Machine Learning and Deep Learning Algorithms for Enhanced Maize Plant Disease Diagnosis and Prognosis in Agriculture

Prasanthi Potnuru[1], Panduranga Vital Terlapu[2*], Potnuru Harika[3], Kavya Metturu[4], Jami Manasa[5], Pasupureddi Lakshmideepak[6]

[1,3,4,5,6] Department of Information Technology, Aditya Institute of Technology and Management, Tekkali-532201, India.

[2] Department of Computer Science & Engineering, Aditya Institute of Technology and Management, Tekkali-532201, India.

{Prasanthi35, vital2927*, harikapotnuru2002, kavyametturu2020, manasa.jami1205, deepakpasupureddi}@gmail.com

Abstract. Maize plant diseases can have a severe impact on agricultural productivity, making detection and control challenging for farmers. Early identification of diseases is crucial for minimizing losses. This study proposes a new approach that integrates machine learning (ML) and deep learning (DL) algorithms to improve maize disease diagnosis and prognosis. The research employs traditional machine learning algorithms, such as Support Vector Machine (SVM) and Multilayer Perceptron (MLP), along with extracted features of Transfer Learning models, such as InceptionV3, VGG19, and Dense-Net201. The objective is to develop a robust system for early disease detection in maize leaves using image analysis. Optimization techniques, such as the Adam optimizer, and activation functions, such as tanh and sigmoid, are also explored. The results indicate that the Adam optimizer MLP achieves the highest accuracy (MLP(100,100) layers PCA(300) accuracy 0.95107) as well as SVM (RBF kernel) with PCA(100) accuracy (0.95585) exceptional other classification methods. This integrated approach promotes agricultural sustainability and crop yield by enabling prompt disease management.

Keywords: Machine Learning, Deep Learning, Transfer Learner, SVM, MLP

1 Introduction

Plant diseases like blight, common rust, and grey leaf spot significantly impact global agricultural productivity, particularly in maize. Early detection and precise evaluation are crucial for sustainable agricultural management and economic prosperity. Traditional methods are laborious and can misread symptoms. Automatic disease detection can detect signs early, minimizing crop monitoring labor. Maize is susceptible to viruses, fungi, and bacteria, and misinterpretation of traditional disease identification procedures leads to inefficient pesticide applications. Speed and accuracy are essential for monitoring and treating infections. Machine learning and deep learning have revolutionized agriculture by improving plant disease diagnosis and prognosis. ML algorithms classify and predict diseases, while CNNs learn hierarchical representations. Deep learning uses neural networks to classify and detect features in data. This systematic review explores the use of these technologies in agriculture, aiming to

K. R. Madhavi et al. (eds.), *Proceedings of the International Conference on Computational Innovations and Emerging Trends (ICCIET 2024)*, Advances in Computer Science Research 112,
https://doi.org/10.2991/978-94-6463-471-6_15

improve efficiency and sustainability. An innovative approach to maize disease diagnosis and prognosis uses traditional algorithms and advanced CNN architectures, enhancing model performance and improving agriculture's sustainability and food security.

2 Literature Survey

Sonkar et al. [1] developed deep learning models for precise plant disease detection and classification using Python and popular frameworks like Anaconda, Keras, and TensorFlow. Hasan et al. [2] highlighted the importance of deep learning in early plant disease detection and classification. Prabavathi et al. [3] developed a Deep CNN system for accurate plant leaf disease classification and pesticide recommendations, achieving 93.18% accuracy across twelve diseases. Fenu et al. [4] created a multioutput learning system for diagnosing plant diseases and stress severity. Abade et al.'s [5] systematic review of 121 papers identifies trends and research gaps in convolutional neural networks (CNNs) for precise plant disease detection, highlighting areas for future research. Tugrul et al.'s review [6] discusses the use of deep convolutional neural networks for early disease detection of plant leaf diseases, highlighting challenges in recognizing multiple diseases on the same leaf. Shoaib et al.'s study [7] on ML and deep learning techniques for accurately identifying and classifying plant diseases using digital images shows promising results. [8] found that the VGG-16 and VGG-19 models had higher efficiency and accuracy rates for plant disease detection, while the ResNet-50 and ResNet-101 models had lower accuracy rates. The study used transfer learning and deep learning approaches on 87,570 records. Bharanidharan et al. [9] have developed a new system using CNN technology to classify plant diseases and recommend appropriate pesticides. This method uses image processing, pattern recognition, and classification techniques for efficient disease prediction and enhanced crop management. Kumar et al. [10] have used deep learning techniques to detect crop diseases in tomatoes and grapes with high accuracy rates. They proposed a model integrating PDCNN and EN-CNN segmentation, demonstrating improved precision in identifying plant diseases. This research contributes to automated crop disease diagnosis and agricultural management.

