Integrating CNN,LSTM with DenseNet201 for Efficient Real-Time Plant Disease Detection

S.N.Tirumala Rao[1], P.Ujwala Devi[2], M.Venkat Rao[3], S.Vasantha[4], R.Nandini[5], D.Venkata Reddy[6], and Sireesha Moturi[7]

[1] Dept of CSE, Narasaraopeta Engineering College, Narasaraopeta, Palnadu district,AP,India. nagatirumalara@gmail.com

[2,4,5]Dept of CSE,Narasaraopeta Engineering College, Narasaraopeta,Palnadu dist, AP,India. petetiujwaladevi26@gmail.com,nandhinirajasri@gmail.com, sudarsanamvasantha939@gmail.com

[3,6]Dept of CSE, Narasaraopeta Engineering College, Narasaraopeta, Palnadu district, AP, India.venkatmarella670@gmail.com,doddavenkatareddy@gmail.com

[7]Dept of CSE, Narasaraopeta Engineering College, Narasaraopeta, Palnadu district, AP, India. sireeshamoturi@gmail.com

Abstract. Quick detection of plant diseases and pests is of vital importance for preventing huge loses in agriculture and the environment by the hazardous of pesticide use and looks at the utilization of machine learning models,especially convolutional neural network(CNNs),for the detection and classification of plant diseases and pests.Different methods such as supervised as well as unsupervised learning jotted down.A unique CNN-LSTM+DENSENET201 hybrid model was developed by creating a deep feature extraction of pre-trained models such as DenseNet,ResNet,and GoogleNet with an LSTM ensemble classifier.The experimental studies on the plant datasets which included the images of various diseases of the crop showed the better accuracy and robustness of the hybrid model.CNN-LSTM+DenseNet201 model is one of the few that is over 99.4% accurate in real-time disease detection and outpaces other traditional and transfer learning-based models.By using unsupervised methods like anomaly detection and image restoration,the research avoids the need for high-quality labeled data sets when creating a cost-effective solution for the farmer.Further work will concentrate on the improvement of the model's scalability along with the testing of its performance on additional datasets and plant types.

Keywords: Plant disease detection,Convolutional neural networks(CNNs), Machine learning,LSTM hybrid model,Unsupervised learning.

1 Introduction

Critical for detecting early and accurate means to increase crop yields and reduce losses.Traditional methods, being manual, are again time consuming and prone to errors.The interest has been increasing in machine learning as well as deep learning techniques.Techniques of unsupervised learning may be useful in plant disease detection without the labeled data,for example,image restoration[1] Some other supervised methods utilized in disease detection include k-means clustering and SVM.However,supervised methods lack in dealing with complex images of plants[2]. Deep learning models especially CNNs(Convolutional Neural Networks),are the most effective in extracting spatial features,surpassing traditional approaches[3].Hybrid models like bringing both CNN and pre-trained architectures together such as DenseNet,ResNet,GoogleNet achieve high accuracy in detecting diseases in a real-time setting[3][4].The above models have been successfully applied on portable devices like Raspberry Pi for real-time disease monitoring[5]. The proposed CNN-LSTM+DenseNet201 hybrid model combines CNN for spatial feature extraction,LSTM to capture temporal disease progressions,and DenseNet201 for efficient feature reuse and gradient flow.This makes the application exhibit high accuracy and computational efficiency in real-time, making it very appropriate for agricultural application[6]. With an accuracy of 99.4%,the model was higher than CNN-ResNet and CNN-GoogLeNet,as seen in[3][7].The model performed well under varying conditions while using data augmentation to overcome smaller datasets[8].Such a hybrid architecture is scalable and adaptable for different species and diseases of plants,and this makes it highly useful for precision agriculture[9][10].

