JOURNAL OF BASIC SCIENCE AND ENGINEERING

An Ensemble Approach for Tulsi Plants Diseases Detection using MLP Mixer and LSTM

PRABHA.B [1]

Research Scholar, Mother Teresa Women's University, Kodaikanal, Tamilnadu, India.

Dr. K.KAVITHA [2]

Assistant Professor, Department of Computer Science, Mother Teresa Women's University, Kodaikanal, Tamilnadu, India.

DOI: https://doie.org/10.0210/Jbse.2025142029

ABSTRACT:

Tulsi belongs to the family Lamia ceae and is considered as a holy plant with multipurpose uses in agri horticulture and medicinal field. Diseases in tulsi plants usually develop unknown to the farmer, thus timely and proper diagnosis plays an important role in obtaining high yield and quality plants. This research outlines the use of advanced preprocessing, training, and classification methodologies for detecting tulsi plant diseases using an ensemble-based model. The preprocessing phase of the Feature-Enhancing technique uses the Anisotropic Diffusion Filtering (ADF) for improving contrast and edge sharpness of images and getting rid of excessive image noise. After that, the Convolutional Neural Networks (CNN) is employed for feature extraction since the network is capable of learning hierarchical features from plant images. The extracted features are then fed to LSTM networks as well as MLPs to capture both temporal relatedness and other more realistic nonlinear temporal characteristics. In classification task, a SVM is used to accurately classify the diseased and healthy leaves. The proposed ensemble method outperformed the individual models in all the experiments, offering high accuracy for disease diagnosis. This research presents a more reliable and effective approach for real-time diagnosis of tulsi plant diseases.

Keywords: Anisotropic Diffusion Filtering, ensemble, Convolutional Neural Network, Support Vector Machine.

INTRODUCTIONS

Plant diseases can therefore be detected using one or several methods depending on the appearances of the leaves. Experts can assess the status of vitality of a plant by sometimes by observing the state of its leaves, branches or fruit. For this strategy to work, there should be a large samples of number of respondents that must be included in the survey must also be determined. If we had today's technology advanced with automation, we would greatly benefit from establishing a mechanism of diagnosing diseases in plants through an automated system. These gaps have been covered through the various researches. In previous projects Images of plant leaves are incorporated as part of our approach to this issue as well as that of the other studies. Besides identifying sick plants, disease detection systems are capable of identifying the type of disease being conveyed by both the sick and the healthy plants by the use of computer vision. It also helps you in identifying Herb diseases so that it can be diagnosed automatically. Both these species are depended on by farmers for their living. Global crop production has numerous issues that occasion challenges in generating food crops across the world [1]. The establishment of health, however, is dependent on plants [2]. Preservation of vegetation is a crucial goal globally, even though people cannot exist without plant. Among the diverse range of CNN architectures available, Inception v3, ResNet50, and DenseNet, InceptionNet and MobileNet have emerged as powerful tools for image analysis and classification tasks. This study delves into the implementation and comparative evaluation of these three cutting-edge CNN architectures in the domain of medicinal plant leaves identification and disease detection, with a focus on contributing novel insights to the field [3],[4],[5]. Customized CNNs [6] [7], and attention-based techniques [8], [9], [10] have also been deployed for plant disease classification. Recently, the lightweight MLP-Mixer architecture has gained attention due to its lesser architectural complexity and competitive performance on ImageNet dataset [11]. This architecture, which relies solely on multi-layer percep-trons(MLPs) without convolution and attention mechanism, present a promising solution for resource-constrained IoT environments.

Related Work:

Sangeetha and Rani, 2021 [12] A transfer learning-based method using VGG16 and VGG19 is employed. The two models are compared to show which model achieves higher accuracy. It can be seen from the results that VGG16 has an accuracy of 97.79% which is higher than that of VGG19 with 94.7% accuracy. However, the proposed model is trained on tomato leaf images only.

Anandhakrishnan and Jaisakthi, 2022 [13] a novel Deep Convolutional Neural Network (DCNN) with a small number of layers is pro-posed. The proposed DCNN model was trained on tomato leaf images collected from Plant Village dataset and achieved 98.4% accuracy on the test data.

Kaya and GÜrsoy, 2023 [14] a novel multi-headed DenseNet-based architecture is proposed. The model relies on fusing Red-Grean-Blue (RGB) and segmented images. The model achieves an average of 98.17% on 54,000 images with 38 different classes.

