature representations directly from input images. CNN-based architectures have shown very promising results on tomato, potato, cucumber, rice, maize and other economically important crops for disease identification [19]. Some studies have found that CNN models outperform traditional machine learning methods due to their ability to learn complex visual features that are related to plant diseases. However, the performance of the standalone CNN architectures may suffer from low performance if the disease symptoms have a high visual similarity or if there are high variations in the light, background, and orientation of the leaves in the dataset[24].

To further boost the classification accuracy, current research has been directed towards the hybrid deep learning models using CNN with the addition of other supporting learning models. Hybrid architectures use the superior feature extraction ability provided by CNNs and high-performance classifiers or sequential learning models for decision making[5]. CNN-SVM models consist of convolution layers for extracting features and SVM as last classifiers which leads to better class separation and less classification errors. Likewise, CNN-LSTM models combine the convolutional feature extraction with the Long Short-Term Memory network to obtain the complex feature relationship and enhance the recognition performance of plant disease datasets with more than two classes[17].

In recent times, a number of works have worked on Vision Transformers (ViT), Capsule Networks (CapsNet), and attention-based deep learning architectures for plant disease detection. While Capsule Networks have been seen to enhance the recognition of visually similar disease symptoms by maintaining spatial relationships among image features, the Vision Transformer models have demonstrated their ability to effectively model global image relations[1], [7]. There are multiple hybrid models that mix CNN, Vision Transformer and Capsule Network architectures that have resulted in better classification performance on various crop datasets. But the typical models have high computational costs and demand large-scale, labeled datasets to perform properly[12], [13].

While considerable work has been done in the field of automated diagnosis of plant diseases, the classification of capsicum leaf disease in the context of multiple classes that include benchmark images and real-time field images is comparatively under-explored. The current studies are done on a single deep learning architecture or have focused on relatively small data sets and a few types of diseases. Also, the different illumination, complex backgrounds and other visual symptoms of different diseases still pose a challenge for good classification in real agricultural conditions.

To overcome these, this research work presents comparative study of CNN, CNN-SVM, and CNN-LSTM models using a large dataset of 7,735 images of capsicum leaves acquired from Mendeley Pepper Bell Leaf Disease Dataset as well as and real time agricultural fields in Ahilyanagar District, Maharashtra, India. This proposed study is based on the effectiveness of hybrid deep learning methods to classify multi-class diseases such as Cercospora Leaf Spot, Bacterial Spot, Leaf Curl, Nutrition Deficiency, Powdery Mildew and Healthy leaves. The performance testing of the proposed models are then tested for accuracy, precision, recall, specificity, F1 score & multiclass confusion matrix to find the best architecture for the automated disease detection of capsicum leaf.

3. Material & Methods:

This proposed method aims to develop and evaluate an automatic multiclass capsicums leaf disease detection system by employing image processing and hybrid deep learning approach. The overall process of proposed system is divided into 5 major stages: Data set acquisition, image pre-processing, data set partitioning, model development and performance evaluation. The overall framework used in this study is shown below in Figure 1.