3 Models and Materials

The research paper discusses the study's methodology for improving maize plant disease diagnosis and prognosis using machine learning and deep learning, utilizing algorithms like SVM, MLP, advanced CNN architectures like IV3, Dense-Net201, and VGG-19, and optimizing techniques.

3.1 Proposal Model

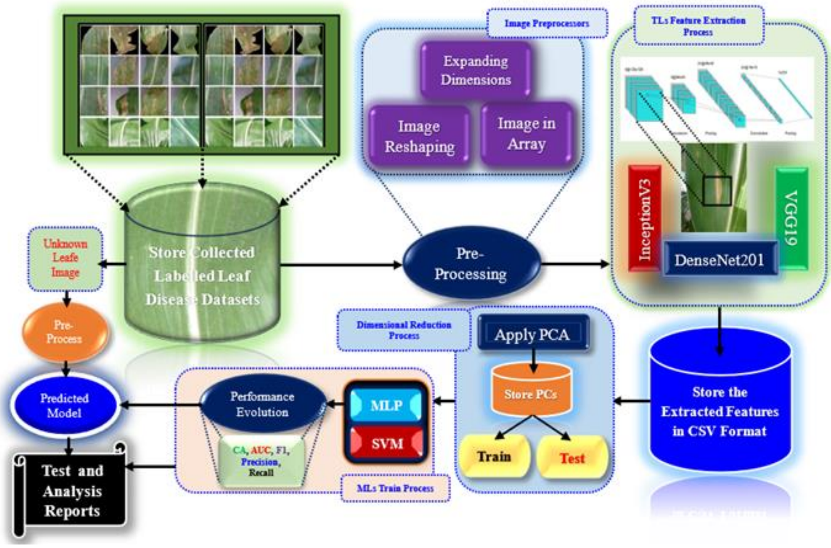


Fig. 1. Maize leaf diseased Detection System Proposal Model using TL PCA+ML

Maize leaf image analysis involves preprocessing, feature extraction, and classification using transfer learners, PCA, and machine learning models, focusing on diseased and healthy leaf images. **The Data Collection and Storage** step involves gathering a leaf image dataset of diseased and healthy samples for ML models, particularly for leaf disease prediction. Sources include online databases, research collaborations, and high-quality field-captured images. **Data preprocessing** is crucial in ML models, especially for image data. It transforms raw input data into a suitable format for training and analysis. Normalization and standardization are optional steps to ensure features are similar, improve model performance, and address challenges like varying image sizes and formats. Transfer learning is an ML technique utilizing pre-trained CNN models like Inception V3, VGG-19, and DenseNet201 for image classification tasks. It efficiently utilizes limited labeled data and preserves hierarchical representations for further processing.

Principal Component Analysis (PCA) is a technique that reduces feature space dimensionality while retaining essential information. It projected high-dimensional vectors onto a lower-dimensional subspace, reducing computational complexity and alleviating the curse of dimensionality. Principal components and target image labels are stored for association. The study uses Multi-Layer Perceptrons (MLP) and Support Vector Machines (SVM) to classify leaf images as diseased or healthy. Performance metrics like classification accuracy, AUC, F1-score, precision, and recall are evaluated. The predictive models are built through an iterative process, enabling timely and accurate diagnosis of leaf diseases.

3.2 Maize Dataset Description

The maize dataset is a collection of images categorized into four classes: blight, common rust, grey leaf spot, and healthy. The blight class includes 1146 images of blight-affected leaves. 1306 images of ordinary rust. 574 images of grey leaf spots.

1162 images of healthy leaves. The balanced distribution across classes allows the model to learn effectively from each category, enhancing its effectiveness in disease detection and classification of maize leaf conditions. Figure 2 shows the images for the maize leaf with diseases and Healthy.