Pandian et al., 2022 [15] a new dataset was created using a number of open-source plant leaf datasets. Three different data augmentation techniques were applied to balance the dataset Basic Image Manipulation (BIM), Deep Convolutional Generative Adversarial Network (DCGAN) and NST. The systems achieved a high accuracy of 98.0.5%.

Singh et al. (2018) [16] talked about the new trends and future prospects of deep learning in plant stress phenotyping. They emphasized the need for people from different elds to work together and use data-driven methods. Singh et al. (2020) [17]also looked at different imaging methods that can be used to and plant diseases. They stressed how important it is to choose the right methods based on the imaging modality and the situation. Saleem et al. (2019) [18] talked about the role of deep learning in nding and classifying plant diseases, focusing on how it could improve farming methods and lower crop losses. All of these studies show how deep learning has changed the way plant diseases are diagnosed and how farming is done in general.

In a prior study by Ahmad W et al. [19], the methodology involved the utilization of Directional Local Quinary Patterns (DLQP) to determine keypoints within the input image during the initial stage. Subsequently, plant disease classification results were achieved by training a Support Vector Machine (SVM) classifier using the computed keypoints. In a separate study focused on the detection of tomato leaf diseases by Zhang et al. [20], various deep learning models, specifically AlexNet, GoogleNet, and ResNet, were employed. These models were subjected to experimentation with both the Stochastic Gradient Descent (SGD) and Adam optimizers. Remarkably, the ResNet model exhibited the highest level of accuracy, achieving a remarkable 97.28% accuracy rate.

Joshi et al. [21] put forth a framework for ensemble learning that utilizes Plant Balance and was able to attain a 93% accuracy on their test data.

Vijayaganth V et al. [22] proposed a novel Oppositional Adaptive Galactic Swarm Optimization (OA-GSO) ensemble learning model that integrates soft computing and deep learning for plant leaf multi-disease classification.

Kaur et al. [23] presented a modification to the InceptionResNet-V2 model for identifying diseases in tomato leaves. The model was trained using a combination of public and self-collected datasets. In terms of evaluation, the model demonstrated a 98.92% classification accuracy and a 97.94% f1-score.

Methodology

TULSI Leaf Dataset
Data Spliting **(Training and Testing)**
Data Preprocessing **(Anisotropic Diffusion Filtering)**
Feature Extraction **(MobileNet, DenseNet121,169,201)**
Model Training **(LSTM,MLP-Mixer)**
Classification **(Support Vector Machine)**
Diseases Predictions **Healthy** **Bactirial** **Fungal** **Pests**

TULSI Leaf Dataset

This dataset consists of 2274 images of four different classes of Tulsi leaf disease images captured under real-world conditions and also from the internet. The images of four different leaf diseases such as ‘Fungal’, ‘Bacterial ’, ‘Pests’ and ‘healthy plant’ leaves images were present in this dataset. The number of sample images present in each class of the Tulsi Dataset has been presented in Table 1.This comprehensive dataset, accessible through Kaggle.com, serves as a fundamental resource for researchers, offering high-quality, and annotated retinal images categorized.

S.No	Diseases	Sample Images
1	Bacterial	204
2	Fungal	490
3	Pests	765
4	Healthy	815
	Total	**2274**

Table: 1

SAMPLE IMAGES OF DATASET

Fig.1 Healthy

Fig.2 Fungal

Fig.3 Bacterial

Fig.4 Pests

DATA SPLITING

In the first step, the dataset has been split into training and test set. The dataset has been split into the ratio of 0.8:0.2, 80% of the data was used for training and remaining 20% were used for the training.

DATA PREPROCESSING

Anisotropic Diffusion Filtering (ADF), also known as Perona-Malik filtering, is a powerful edge-preserving image processing technique often used for noise reduction while retaining important details like edges. This makes it particularly useful in preprocessing plant disease images, where maintaining disease spot boundaries are crucial.

ADF Algorithm:

1. Gradient Computation:
Compute the magnitude of the gradient $|\nabla I(x, y)|$ and the direction $\theta(x, y)$ for every pixel (x, y).

2. Diffusion Coefficient:
Define a function $g(\cdot)$ to compute the diffusion coefficient based on the gradient

$$c(x, y) = g(|\nabla I(x, y)|) \qquad 1$$

3. Diffusion Process:
Apply the heat equation iteratively

$$\partial I/\partial t = \nabla \cdot (c(x, y)\, \nabla I(x, y)) \qquad 2$$

Anisotropic diffusion filtering is an underscores the importance of validating against ground truth data and conducting a comprehensive analysis of preprocessing impacts to guarantee the credibility and applicability of the findings, notwithstanding potential challenges. This technique is particularly beneficial in the context of studying plant morphology and cellular structures, where clarity and detail are essential.