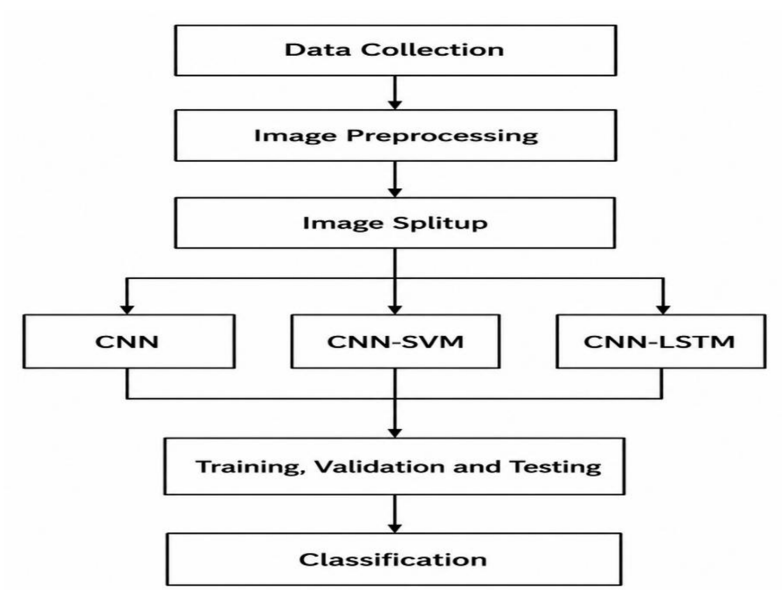

Figure 1: Framework for capsicum leaf disease detection

A detailed dataset of images was created initially by merging the Mendeley Pepper Bell Leaf Disease Dataset with real time images captured from the agricultural fields of Ahilyanagar District, Maharashtra, India, that contain 7,735 capsicum leaf images. The data are from six disease classes: Cercospora Leaf Spot, Bacterial Spot, Leaf Curl, Nutrition Deficiency, Powdery Mildew, & Healthy leaves. The use of publicly available images and field-acquired images increases the variety of the images and thus increases the robustness of the models developed under practical agricultural conditions.

All images were passed through a preprocessing pipeline prior to training the deep learning models, to ensure data consistency and convergence of the models. All images were resized to 256 × 256 pixels and normalized by rescaling the intensity values of the pixels to values in the range 0-1. The training set was further augmented with random rotations, horizontal and vertical flips, zooms, width and height shifts to improve the generalization of the model and avoid overfitting. The resulting training set was fairly balanced, representative and contained the same disease characteristics found in the original data.

The preprocessed data set was divided into training set, validation set & testing set in the ratio of 70:15:15. The training set was utilized for the model parameters training, the validation set is applied for evaluating the model convergence and tuning the hyperparameters while the testing set is applied only for evaluating the model performance. Three deep learning models were developed for comparative evaluation; Convolutional Neural Network (CNN), Convolutional Neural Network–Support Vector Machine (CNN-SVM), and Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM).

CNN model is used as baseline model and all hierarchical spatial features are automatically extracted from the images of the leaf by convolution and pooling layers and then using fully connected layers for the classification of the disease [4]. The CNN-SVM model is the same as the CNN model except that the deep features, which are extracted by the convolutional layers, are classified by a Support Vector Machine (SVM) classifier instead of the conventional Softmax layer. This hybrid approach improves the classification accuracy for multiclass datasets by optimizing decision boundaries. The CNN-LSTM model features convolutional feature extraction followed by a Long Short-Term Memory (LSTM) network, which allows higher-level feature dependencies to be learned prior to the final classification step. This hybrid architecture allows to consider both the spatial and discriminative feature relationships, in order to obtain better disease recognition accuracy.

All three models were trained with the same settings of the experiments for a fair comparison. The deep learning framework TensorFlow–Keras was used to train the models with 25 epochs, a batch size of 32, a learning rate of 0.001 and the Adam optimizer. The classification problem has been solved using Rectified Linear Unit (ReLU) activation function in hidden layers, categorical cross-entropy loss function, and Softmax activation function in the output layer.

The performance of the developed models was tested by the standard multiclass classification metrics such as Accuracy, Recall (True Positive Rate), Precision, Specificity (True Negative Rate) and F1-score. Moreover, multiclass confusion matrices are generated for analysing results of classification in each disease class level. Comparative analysis of CNN, CNN-SVM and CNN-LSTM clearly indicates the effectiveness of the hybrid deep learning methods in automated capsicum leaf disease detection.

3.1 Dataset Description:

A thorough image dataset was constructed for multiclass capsicum leaf disease detection by amalgamating images from the Mendeley Pepper Bell Leaf Disease Dataset along with real-time images captured from the agricultural farms in Ahilyanagar District, Maharashtra, India. By adding both benchmark and field acquired images, the diversity of the image set is enhanced and the proposed models are able to learn the disease characteristics under controlled and natural environmental conditions.

The final dataset is composed of 7,735 leaf images which correspond to 6 different disease categories, namely Bacterial Spot, Cercospora Leaf Spot, Leaf Curl, Nutrition Deficiency, Powdery Mildew and Healthy Leaves. The table below (Table 1) shows the data as distributed among the students in a class.

Table 1. Distribution of Capsicum Leaf Image Dataset

Sr. No	Disease Category	Number of Images
1	Bacterial Spot	3563

2	Cercospora Leaf Spot	1662
3	Leaf Curl	720
4	Nutrition Deficiency	444
5	Powdery Mildew	383
6	Healthy	963
	Total	7735

3.2 Image Preprocessing:

To enhance the quality of the images, consistency of the data and better capability to learn the deep learning models, image preprocessing was performed. All images were resized to 256 X 256 pixels initially to give a uniform dimension for the input of the neural networks. The intensity values of the pixels were then normalized by rescaling them to the range 0–1, ensuring quicker convergence of the model during training.