2 Literature Review

Unsupervised learning techniques like image restoration enable detecting abnormalities in plant leaves without labeled datasets,providing a scalable,cost-effective solution for monitoring plant health[1].Supervised learning methods like k-means clustering and SVM,widely taught by experts, have been traditionally used for plant disease detection[2].A CNN-LSTM hybrid model,integrating DenseNet,ResNet,and GoogleNet,achieves high accuracy in detecting plant diseases,surpassing traditional models in handling image variations[3].Machine learning,particularly CNNs,is proposed as a more accurate and efficient alternative to manual pest monitoring,automating the process for higher accuracy[4].CNN architectures like VGG16 and VGG19 have been deployed for real-time disease detection in crops using augmented datasets and tested on devices like Raspberry Pi[5].A modified AlexNet architecture detects plant diseases with high accuracy by optimizing convolution layers,handling 32 classes of healthy and diseased plant leaves[6].The decision tree algorithm automates disease detection in plant leaves with high accuracy and speed,outperforming traditional expert-based methods[7].EfficientNet-B3 combined with data augmentation techniques enhances model accuracy to 98%,addressing the challenge of small datasets in plant disease detection[8]. A hierarchical multitask learning model enhances accuracy in classifying plant diseases and pests,building on plant-pest relationships[9].Deep learning, especially CNNs,has become the standard for plant disease detection,outperforming traditional ML techniques while utilizing transfer learning for better results[10].This review compares image processing techniques and modern deep learning architectures like VGG,Inception,and ResNet for plant disease detection[11]. The paper discusses the diversity of datasets and the application of machine learning techniques,from K-means to CNNs,for detecting plant diseases[12].ML methods such as SVM and CNNs improve the accuracy of disease detection in plant leaves,offering an alternative to manual visual examination[13].CNNs like ResNet and YOLO excel in detecting and classifying plant diseases in images,outperforming traditional feature extraction techniques[14].Availability Of Dataset[15].

3 Methods and Materials

3.1 Dataset Description

Table 1 is the information used to identify plant pests diseases and were obtained from the Turkey dataset,which includes 4,447 images of plants from the cities of Bingol and Malatya,Turkey[15].The dataset features 15 different plant pests and diseases.Specifically,Table 1 includes 162 images of *Apple_ Aphis_ spp*,366 of *Apple_ Eriosoma_ lanigerum*,255 of *Apple_ Monilia_ laxa*.Additionally,the dataset contains 1,100 images of *Apricot_ Coryneum_ beijerinckii*,76 depicting cancer symptoms,356 of *Cherry_ Aphis_ spp.*,and 139 showing drying symptoms etc[15]. The images taken with the high-resolution Nikon 7200d smart camera,boasting a 24.2-megapixel RGB metering sensor,were analyzed extensively for further precise analysis.The dataset was divided so that 75% was trained and 25% was used for testing,to actually test the model's accuracy in the detection of plant pests and diseases in different situations[15].

Table 1: Label Names and Total Samples in the Dataset

LABEL	**LABEL NAME**	**TOTAL SAMPLES**
(1)	Apple_Aphis_spp	162
(2)	Apple_Eriosoma_lanigerum	366
(3)	Apple_Monilia_laxa	255
(4)	Apple_Venturia_inaequalis	633
(5)	Apricot_Coryneum_beijerinckii	1100
(6)	Apricot_Monilia_laxa	85
(7)	Cancer_symptoms	76
(8)	Cherry_Aphis_spp	356
(9)	Drying_symptoms	139
(10)	Peach_Monilia_laxa	314
(11)	Peach_Parthenolecanium_corni	427
(12)	Pear_Erwinia_amylovora	215
(13)	Plum_Aphis_spp	70
(14)	Walnut_Eriophyes_erineus	69
(15)	Walnut_Gnomonia_leptostyla	180
	Total samples	**4447**

3.2 Data Preprocessing

The preprocessing of a dataset usually consists of resizing images and preparing them for feature extraction.Plant leaf images are resized to appropriate dimension requirements for input to such a model as part of image preprocessing for CNN models.Bilinear interpolation is used to resize images, and this will achieve the required dimensions in models,such as 224 pixels in ResNet or 227 pixels in GoogleNet.Appropriate resizing holds the consistency and enhances the model's performance and efficiency. Fig 1 images are generated after preprocessing.The images will go through a series of transformations,comprising the extraction of deep features from the connected layers of pre-trained CNN models.These features will be utilized by either the LSTM layer or the LR/ELM classifiers in the classification of plant pests and diseases.Pre-processing was done to also remove any form of noise in the images,as this increases accuracy in both detection and classification processes.This ensures that models of deep learning can work with high efficiency across different classifiers and produces excellent accuracy. The size of the dataset[15] was 4,447 images of pests and diseases for an