Fig.5. Preprocessing Image

Then in the next step, pre-processed training set images were used to train the models (Mixer and LSTM) present at the level 1 (iii) After the level 1 models are trained, the level 2 support vector machine classifier is trained using the features that are extracted from these models (as an output of these models). (iv)After training the models present at both levels, the test set images were first given as input to the trained models present at level 1 to draw the features. Then drawn-out features of these models were concatenated and then given as an input to the trained SVM model present at level 2 to reach the final decision.

Feature Extraction

In the context of Tulsi Leaf diseases detection, features are extracted using advanced texture analysis and leveraging pre-trained deep learning models such as MobileNet and DenseNet (DenseNet121, DenseNet169, and DenseNet201). The input images must be resized to the input dimensions expected by the models (224x224 for MobileNet and DenseNet). MobileNet uses depthwise separable convolutions to create a lightweight network suitable for devices with limited computational power. DenseNet121 consists of 121 layers with dense connections between them, allowing for better feature propagation and reducing the number of parameters. Similar to DenseNet121 but with more layers (169), DenseNet169 enhances the model's capacity to learn intricate features. Similar to DenseNet121 but with more layers (169), DenseNet169 enhances the model's capacity to learn intricate features. DenseNet201 extends the concepts of DenseNet further with 201 layers, providing even deeper connectivity. LSTM model has been used to learn the distinguishing characteristics present in the one-dimensional combined feature vector obtained after combining the feature set obtained from the MobileNet, DenseNet121, and DenseNet201 and DenseNet169 models. Both models when used together in the meta-ensemble at level 1

MODEL TRAINING

1) MLP MIXER MODEL

MLP Mixer model accepts images in feed forward form as its input patches, thus, before the pre-processing of the input images to the MLP Mixer model, the disclosure being that each image has been divided into several patches and each of these patches has been further projected into D dimensional space (here, D =128) of fixed size called projected embedding's 'tokens'. This research aims to explain the basic abilities of the Mixer architecture lies in its mixer layers. Mixer layers composed of MLPs which execute two dissimilar functions, namely blending of the tokens and the channels. Further, the token mixing enables the MLP Arrange mixer architecture to learn the spatial relationship of are used for the tokens (patch embeddings); however, the channel mixing The structure of MLP implies the possibility for the model to detect the dependence between the channels already built into the single token itself.
Consequently, in any mixer layer an input matrix of shape It is recommended to use the model of the form (NXD, N = 9, D = 128) where N is the number of Patches and D is the embedding dimension, passes through the token mixing and channel mixing MLP by transposing the input matrix accordingly. An MLP in the mixer layer comprised by two fully connected (FCN) layers with Gaussian Error Linear Unit (GELU) non-linearity. Thus, in any mixer layer: The three operations that are performed in the Bert layer include layer normalization, GELU non-linear transformation and skip connection between the two MLPs are employed for the smoother flow of the gradient from one layer to other. Because increasing the number of mixer layers also increase the MLP or the number of hidden layers in the network. Mixer more difficult, an ideal number of mixer layers (seven In this case) has been chosen for the current plant disease classification assignment. The last layer of the mixer is the output mixer layer is passed through the normalisation layer first, the dropout Layer has a rate of 0.25, and the last layer is global average pooling (GAP) layer and then a categorisation layer with an activation function Softmax. This is similar to applying ''softmax'' on the elements of the input matrix considering each row at a time. Using Equations 1and 2, the mixer layer in the MLP Mixer model can be represented.

$$U_{*,i} = X_{*,i} + W2\ \sigma\ W1 \cdot \mathrm{LayerNorm}(X)_{*,i}, \text{ for } i = 1 \ldots C, \tag{3}$$
$$Y_{j,*} = U_{j,*} + W4\ \sigma\ W3 \cdot \mathrm{LayerNorm}(U)_{j,*}, \text{ for } j = 1 \ldots S. \tag{4}$$

Where U and Y symbolizing the output of the first and the second FCN layers. LN stands for the layer normalisation process. W 1, W 2, W 3 and W 4, represent the weight matrices. X denotes the initial configuration in the first FCN layer. C and S denote the number of as the communication channels and the tokens separately.