Several data augmentation methods were used to enhance the models and prevent overfitting of the training data. These methods involved zooming, width and height shifting, horizontal flipping and random image rotation. The models were enhanced in their generalization ability by the data augmentation process that created more variations of the images while maintaining the disease characteristics.

The preprocessing workflow consists of the following stages:

- Image resizing (256 × 256 pixels)
- Pixel value normalization (0–1)
- Image augmentation
- Dataset partitioning

3.3 Dataset Partitioning:

The dataset was split into three subsets after the pre-processing stage for model development and testing.

Table 2: *Dataset Partitioning*

Sr.	**Dataset**	**Percentage**	**Number of Images**
1	Training	70%	5414
2	Validation	15%	1160
3	Testing	15%	1161
	Total	100%	7735

For the training set, the model parameters were learned for the validation set, the convergence of the model and the optimum choice of the hyperparameters were monitored. The test set was fully independent and was only used for final evaluation of classification performance.

3.4 CNN Architecture:

Convolutional Neural Network (CNN) model is the basic deep learning model used in classification of capsicum leaf disease. The model automatically learns hierarchical visual features from the input leaf images with a number of convolutional and pooling layers.

The CNN architecture is proposed to be divided into the following layers:

- Input Layer (256 × 256 × 3)

- Convolution Layer (32 filters, 3 × 3)
- ReLU Activation
- Max Pooling Layer (2 × 2)
- Convolution Layer (64 filters, 3 × 3)
- ReLU Activation
- Max Pooling Layer (2 × 2)
- Convolution Layer (128 filters, 3 × 3)
- ReLU Activation
- Flatten Layer
- Dense Layer (256 neurons)
- Dropout Layer (0.5)
- Softmax Output Layer (6 Classes)

CNN automatically learns the spatial features from the leaf images and multiclass disease classification is done by the Softmax classifier.

3.5 CNN-SVM Architecture:

The CNN-SVM model is a fusion of CNN's feature extraction capability and Support Vector Machine (SVM) classification ability. Firstly, CNN's convolutional layers are used to get deep image features from the resized images of capsicum leaves. The extracted feature vectors are fed to the SVM classifier, rather than using the Softmax classifier. SVM builds optimal decision boundaries by maximizing class discrimination, especially for classes with similar visual symptoms, such as disease categories.

The CNN-SVM framework consists of:

- CNN Feature Extraction
- Feature Flattening
- Support Vector Machine Classifier
- Multiclass Disease Prediction

The proposed CNN-SVM architecture helps to make the classification more robust and decreases the misclassification rates of visually similar disease classes.

3.6 CNN-LSTM Architecture:

CNN-LSTM, which combines the CNN with LSTM networks, is used to enhance the accuracy of predicting disease classification. First, CNN is used to learn high-level spatial features of the images of the capsicum leaves. These extracted feature vectors are then fed into an LSTM layer for learning complex feature dependencies before the final classification stage. The joint structure not only extracts the spatial information but also extracts the discriminating feature information, leading to high recognition accuracy.

The CNN-LSTM architecture includes:

- CNN Feature Extraction
- Feature Flattening

- LSTM Layer (128 Units)
- Dense Layer (128 Neurons)
- Dropout Layer
- Softmax Output Layer

The CNN-LSTM model outperforms the classic CNN and CNN-SVM model, especially in the case of multiclass disease detection, in terms of feature representation.

3.7 Experimental Setup:

To make a fair comparison between the three models for the experiments, the same training conditions were kept for all experiments.

Table 3: Experimental Parameters

Sr.	**Parameter**	**Value**
1	Framework	TensorFlow – Keras
2	Programming Language	Python
3	Image Size	256 × 256 × 3
4	Optimizer	Adam
5	Learning Rate	0.001
6	Epochs	25
7	Batch Size	32
8	Activation Function	ReLU
9	Output Activation	Softmax
10	Loss Function	Categorical Cross-Entropy
11	Dataset Split	70% : 15% : 15%

The Adam optimization algorithm was chosen, due to its ability of adaptive learning and rapid convergence. The same hyperparameters were used in training all the models for 25 epochs.

3.8 Performance Evaluation:

Standard multiclass classification metrics were used for the evaluation of the performance of developed models. To analyse the disease-wise classification performance, a confusion matrix of size 6 × 6 was created for each model.