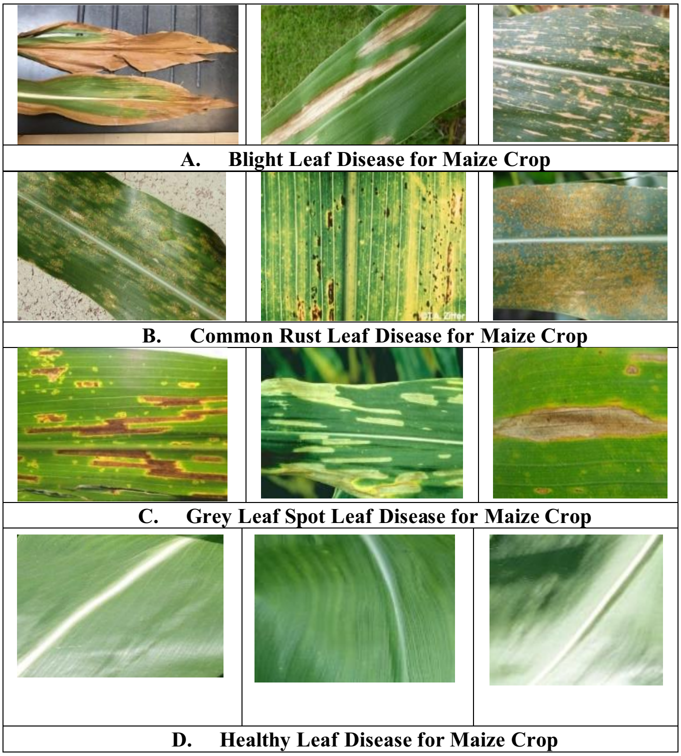


Fig. 2. Maize Leaf Diseased and Healthy Dataset Image Samples

3.3 TL Models and its Description

A. Densenet201

Densenet201 is a network that uses dense connectivity to promote feature reuse and discriminative learning. Transition layers control parameter numbers and reduce feature map dimensions. The network gradually decreases spatial dimensions while increasing channels, facilitating hierarchical feature extraction. Global average pooling reduces spatial dimensions to a single vector, improving model efficiency and reducing overfitting. The model uses a convolutional layer and pooling layer to create feature maps of 112x112.

B. Inception V3

The Inceptionv3 architecture uses multiple inception modules to extract hierarchical features from input images. It employs convolutions and pooling layers, with global average pooling reducing feature maps' spatial dimensions. The linear layer produces the final feature representation, which is fed into a SoftMax layer for classification.

layers	Inceptionv3	Input size
Convolution	3×3 conv, stride 2	$299 \times 299 \times 3$
Convolution	3×3 conv, stride 1	$149 \times 149 \times 32$
Convolution padded	3×3 conv, stride 1	$147 \times 147 \times 32$
Pooling	3×3 conv, stride 2	$147 \times 147 \times 64$
Convolution	3×3 conv, stride 1	$73 \times 73 \times 64$
Convolution	3×3 conv, stride 2	$71 \times 71 \times 80$
Convolution	3×3 conv, stride 1	$35 \times 35 \times 192$
$3 \times$ Inception	Module 1	$35 \times 35 \times 288$
$5 \times$ Inception	Module 2	$17 \times 17 \times 768$
$2 \times$ Inception	Module 3	$8 \times 8 \times 1280$
Pooling	8×8	$8 \times 8 \times 2048$
Linear	Logits	$1 \times 1 \times 2048$
Softmax	Classifier	$1 \times 1 \times 1000$

Fig. 3. Densenet-201 Transfer Learner Model Structure

Layers	Densenet-201	Output Size
Convolution	7×7 conv, stride 2	112×112
Pooling	3×3 max pool, stride 2	56×56
Dense Block-1	$\begin{bmatrix}1 \times 1\ conv \\ 3 \times 3\ conv\end{bmatrix} \times 6$	56×56
Transition Layer-1	1×1 conv	56×56
	2×2 avg pool, stride 2	28×28
Dense Block-2	$\begin{bmatrix}1 \times 1\ conv \\ 3 \times 3\ conv\end{bmatrix} \times 12$	28×28
Transition Layer-2	1×1 conv	28×28
	2×2 avg pool, stride 2	14×14
Dense Block-3	$\begin{bmatrix}1 \times 1\ conv \\ 3 \times 3\ conv\end{bmatrix} \times 48$	14×14
Transition Layer-3	1×1 conv	14×14
	2×2 avg pool, stride 2	7×7
Dense Block-4	$\begin{bmatrix}1 \times 1\ conv \\ 3 \times 3\ conv\end{bmatrix} \times 32$	7×7
Classification Layer	7×7 global avg pool	1×1
	1000 D fully connected, softmax	