MODEL 11

LONG SHORT TEAM MEMORY (LSTM)

Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) architecture that addresses the vanishing gradient problem in regular RNNs. LSTMs regulate information flow by using a memory cell and three gates (input,forget, and output). The cell stores information across the long sequences, allowing the network to capture and learn data dependencies more efficiently. Their capacity to handle
Long range dependencies make them ideal for a variety of sequential data application.
In many recent prediction models, LSTM has been showing effective performance in time series data prediction. Their capacity to handle long-range dependencies makes them ideal for a variety of sequential data applications. The reason for choosing LSTM architecture for the proposed ensemble is that the LSTM model applies operations directly to the data and does not use the convolution concept as well as the attention mechanism. Therefore, LSTM is also lightweight in comparison to CNN and ViT architectures. Thus, LSTM has also been deployed for the development of the proposed ensemble. Though it is not reasonable to train the LSTM directly on input images, considering the raw information present in an input image; therefore, the features drawn out from the last convolution layer of ImageNet-trained CNNs were used to train the proposed LSTM. The cell in the LSTM transfers the information at randomly chosen time intervals. The input and output data flow is traced by the gates. The computation of nodal outputs of an LSTM network is shown in the following equations:

$$ing_{tm} = \sigma (wm_{ing} . [hs_{tm-1}, EF_d] + bv_{ing} \quad (5)$$

$$hs_{tm} = og_{tm} * \tan h (ce_{tm}) \quad (6)$$

Here, the term EF_d denotes the input variable at a time tm: The weight matrices are indicated by wm_{ing} the input gates are represented by ing_{tm}: The symbol r represents the sigmoid activation function and the hidden calculation for state outputs at a time tm is denoted by hs_{tm}: The biased values of different gates are represented by bv_{ing}

CLASSIFICATION

SUPPORT VECTOR MACHINE

The SVM method is trained to choose the best hyperplane that maximizes the margin between distinct classes, thereby enabling it to distinguish feature vectors of various classes (species). Finding the hyperplane that best divides the data points requires solving an optimization issue. Non-linear correlations between features can be handled by SVM by using different kernel linear functions to change the feature space. When there is no linear separability of the feature space, this is especially helpful. Upon training, the SVM model establishes a decision boundary in the feature space that divides several classes. The extracted features are fed through the trained support vector machine (SVM) model for every new leaf image. The model classifies the image according to the side of the decision boundary where the feature vector lies. As a result, the leaf image is associated with a particular type of plant disease detection. The SVM classifier has also been proven to be superior to other classifiers in the context of the current categorization task, and the related experimental findings are presented in the results part of the current publication.

COMBINING BOTH LEVELS

Vol. 22, No. 1, (2025)
ISSN: 1005-0930

The suggested technique has been divided into two levels: level 1 of the proposed ensemble contains the MLP Mixer and LSTM models, while level 2 of the ensemble contains the SVM classifier.
The overall objective of this study is to build a lightweight framework MLP-mixer and LSTM were found suitable to create ensemble since they are lightweight, more accurate and accelerates the prediction time. Pre-processed augmented training set images were used to train the MLP Mixer model present at level 2 while the LSTM model has been trained on the concatenated features, drawn out from the four different ImageNet-trained CNNs. All images were resized to 64 × 64 before passing them to ImageNet-trained CNNs for drawing out the features from them. The features drawn out from the pre-trained MobileNet, DenseNet121, DenseNet169 and DenseNe201 architectures were concatenated to form the combined feature vector of shape which is used to train LSTM. After training both the models present at level 1, the prediction probabilities of these trained models were recorded by providing training set images as input to them. The prediction probabilities obtained from these models (LSTM and MLP-Mixer), were concatenated and then passed as input to the trained SVM classifier to make the final decision about the class of an input test set images. The testing phase of the proposed ensemble can be represented mathematically using Eq.7- 11.

$$X_{test\text{-}LSTM} = [F_{MobileNet}, F_{DenseNet121}, F_{DenseNet169}, F_{DenseNet201}] \quad (7)$$

$$P_{LSTM} = LSTM\ (X_{LSTM}, LSTM) \quad (8)$$

$$P_{Mixer} = MLP\_Mixer(X_{Mixer}, Mixer) \quad (9)$$

$$P_{Concat} = [P_{Mixer}, P_{LSTM}] \quad (10)$$

$$Y_{Final} = SVM\_Predict(P_{Concat}, SVM) \quad (11)$$

Xtest-LSTM shown in Eq. 7 denotes the combined feature vector obtained after combining the feature vectors obtained from the MobileNet, DenseNet121, DenseNet169, and DenseNet201 models by giving test set images as input to these pre-trained deep CNN models. LSTM and MLP Mixer, in Eq. 8 and Eq. 9, denote the trained LSTM and MLP-Mixer models, and PLSTM and PMixer denote the predicted probabilities of these models. After concatenating these probabilities into a vector, the final matrix denoted by PConcat in Eq. 10 is used to test the SVM model trained during the training phase, as shown in Eq. 11.