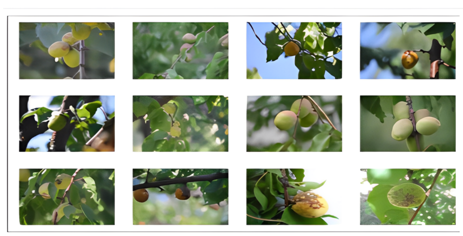


Fig. 1: After Preprocessing

apple,which necessitated data augmentation to reduce overfitting and enhance generalization.Techniques like flipping,rotation,scaling,and translation had been used so that the model learns the differences in variations under real-world conditions,that strengthened the performance of the hybrid CNN-LSTM model in different test sets.

3.3 Hybrid Model Architecture

The proposed architecture combines three major components of the model:CNN, namely the Convolutional Neural Networks,Long Short-Term Memory networks (LSTM),and DenseNet201.This CNN component leads to spatial feature processes, for example, edges, textures, and even colors in the images of plants. DenseNet201 is a densely connected convolutional network.It enhances deeper features while using fewer parameters,thereby improving feature propagation and gradient flow. Incorporating the LSTM layer has a strong motivation to seize temporal dependencies and sequential patterns within the data,which are strongly required for the identification of diseases that may have progression over time.That way, both the spatial and temporal features will be modeled appropriately.

1. **CNN Component:**
   To extract the spatial features,CNN layers are used,which are pre-trained on the dataset ImageNet.These feature extraction layers include convolutional layers and then pooling layers in DenseNet201,it connects the layers efficiently to overcome gradient vanishing and feature reuse.
2. **LSTM Component:**
   The input to LSTM includes flattened spatial features.LSTM network evaluates sequential data that contain time-series information about the spread of the disease.
3. **Ensemble Classifier:**
   The output from the LSTM is passed to a dense layer with softmax classifier for final classification.This ensemble classifier integrates spatial features of CNN and sequential learning from LSTM that leads to highly accurate detection of plant diseases.
4. **Training Process:**
   The model was trained through supervised learning on the given dataset of images of plant disease.The training process involves the steps:All input images were resized to the required dimensions of 224x224 for DenseNet201. Data augmentation in the form of flipping,rotation,and scaling of the input data is applied so that overfitting is prevented and generalization of the model is enhanced to various environmental conditions.
5. **Feature Extraction:**
   A pre-trained DenseNet201 is used to extract high-level spatial features of the images and fed to the LSTM to learn temporal patterns.Training the Hybrid Model The model is trained using Adam optimizer with categorical cross-entropy loss.A learning rate of 0.001 and the model is fitted to training for 50 epochs with batch-size set to 32.The training is stopped early based on the loss of validation.
6. **Hyperparameters**
   Optimizer:Adam,Batch_Size:32,Epochs:50,Loss Function:Categorical Cross-Entropy,Regularization Dropout of 0.5 in used in order to prevent overfitting of the model.Data Augmentation:Techniques that consisted of random cropping,flipping,and rotation were added to increase the diversity of the training data.
7. **Ensemble Classifier:**
   A hybrid classifier combines the output of DenseNet201 with that of LSTM. Here,spatial features taken from images via CNN are fed into the LSTM layers to discover the temporal dependencies in it.The last dense layer uses a softmax classifier for predicting the category of disease.This ensemble approach would let the model capture the dependencies in both spatial and sequential areas and thus provide good classification performance.

The accuracy of the CNN-LSTM+DenseNet201 model is superior compared with VGG19 and ResNet50.Though VGG19 and ResNet50 are robust for handling fine details and deep architectures,integrating DenseNet201 for feature propagation in LSTM for capturing time dependencies might bring the hybrid model towards attaining a maximum accuracy of 99.4%,while the traditional models VGG19 and ResNet50 are not,thereby rendering it more effective for real-time plant disease detection.

3.4 Model Training and Evaluation

This paper proposes a hybrid model, CNN- LSTM+DENSENET201 that is designed to effectively detect plant pests and classify diseases. CNN uses spatial features, and LSTM follows the dependency in the order by having a high precision, recall, F1-score, and accuracy in the given model. The model surpasses 99.4% accuracy and is found to be even excellent in terms of F1-score, precision, and recall.