Fig. 4. Inception V3 Transfer Learner Model Structure

Stage	Layer	Operation	Filters	Stride	Padding	Output size
1	Conv1_1	Convolution	64	1	Same	112x112x64
	Conv1_2	Convolution	64	1	Same	112x112x64
	Batch Norm 1	Batch normalization	64	-	-	112x112x64
	ReLU 1	Activation (ReLU)	64	-	-	112x112x64
	MaxPool1	Max pooling	-	2	Same	56x56x64
2	Conv2_1	Convolution	128	1	Same	56x56x128
	Conv2_2	Convolution	128	1	Same	56x56x128
	Batch Norm 2	Batch normalization	128	-	-	56x56x128
	ReLU 2	Activation (ReLU)	128	-	-	56x56x128
	MaxPool2	Max pooling	-	2	Same	28x28x128
3	Conv3_1	Convolution	256	1	Same	28x28x256
	Conv3_2	Convolution	256	1	Same	28x28x256
	Conv3_3	Convolution	256	1	Same	28x28x256
	Conv3_4	Convolution	256	1	Same	28x28x256
	Batch Norm 3	Batch normalization	256	-	-	28x28x256
	ReLU 3	Activation (ReLU)	256	-	-	28x28x256
	MaxPool3	Max pooling	-	2	Same	14x14x256
4	Conv4_1	Convolution	512	1	Same	14x14x512
	Conv4_2	Convolution	512	1	Same	14x14x512
	Conv4_3	Convolution	512	1	Same	14x14x512
	Conv4_4	Convolution	512	1	Same	14x14x512
	Batch Norm 4	Batch normalization	512	-	-	14x14x512
	ReLU 4	Activation (ReLU)	512	-	-	14x14x512
	MaxPool4	Max pooling	-	2	Same	7x7x512
5	Conv5_1	Convolution	512	1	Same	7x7x512
	Conv5_2	Convolution	512	1	Same	7x7x512
	Conv5_3	Convolution	512	1	Same	7x7x512
	Conv5_4	Convolution	512	1	Same	7x7x512
	Batch Norm 5	Batch normalization	512	-	-	7x7x512
	ReLU 5	Activation (ReLU)	512	-	-	7x7x512

Fig. 5. VGG-19 Transfer Learner Model

C. VGG-19

VGG 19 is a dynamic deep learning model with 19 layers, including convolutional, batch normalization, ReLU activation, and max-pooling layers. It uses small 3x3 filters in convolutional layers for object recognition and detection. It uses 64 filters, 128 filters, and 256 filters for processing. It requires careful analysis for optimal performance.

3.4 Performance Analysis

The accuracy ratio of a model is a measure of its effectiveness, calculated as CA = (TN + TP) / (TP + FP + TN + FN), where TN is True Negatives, TP is True Positives, FP is False Positives, and FN is False Negatives. PRE-Precision is denoted as PRE = TP / (TP + FP). Recall measures the proportion of actual positives accurately identified, focusing on the model's ability to capture true positives. The F1-score balances these two measures, ensuring a balanced approach to model effectiveness.