The following set of evaluation measures were used:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$Specificity = \frac{TN}{TN+FP} \quad (4)$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

These evaluation parameters were used for comparison of the CNN, CNN-SVM and CNN-LSTM models, in addition to multiclass confusion matrices. The experimental results demonstrated that the CNN-LSTM model successfully achieved high classification accuracy of 98.9% followed by CNN-SVM model having accuracy of 96.7% and CNN model with the accuracy of 95.3%, which proved the effectiveness of the proposed hybrid deep learning approaches for the automatic capsicum leaf disease detection.

4. Results and Discussion:

4.1 Experimental Results:

The deep learning models were tested with the Capsicum Leaf Disease Image Dataset, comprising 7735 images across 6 disease categories: Cercospora Leaf Spot, Bacterial Spot, Leaf Curl, Nutrition Deficiency, Powdery Mildew and Healthy leaf. After Pre-processing the data was split into three parts 70% training, 15% validation and 15% testing. The performance of all three models is compared using the same hyperparameters, as a fair comparison would be to use different hyperparameters.

For CNN, CNN-SVM and CNN-LSTM models the loss of both training and validation decreased steadily for the first 25 epochs during training, and the loss did not show any sudden jumps or changes. The training and validation accuracy curves illustrate the performance of the proposed models, highlighting their ability to learn the disease-specific features and possess good generalization ability on unseen validation sets. The CNN-LSTM model exhibited the best validation accuracy and the fastest convergence rate without overfitting, among the three architectures.

The independent test set was used to test the final performance for each model. Each model was evaluated using a 6 × 6 confusion matrix and overall performance was evaluated using measures of Accuracy, Precision (TPR), Specificity (TNR), and F1-score.

4.2 Comparative Performance Analysis:

Table 4: A comparison of deep learning models in terms of performance

Sr.	**Model**	**Accuracy (%)**	**Precision (%)**	**Recall (TPR) (%)**	**Specificity (TNR) (%)**	**F1-score (%)**
1	CNN	95.3	93.0	94.1	98.8	93.5
2	CNN-SVM	96.7	95.4	96.0	99.2	95.7
3	CNN-LSTM	98.9	98.4	98.7	99.8	98.5

Based on Table 4, it is observed that the CNN-LSTM model works best overall among the three architectures evaluated. The proposed CNN-LSTM model successfully classified the images with a total accuracy of 98.9%, recall of 98.7%, precision of 98.4%, specificity of 99.8% and F1 scores of 98.5%. The results showed that the implementation of convolutional feature extraction with Long Short-Term Memory network for multiclass capsicum leaf disease classification is effective.

The CNN-SVM model also performed well, with an overall accuracy of 96.7%. The model was evaluated by comparing the classification performance with the baseline CNN model, showing that the use of the Support Vector Machine (SVM) classifier outperforms the Softmax classifier in terms of improved class separation and reduced classification errors. That shows the hybrid CNN-SVM system is capable of improving the decision boundaries for the multiclass disease recognition.

The overall accuracy of the conventional CNN model was 95.3%. It achieved satisfactory performance but its precision, recall, specificity, and F1-score were not as high as that of the hybrid models. The degradation in performance can be explained by the challenge of performing nontrivial classification of diseases which have similar visual symptoms only by relying on convolutional feature extraction.

4.3 Confusion Matrix Analysis:

The confusion matrix for the three models also illustrates their ability to classify the individual disease categories. Most leaf images were correctly labelled with disease classes with only some misclassifications between leaf images that were similar in appearance such as Cercospora Leaf Spot, Bacterial Spot and classes and Nutrition Deficiency & Healthy classes.

The CNN-LSTM confusion matrix had the maximum number of correct classifications along the main diagonal, signifying a high level of classification accuracy for all six disease categories when compared to the other models evaluated. The CNN model generated relatively more off-diagonal entries, indicating more classification errors.

CNN-LSTM outperforms CNN, indicating that the sequential learning ability of LSTM complements the discriminative power of CNN, facilitates capturing more subtle disease characteristics and contributes to the recognition of these features.

4.4 Training and Validation Performance:

The accuracy and the loss during training and validation for CNN, CNN-SVM, CNN-LSTM are shown in Figures 2, 3 and 4, respectively. The learning behaviour of all three models remained stable during the training process, and the accuracy values incremented steadily while the corresponding loss values decreased.