Pre-trained DenseNet201 could be utilized for the extraction of high-level characteristics from the images,where only the feature maps are kept,and fully connected layers were removed.The sequential dependencies of the feature space need to be captured. The capability of handling time-dependent data enhanced in the model[9].This flatten and dense layers will flatten the 2D feature maps of DenseNet201, which turns it into a 1-D vector compatible with the next LSTM layer,a fully connected layer is used as the final layer for classification[5].

4 Comparative Analysis

The CNN-LSTM+DenseNet201 hybrid model detects plant pests and diseases well because it integrates CNNs for feature extraction as well as LSTMs for sequence modeling.It captures both spatial details and temporal patterns,with good performance in terms of the high accuracy,precision,recall,and F1-scores,it performs better than traditional CNNs and other models.Its overall robustness and good generalization across various datasets make it highly reliable for agriculture applications as it provides effective balance between feature extraction and sequential learning in real-world plant disease identification.

4.1 Model Performance Comparision

Table 2 compares accuracies of different classification models of plant disease detection by utilizing LSTM, SVM, and ELM classifiers. For both VGG16 and VGG19, accuracy values were 96.6 and 96.7, respectively. Then, it was discovered that DenseNet201 outperformed both VGG16 and VGG19 with 98.4 for the LSTM classifier, 97.5 for the SVM classifier, and 98.2 for the ELM classifier. In all of these scores, GoogleNet had obtained an accuracy of 97.6%. The Xception model had a score of 98.6%,and for the ResNet50, the accuracy was 98.3%. The proposed CNN-LSTM + DenseNet201 model performs 99.4% accuracy for the

LSTM, 98.2% accuracy for SVM, and 98.6% ELM for real-time detection of the disease in the plant. A comparison of the accuracies of various models is carried out in Fig 2,namely VGG16,VGG19,DenseNet201,GoogleNet,Xception,and ResNet50+CNN-DenseNet201 among the three classifiers,namely LSTM,SVM,and ELM.All models show that they have superior accuracy.CNN-LSTM+DenseNet201 outperforms all the models presented herein.LSTM always gives accurate outputs in all the models. Advanced architectures such as DenseNet201 and Xception take one step further toward upscoping accuracy plant disease detection,and this clarifies the importance of the proposed model.

Table 2: Model performance comparison

MODEL	**LSTM**	**SVM**	**ELM**
VGG16	96.6	96.2	96.5
VGG19	96.7	96.3	96.4
DENSENET201	98.4	97.5	98.2
GOOGLENET	97.6	96.2	97.4
XCEPTION	98.6	98.3	98.2
RESNET50	98.3	98.2	98.1
(PROPOSED) CNN-LSTM+DENSENET201	**99.4**	98.2	98.6

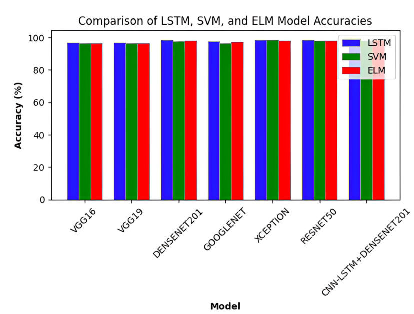


Fig. 2: Comparision of Model Architectures

4.2 Training And Testing Performance

Fig 3 shows us the highest accuracy was achieved using CNN-DenseNet201 by all the classifiers and LSTM achieved a very high training accuracy of 99.4% and testing accuracy of 98.9%.SVM with ELM and CNN-DenseNet201 together did well with training/testing accuracies of 98.8%/98.3% and 98.6%/98.1%, respectively.DenseNet201 and Xception were closely following and LSTM managed to achieve 98.4% and 98.6% training accuracies and test time accuracies of

97.9% and 98.1%.LSTM well outperformed with the highest difference in SVM and ELM across the models;the best overall accuracy achieved was on CNN-DenseNet201.