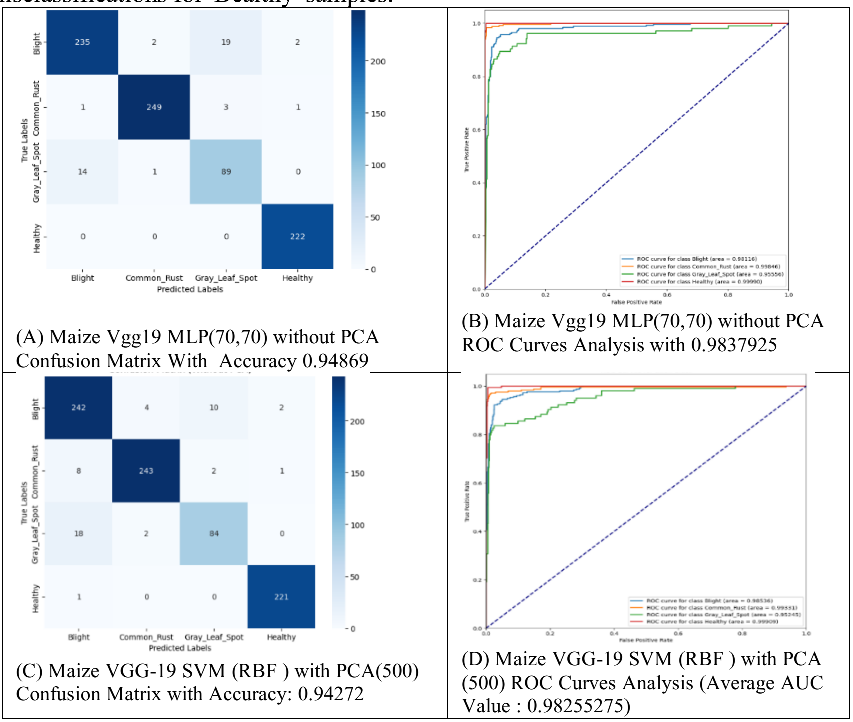
4 Results and Discussion

The paper explores the use of ML and ML in improving disease diagnosis and prognosis in maize plants in the agricultural sector. It highlights the potential for advanced, accurate, and efficient solutions to enhance crop management and productivity.

A. VGG 19+PCA+ML Model Analysis

a. VGG 19 Features+PCA+SVM|MLP Confusion Matrix and ROC Curves analysis

The study analyzes the Confusion Matrix and ROC AUC values for maize VGG-19 features and MLP without PCA. The model achieves high accuracy in classifying four maize diseases with minimal misclassification, with a healthy class having the highest AUC. The Maize disease classification model achieves 94.272% accuracy, with low misclassifications for 'Bealthy' samples.



(A) Maize Vgg19 MLP(70,70) without PCA Confusion Matrix With Accuracy 0.94869

(B) Maize Vgg19 MLP(70,70) without PCA ROC Curves Analysis with 0.9837925

(C) Maize VGG-19 SVM (RBF) with PCA(500) Confusion Matrix with Accuracy: 0.94272

(D) Maize VGG-19 SVM (RBF) with PCA (500) ROC Curves Analysis (Average AUC Value : 0.98255275)

Fig. 6. Detailed analysis Confusion Matrix and ROC-AUC analysis of VGG 19 Features+PCA+SVM|MLP

b. VGG 19 Features+PCA+SVM|MLP Performance Parameters analysis

The VGG19 TL-DL model's efficacy in classifying diseases was highly accurate, with most configurations exceeding 90%. PCA with 100 components improved accuracy, while the RBF kernel in SVM and Multi-Layer Perceptron (MLP) achieved high accuracy. SVM with RBF kernel was more favorable, while MLP with 70 neurons performed slightly better.

Table 1. High Performed Models SVM with VGG-19 Features

VGG19+ML Models	CA	PRE	F1	REC
SVM linear without PCA	0.89976	0.87	0.87	0.87
SVM poly without PCA	0.93437	0.93	0.91	0.90
SVM poly without PCA	0.93437	0.93	0.91	0.90
SVM linear pca(100)	0.91647	0.89	0.89	0.90
SVM linear pca(300)	0.90573	0.88	0.88	0.89
SVM linear pca(500)	0.90955	0.87	0.87	0.87
SVM poly pca(100)	0.91169	0.92	0.88	0.86
SVM poly pca(300)	0.90692	0.91	0.87	0.86
SVM poly pca(500)	0.90692	0.92	0.87	0.86
SVM rbf pca(100)	0.93556	0.93	0.92	0.91
SVM rbf pca(300)	**0.94153**	**0.93**	**0.93**	**0.92**
SVM rbf pca(500)	**0.94272**	**0.93**	**0.93**	**0.92**

Table 2. High Performed Models MLP with VGG-19 Features

Methods	CA	PRE	F1	REC
mlp(100,100) without pca	0.93675	0.91	0.92	0.92
mlp(70,70) without pca	**0.94869**	**0.93**	**0.93**	**0.94**
mlp(70,70) pca(100)	0.93675	0.92	0.92	0.92
mlp(70,70) pca(300)	0.93556	0.92	0.92	0.92
mlp(70,70) pca(500)	0.93675	0.92	0.92	0.92
mlp(100,100)pca(100)	**0.94153**	**0.92**	**0.92**	**0.93**
mlp(100,100) pca(300)	0.93079	0.91	0.91	0.91
mlp(100,100) pca(500)	0.93556	0.92	0.92	0.92

Table 3. Highest Performer Models SVM and MLP

Methods	CA	PRE	F1	REC
mlp(70,70) without pca	0.94869	0.93	0.93	0.94
SVM rbf pca(500)	0.94272	0.93	0.93	0.92

B. Inception V3 (Features)+PCA+ML Model Analysis

a. Inception V3 Features+PCA+SVM|MLP Performance Analysis

The InceptionV3 model is a reliable tool for detecting maize plant diseases in agriculture, influenced by factors like PCA and linear SVMs. Its performance is influenced by factors like PCA, Radial Basis Function SVM, and multilayer Perceptron models. Future research could focus on fine-tuning hyperparameters and ensemble methods.