Result and Discussion

The performance of the proposed method has been analyzed on the validation set and measure the correct generalizability of the proposed model. To test the generalization of the MLP Mixer and LSTM models used in the proposed ensemble, training and validation accuracy and loss curves have also been plotted for dataset as shown in Fig. 6 and Fig. 7 respectively. It can be analyzed from the training and validation accuracy curves that trained models have neither the high bias nor the high variance and both the models (MLP Mixer and LSTM) have achieved convergence. It can also be observed from Fig. 6 and Fig. 7that the convergence in the case of LSTM architecture is faster than the convergence of MLP Mixer architecture.

MODEL	ACCURACY	LOSS

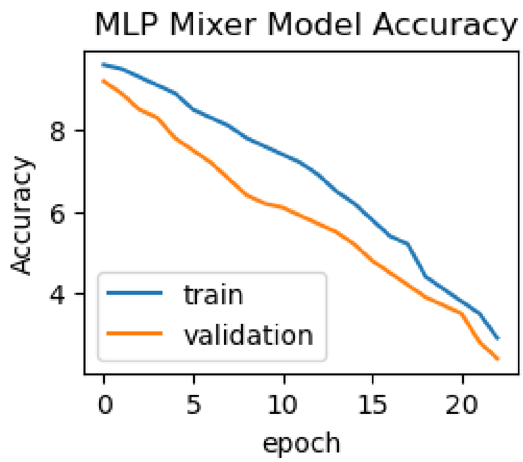
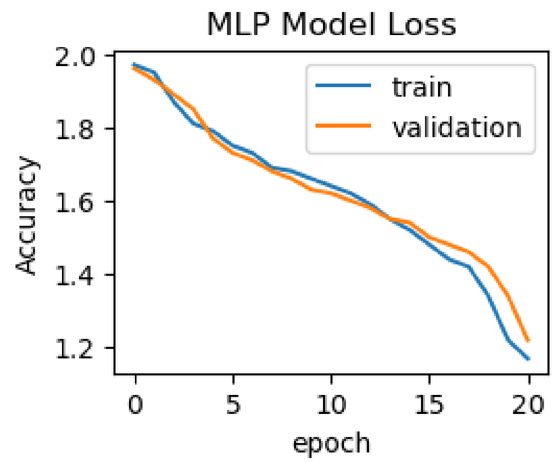
<table>
<tr><td>MLP MIXER</td><td>
</td><td>
</td></tr>
</table>

Fig.6. MLP Mixer Model Accuracy and Loss

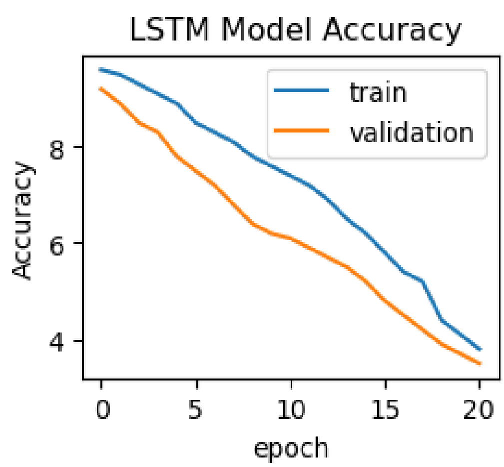
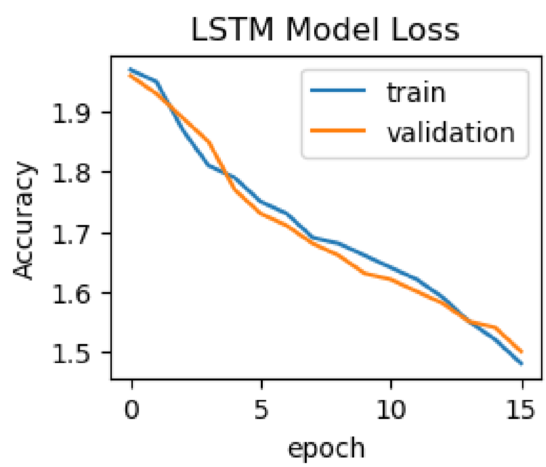
<table>
<tr><th>MODEL</th><th>ACCURACY</th><th>LOSS</th></tr>
<tr><td>LSTM</td><td>
</td><td>
</td></tr>
</table>