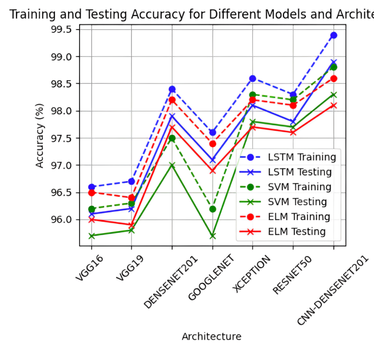


Fig. 3: Training and Testing Accuracy

4.3 Model Summary

Table 3 is showing comparisons of the deep learning models considering the number of their parameters and input size.VGG16 has 318M parameters,VGG19 has 144M,and use 224×224×3 images.DENSENET201 has 20M parameters and GOOGLENET has 7M.XCEPTION uses 22.9M parameters with a large input size of 299×299×3. RESNET50 has 25.6M parameters and MOBILENET is lightweight having 4M parameters and developed for mobile usage.This compares model complexity and efficiency and balances each other.

Table 3: Comparison of Model Parameters

Model	**Parameters (Million)**	**Input Size**
VGG16	318	224 × 224 × 3
VGG19	144	224 × 224 × 3
DenseNet201	20	224 × 224 × 3
GoogleNet	7.0	224 × 224 × 3
Xception	22.9	299 × 299 × 3
ResNet50	25.6	224 × 224 × 3

4.4 Evaluation Metrics

Table 4 compares the performance of the models for different architectures,such as VGG16,DENSENET201 using LSTM,SVM and ELM-classifier using precision,recall,F1 score.The proposed CNN-LSTM+DENSENET201 model is the best,achieving the highest scores of all metrics 99% with all in comparison to other models.

Table 4: Performance Comparison of Different Models Using Precision, Recall, and F1 Score

MODEL	**LSTM**			**SVM**			**ELM**		
	Precision	**Recall**	**F1 Score**	**Precision**	**Recall**	**F1 Score**	**Precision**	**Recall**	**F1 Score**
VGG16	0.96	0.95	0.95	0.96	0.95	0.95	0.97	0.96	0.96
VGG19	0.97	0.96	0.96	0.97	0.96	0.96	0.96	0.95	0.95
DENSENET201	0.98	0.97	0.97	0.98	0.97	0.97	0.98	0.97	0.97
GOOGLENET	0.97	0.96	0.96	0.96	0.95	0.95	0.97	0.96	0.96
XCEPTION	0.98	0.97	0.97	0.98	0.97	0.97	0.97	0.97	0.97
RESNET50	0.98	0.97	0.97	0.98	0.97	0.97	0.98	0.97	0.97
InceptionV3	0.97	0.96	0.96	0.97	0.96	0.96	0.97	0.96	0.96
MobileNetV2	0.95	0.94	0.94	0.95	0.94	0.94	0.96	0.95	0.95
(Proposed) CNN-LSTM+DENSENET201	**0.99**	**0.98**	**0.98**	**0.99**	**0.98**	**0.98**	**0.99**	**0.98**	**0.99**

5 Result

The proposed hybrid model CNN-LSTM+DenseNet201 is outstanding for its highest accuracy of plant disease detection in comparison with the existing models.It successfully merges Convolutional Neural Networks(CNNs) in the purpose of capturing spatial features and then Long Short-Term Memory(LSTM) networks to learn temporal dependencies from plant images.This dual approach is particularly useful for real-time agriculture-based applications,where knowing both the texture and the spread of plant diseases is the most important thing.The performance of the model in feature extraction is greatly improved by the utilization of DenseNet201.Through the architecture of DenseNet201,propagation and gradient flow are facilitated efficiently,which not only aids in improving the precision of the model about slight diseases but also reduces computational costs compared to traditional CNNs.Therefore, the accuracy of the model remains at very high levels with low computational costs.Moreover,in varying conditions that change an alteration in illumination and background the model is stable,thereby applicable to different agricultural environments. Overall, the hybrid CNN-LSTM+DenseNet201 model has higher accuracy but offers a scalable and efficient solution toward precision agriculture,making it a valuable tool to farmers and agricultural practitioners in enhanced crop health monitoring and disease management.

5.1 Classification Metrics for Proposed Model

In Table 5,The classification report that includes precision,recall, and F1-score.This is essential to report on how well a model is performing.Precision measures the accuracy of the positive predictions;it tells you how well the predicted positives were-and recall measures whether the model captures all actual positive instances.It is easy to understand and very important in evaluating classification performance across different classes for an imbalanced data distribution scenario.