Table 4. Highest Performer Models SVM with IV3 Features

SVM with IV3 Tl	CA	PRE	F1	REC
SVM linear without pca	0.93198	0.91	0.91	0.92
SVM poly without pca	0.94033	0.92	0.92	0.92
SVM rbf without pca	0.94272	0.93	0.93	0.92
SVM linear with pca(500)	0.92721	0.90	0.91	0.91
SVM linear with pca(100)	0.9105	0.89	0.89	0.89
SVM linear with pca(300)	0.91647	0.89	0.89	0.90
SVM poly with pca(500)	0.8926	0.91	0.85	0.83
SVM poly with pca(100)	0.90573	0.91	0.87	0.85
SVM poly with pca(300)	0.89618	0.91	0.86	0.84
SVM rbf with pca(500)	**0.94391**	**0.94**	**0.93**	**0.92**
SVM rbf with pca(100)	0.93914	0.93	0.92	0.92

SVM rbf with pca(300)	**0.94511**	**0.94**	**0.93**	**0.93**

Table 5. Highest Performer Models MLP with IV3 Features

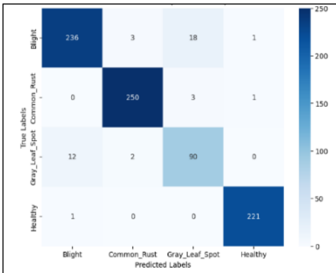
MLP with IV3 TL	**CA**	**PRE**	**F1**	**REC**
mlp(100,100) without pca	0.92243	0.90	0.90	0.92
mlp(70,70) without pca	0.93317	0.91	0.92	0.92
mlp(70,70) layers pca(500)	**0.93914**	**0.92**	**0.92**	**0.92**
mlp(70,70)layers pca(100)	0.91885	0.90	0.90	0.90
mlp(70,70)layers pca(300)	0.92721	0.90	0.91	0.91
mlp(100,100) layers pca(500)	**0.9463**	**0.93**	**0.93**	**0.93**
mlp(100,100)layers pca(100)	0.92124	0.90	0.90	0.91
mlp(100,100)layers pca(300)	0.92601	0.90	0.90	0.91

Table 6. Highest Performer Models SVM and MLP

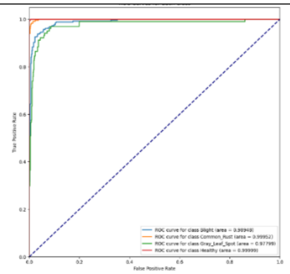
Methods	**CA**	**PRE**	**F1**	**REC**
SVM rbf with pca(300)	0.94511	0.94	0.93	0.93
mlp(100,100) layers pca(500)	0.9463	0.93	0.93	0.93

C. Densenet201 Features Analysis

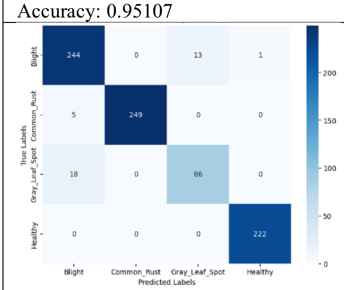
a. Densenet201+PCA+SVM|MLP Confusion Matrix and ROC Curves analysis



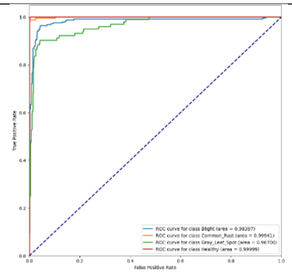
(A)Maize Densenet201 MLP(100,100) Layers PCA(300) Confusion Matrix Analysis with Accuracy: 0.95107



(B) Maize Densenet201 MLP(100,100) Layers PCA(300) with Average AUC value: 0.991745



(C)Maize Densenet201 MLP(100,100) Layers PCA(300) Confusion Matrix Analysis with Accuracy: 0.95585