The CNN-LSTM model showed the best generalization ability and least overfitting by converging quickly and having the least difference between the training performance and validation performance. The CNN-SVM model also exhibited better convergence than the traditional CNN model, because of its better classification ability. The CNN model took relatively more number of epochs to converge and had a small amount of validation performance fluctuations as well.

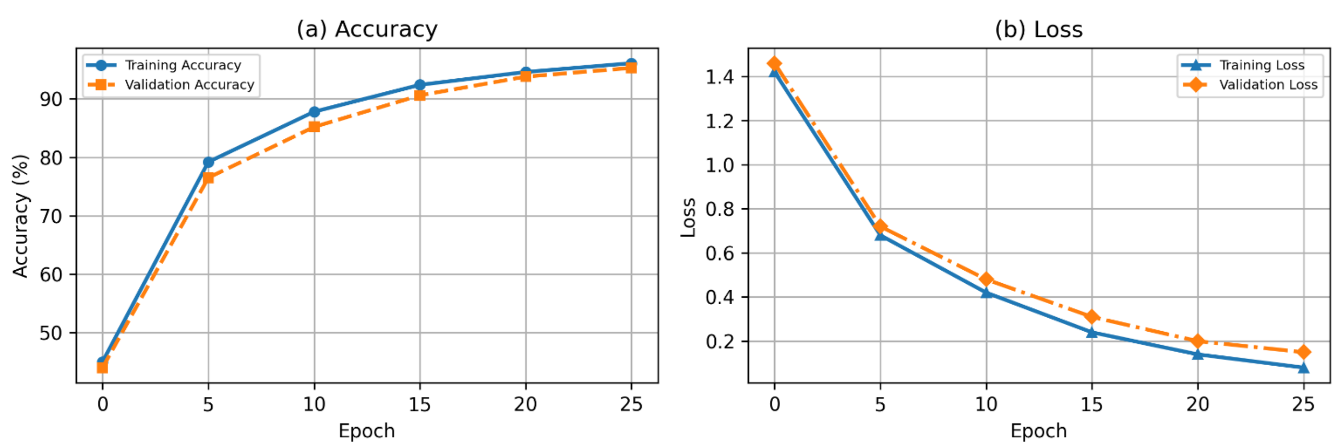

Figure 2: Performance of the CNN model

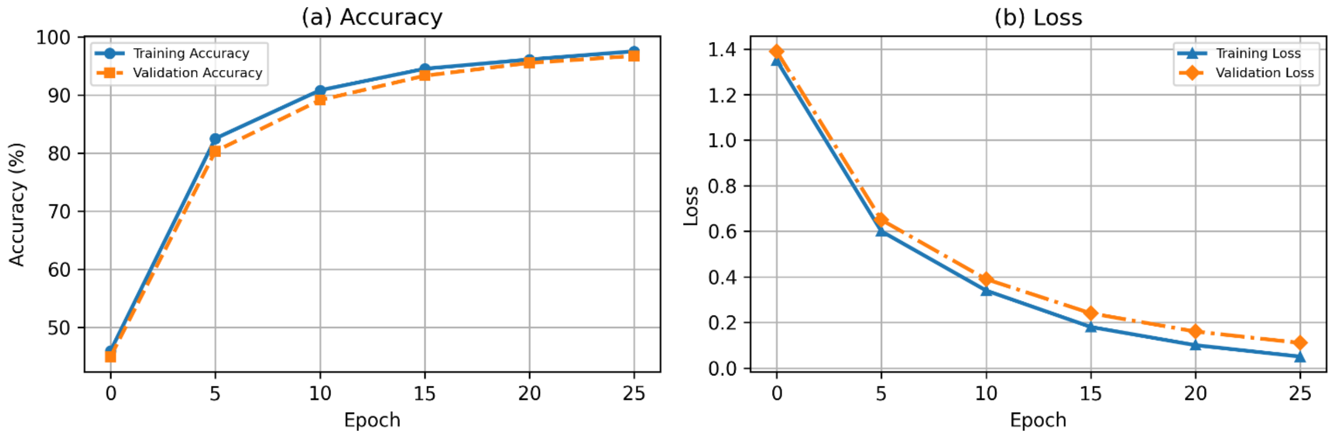

Figure 3: Performance of the CNN-SVM model

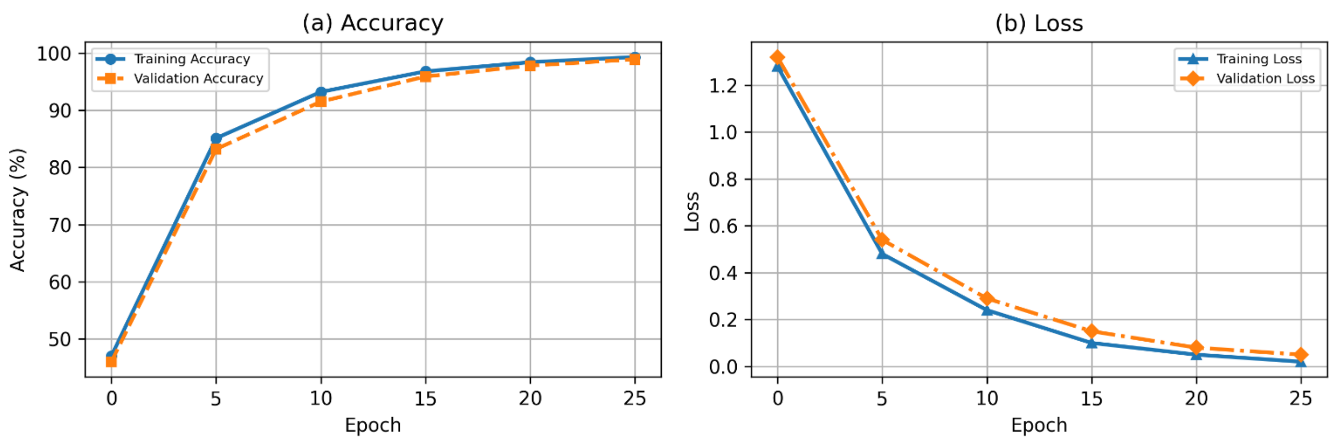

Figure 4: Performance of the CNN-LSTM algorithm

4.5 Discussion:

The experimental results are clearly revealed that the hybrid deep learning models are far better than the conventional CNN models in detecting the multiclass capsicum leaf disease. The superiority of CNN-LSTM model can be explained by the capability of the model to perform both spatial feature extraction and sequential feature learning, which allows the network to learn more complex relationships between the image features related to a specific disease. Furthermore, CNN-SVM model also achieved higher classification accuracy using an SVM classifier with deep convolutional features to boost the class discrimination ability among visually similar disease categories.

The comparative analysis reveals that the CNN performance is significantly enhanced when a complementary learning mechanism is integrated, especially for multiclass agricultural image datasets with a large leaf variation and environmental changes. The results suggest that the CNN-LSTM-based automated diagnosis and recognition system for capsicum leaf diseases is a reliable and effective method and can be potentially applied to an intelligent precision agriculture system.

5. Conclusion:

This research work aimed to perform a comparative evaluation of three deep learning models namely Convolutional Neural Network (CNN), Convolutional Neural Network–Support Vector Machine (CNN-SVM) and

Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) for the automated detection of multiclass capsicum leaf diseases based on image processing techniques. To assess the performance of the proposed models, a comprehensive dataset of 7,735 capsicum leaf images was used, which was obtained from the Mendeley Pepper Bell Leaf Disease Dataset and live agricultural fields in the Ahilyanagar District in Maharashtra, India. The data set consisted of six disease categories which were Cercospora Leaf Spot, Bacterial Spot, Leaf Curl, Nutrition Deficiency, Powdery Mildew & Healthy leaves.

To achieve good image quality and improve the generalisation ability of the deep learning models, they have used a systematic pipeline that includes resizing, normalisation and data augmentation. The data set was divided in a 70:15:15 ratio into training, validation and testing subsets, and the three models were trained under the same experimental conditions to allow a fair comparison between the three models. The performance was measured using accuracy and precision, recall and specificity were used and multiclass confusion matrix analysis was done.

The result of the experiment showed that the CNN-LSTM model gained the best classification accuracy, 98.9%, followed by CNN-SVM (96.7%), the conventional CNN (95.3%). The CNN-LSTM architecture is more effective, highlighting the advantages of combining the convolutional feature extraction with LSTM networks in terms of disease-specific characteristics representation and the accuracy of multiclass classification. The CNN-SVM model also achieved better class separation results compared to the CNN model by learning hybrid features and performing classification using machine learning.

The results overall demonstrated that the hybrid approach of deep learning is more effective than the traditional CNN-based approach for automated capsicum leaf disease detection. The proposed framework illustrates promising potential for supporting precision agriculture by detecting diseases early, managing the crop at an opportune time and minimising yield losses.

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