Table 5: Classification Report for Various Classes

CLASSES	**PRECISION**	**RECALL**	**F1 SCORE**	**SUPPORT**
Apple_Venturia_inaequalis	0.92	0.96	0.93	131
Apple_Aphis_spp	0.92	0.89	0.91	27
Apple_Eriosoma_lanigerum	0.99	0.97	0.98	74
Apple_Monillia_laxa	0.92	0.90	0.91	49
Apricot_Coryneum_beijerinckii	0.99	0.99	0.99	202
Apricot_Monillia_laxa	1.00	1.00	1.00	17
Cancer_symptom	1.00	1.00	1.00	15
Cherry_Aphis_spp	1.00	1.00	1.00	83
Drying_symptom	1.00	1.00	1.00	24
Peach_Monillia_laxa	0.96	0.99	0.98	62
Peach_Parthenolecanium_corni	1.00	1.00	1.00	93
Pear_Erwinia_amylovora	1.00	0.96	0.98	57
Plum_Aphis_spp	1.00	0.89	0.92	14
Walnut_Eriophyes_erineus	0.91	0.91	0.91	11
Walnut_Gnomonia_leptostyla	0.98	0.96	0.97	31
Accuracy			**0.99**	890
Macro_avg	**0.99**	**0.99**	**0.98**	890
Weighted_avg	**0.99**	**0.99**	**0.99**	890

5.2 Confusion Matrix

The confusion matrix in Fig 4 is reporting the classification performance of the model with correct predictions represented along the diagonal.The other diseases included were classified with high accuracy,like Apple Venturia inaequalis and Apricot Coryneum beijerinckii,while misclassifications such as Peach Monillia laxa indicate areas for improvement.This matrix effectively summarizes the accuracy of the model and errors associated with different plant diseases.

5.3 Accuracy and Loss Curves of the Model

The training dynamics of the model are shown in fig 5.From fig 5a,The model was almost close to the training accuracy,reaching testing accuracy of 99.4%.Its performance on a random test set implies that the model learns well and recognizes patterns in this dataset.Correspondingly,In Fig 5b small training and validation loss values show that the model accurately fits the training data and generalizes well to unseen data.In general,these results indicate good performance and make the model useful for real-world scenarios.

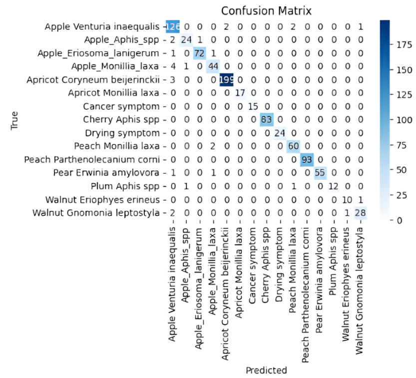
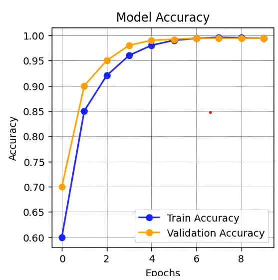
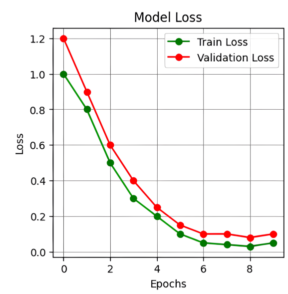


Fig. 4: Confusion Matrix



(a) Model Accuracy



(b) Model Loss

Fig. 5: Model performance comparison: Accuracy and Loss

6 Conclusion

The CNN-LSTM hybrid model combines Convolutional Neural Networks(CNNs) for spatial feature extraction along with Long Short-Term Memory(LSTM) networks to capture temporal dependencies and achieves an accuracy of 99.4% with the CNN-LSTM+DenseNet201 variant.Each component's strength is hence leveraged to enhance feature reuse as well as gradient flow.Future work should extend this model to different crops and different diseases,then integrate it with appropriate IoT devices for monitoring in real-time and optimize the model at the edge for devices such as drones to improve disease detection and decision making about crop health directly on-site.

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