(D)Maize Densenet201 MLP(100,100) Layers PCA(300) Confusion Matrix Analysis with Accuracy: 0.9875925

Fig. 7. Detailed analysis Confusion Matrix and ROC-AUC analysis of VGG 19 Features +PCA +SVM|MLP

a. Densenet201+Features+PCA+SVM|MLP Performance Parameter Analysis

The Densenet201 model effectively diagnoses maize plant diseases, with accuracy scores ranging from 0.92482 to 0.95585. Linear SVM models, polynomial SVM models, Radial Basis Function SVM models, and multilayer Perceptron models perform well for linearly separable datasets and complex pattern recognition tasks. Future research should focus on fine-tuning hyperparameters and ensemble methods.

Table 7. Highest Performer Modles DEN201+SVM

Methods with IV3 TL	**CA**	**PRE**	**F1**	**REC**

SVM linear without pca	0.92959	0.91	0.91	0.92
SVM polynomial without pca	0.9442	0.96	0.95	0.95
SVM rbf without pca	0.94227	0.94	0.94	0.93
SVM linear with pca(500)	0.93556	0.92	0.92	0.92
SVM linear with pca(100)	0.92482	0.90	0.91	0.91
SVM linear with pca(300)	0.93556	0.91	0.92	0.92
SVM poly with pca(500)	0.92959	0.93	0.90	0.89
SVM poly with pca(100)	0.93198	0.93	0090	0.89
SVM poly with pca(300)	0.93079	0.93	0.90	0.89
SVM rbf with pca(500)	0.94465	0.94	0.94	0.94
SVM rbf with pca(100)	**0.95585**	**0.94**	**0.94**	**0.94**
SVM rbf with pca(300)	0.95465	0.94	0.94	0.94

Table 8. Highest Performer Modles DEN201+MLP

Methods with IV3 TL	**CA**	**PRE**	**F1**	**REC**
mlp(70,70) layers	0.93795	0.92	0.92	0.94
mlp(100,100) layers	0.94346	0.94	0.94	0.94
mlp(100,100) layers pca(500)	0.94346	0.94	0.94	0.94
mlp(100,100)layers pca(100)	0.93675	0.92	0.92	0.92
mlp(100,100)layers pca(300)	**0.95107**	**0.93**	**0.94**	**0.94**
mlp(70,70) layers pca(500)	0.94749	0.93	0.94	0.93
mlp(70,70)layers pca(100)	0.94511	0.93	0.93	0.93
mlp(70,70)layers pca(300)	0.94988	0.93	0.94	0.94

Table 9. Highest Performer DEN201+ SVM and MLP

Methods	**CA**	**PRE**	**F1**	**REC**
mlp(100,100)layers pca(300)	0.95107	0.93	0.94	0.94
SVM rbf with pca(100)	0.95585	0.94	0.94	0.94

b. Comparative Analysis

S.NO	**author**	**Description and Analysis**	**Methodology and results**
[13]	Parraga et al. (2019)	The study reveals that TLs and feature concatenation enhance ML models for classifying tomato leaf diseases, with RF being the most accurate classifier. The images were extracted, reduced using Kernel PCA, and classified using popular classifiers SVM, RF, and MLR, using 20% of the dataset.	SVM-85%, Random forest-94%, Decision tree-90%, NASNET-92.4%
[14]	Harakannanavar et al. (2022)	The studey utilized ML techniques for tomato leaf disease classification and disease detection, achieving high accuracy rates. The VGG-16 model achieved good accuracy with 92%	VGG-16-92%, DenseNet-69%, ResNet-74%, Unidentified Model-73%
[15]	Rangarajan et al. (2018)	The study evaluated the efficacy of DL techniques in detecting and diagnosing wheat diseases using real field images, emphasizing the necessity for precise classification.	MobileNet - 91.46%, InceptionV3 - 91.41%, VGG16 - 85.16% Xception - 89.87%
[16]	Bedi et al., (2021)	This study presents an IoT-based plant disease recognition system using various semantic segmentation methods, demonstrating improved F1-score, sensitivity, and intersection over union (IoU) in leaf crop disease allocation.	U-Net - 70.12%, SegNet - 79.54%, Fcn-8s - 70.92%, Deeplabv3- 67.63%, Ced-Net - 73.17%
	Present Study	**Maize Plant Disease Diagnosis and Prognosis in Agriculture**	**DEN201 (features)+ MLP Accuracy - 0.95107 Pre-0.93F1-0.94 Recall-0.94**

5 Conclusion

The research paper introduces a method combining ML and Deep Transfer learning algorithms (InceptionV3, VGG19, and DenseNet201) to enhance maize plant disease diagnosis and prognosis in agriculture using traditional machine learning and Transfer Learning models. The results demonstrate the effectiveness of the proposed approach, with the Adam optimizer MLP achieving the highest accuracy (MLP(100,100) layers

PCA(300) accuracy 0.95107), as well as SVM (RBF kernel) with PCA(100) achieving exceptional accuracy (0.95585) compared to other classification methods.

References

1. Sonkar, Ahmed, M., & Purbey. (2022, May 22). Classification of Plant Leaf Detection by Using Deep Learning. Retrieved May 22, 2022.
2. Hasan, R. I., Yusuf, S. M., & Alzubaidi, L. (2020). Review of the state of the art of deep learning for plant diseases: A broad analysis and discussion. Plants, 9(10), 1302.
3. Prabavathi, S., & Kanmani, P. (2021). Plant Leaf Disease Detection and Classification Using Optimized CNN Model. International Journal of Recent Technology and Engineering, 9(6), 233-238.
4. Chitteti, Chengamma, and K. Reddy Madhavi. "Taylor African vulture optimization algorithm with hybrid deep convolution neural network for image captioning system." Multimedia Tools and Applications (2024): 1-19.
5. Abade, A., Ferreira, P. A., & de Barros Vidal, F. (2021). Plant diseases recognition on images using convolutional neural networks: A systematic review. Computers and Electronics in Agriculture, 185, 106125.
6. Tugrul, B., Elfatimi, E., & Eryigit, R. (2022). Convolutional neural networks in detection of plant leaf diseases: A review. Agriculture, 12(8), 1192.
7. Shoaib, M., Shah, B., Ei-Sappagh, S., Ali, A., Ullah, A., Alenezi, F., ... & Ali, F. (2023). Corrigendum: An advanced deep learning models-based plant disease detection: a review of recent research. Frontiers in Plant Science, 14, 1282443.
8. Rao, K. S., Terlapu, P. V., Jayaram, D., Raju, K. K., Kumar, G. K., Pemula, R., ... & Rakesh, S. (2024). Intelligent Ultrasound Imaging for Enhanced Breast Cancer Diagnosis: Ensemble Transfer Learning Strategies. IEEE Access.
9. Terlapu, P. V., Gedela, S. B., Gangu, V. K., & Pemula, R. (2022). Intelligent diagnosis system of hepatitis C virus: A probabilistic neural network-based approach. International Journal of Imaging Systems and Technology, 32(6), 2107-2136.
10. Kumar, Voruganti Naresh, U. Sivaji, Gunipati Kanishka, B. Rupa Devi, A. Suresh, K. Reddy Madhavi, and Syed Thouheed Ahmed. "A Framework For Tweet Classification And Analysis On Social Media Platform Using Federated Learning." Malaysian Journal of Computer Science (2023): 90-98.
11. PanduRanga Vital, T., Murty, G. S., Yogiswara Rao, K., & Sriram, T. V. S. (2020). Empirical Study and Statistical Performance Analysis with ANN for Parkinson's Vowelized Data set. In Computational Intelligence in Data Mining: Proceedings of the International Conference on ICCIDM 2018 (pp. 767-780). Springer Singapore.
12. Praveen, A. D., Vital, T. P., Jayaram, D., & Satyanarayana, L. V. (2021). Intelligent liver disease prediction (ILDP) system using machine learning models. In Intelligent Computing in Control and Communication: Proceeding of the First International Conference on Intelligent Computing in Control and Communication (ICCC 2020) (pp. 609-625). Springer Singapore.
13. Parraga-Alava, J., Cusme, K., Loor, A., & Santander, E. (2019). RoCoLe: A robusta coffee leaf images dataset for evaluation of machine learning based methods in plant diseases recognition. Data in brief, 25, 104414.
14. Harakannanavar, S. S., Rudagi, J. M., Puranikmath, V. I., Siddiqua, A., & Pramodhini, R. (2022). Plant leaf disease detection using computer vision and machine learning algorithms. Global Transitions Proceedings, 3(1), 305-310.
15. Rangarajan, A. K., Purushothaman, R., & Ramesh, A. (2018). Tomato crop disease classification using pre-trained deep learning algorithm. Procedia computer science, 133, 1040-1047.