Fig.7. LSTM Model Accuracy and Loss

The Test time taken by the proposed ensemble, i.e., the time required in getting output from level 1 models (MLP Mixer and LSTM) and the time required in the categorisation of the outputs obtained from these models by the SVM classifier at level 2, the proposed ensemble is lightweight in comparison to the other ViT and CNN-based models. The % categorisation accuracy obtained by the proposed ensemble is also the best among other models used for comparison purposes. The below table compares different models accuracy with existing literature and architecture used for disease prediction in tulsi leaf research:

Table.2. Model comparison with existing literature on tulsi

Model	Stacking Estimators	Accuracy
Proposed model	**MLP Mixer, LSTM,SVM**	**98.87%**
Model A [24]	SVM , RF	98.25%
Model B [24]	SVM,RF,DT	97.15%

Model C [24]	SVM,RF,DT,MLP	97.35%
[25]	Transfer Learning, SVM	SVM-97% Transferlearning- 98%
[26]	CNN	75%
[27]	CNN, Inception V3 model	77.55%
[28]	k-means clustering	0.59%

The prediction time of the proposed ensemble in comparison to the other Transformer and deep CNN-based models is the lowest and the classification accuracy of the proposed ensemble is also the highest. The Test timing is 0.812 seconds, 0.691 seconds and 1.91 seconds respectively. When the outputs from MLP Mixer and LSTM models in the form of prediction probabilities are utilised as a feature set for training and then testing of the SVM classifier; it results in the overall improvement of the categorization performance of the proposed ensemble. The proposed LSTM model is more time efficient with a smaller number of trainable parameters contrast to MLP Mixer; however, the proposed MLP Mixer model is more accurate in terms of %categorisation accuracy. Hat the in case of the datasets, the best categorisation accuracy has been obtained with the SVM classifier. Therefore, SVM has been chosen as a level 2 classifier in the proposed ensemble. However, at level 1, MLP Mixer and LSTM models have been chosen due to their lightweight nature and, when these models are used in synchronisation with the level 2 model; it results in further improvement of the categorisation performance of the proposed ensemble approach.

CONCLUSION

The Tulsi plants diseases detection are critical for ensuring their health and maintaining their medicinal quality. Adaptive Differential Filtering (ADF) was applied as part of the preprocessing phase to improve image quality and eliminate noise, so that the input data eventually fed to the Convolutional Neural Network (CNN) were optimal for feature extraction. The extracted features were handled using the ensemble approach using the Multi-Layer Perceptron (MLP) and the Long Short Term Memory (LSTM) networks to train the models. Both the MLP and the LSTM were trained to learn complex patterns within the static feature set but the LSTM was able to learn the temporal dependencies and sequential patterns, which were required for data sets with dynamic variations. By adding that combination we were picking out one feature space that we then could use to comprehend the whole feature space so that our system was more robust to plant disease variations. Support Vector Machines (SVM) was used in this case for classification, with the benefit of their ability to work in high dimensional feature spaces and their history of robustness in small to medium size datasets. The diverse and detailed feature representations from the earlier stages allowed SVM to serve as a decisive classifier and the prediction was extremely precise. The proposed ensemble approach has achieved the 98.87% highest accuracy. Tulsi plants disease detection through an ensemble approach was found to be more accurate and reliable than traditional methods or standalone models. The proposed framework demonstrated high performance in terms of feature extraction and classification by combining CNNs, MLP, LSTM and SVM, all techniques with complementary strengths.

References:

[1] Dhaygude Sanjay B, Kumbhar Nitin P. Agricultural plant leaf disease detection using image processing. Int J Adv Res Electr Electron Instrum Eng 2013;2(1).

[2] Mrunalini R Badnakhe, Deshmukh Prashant R. An application of K-means clustering and artificial intelligence in pattern recognition for crop diseases. Int Conf Adv Inf Technol 2011;20. 2011 IPCSIT.
[3] A. Loddo, M. Loddo, and C. Di Ruberto, ‘‘A novel deep learning based approach for seed image classification and retrieval,’’ Comput. Electron. Agricult., vol. 187, Aug. 2021, Art. no. 106269, doi: 10.1016/j.compag.2021.106269.
[4] C. Qian, M. Tong, X. Yu, and S. Zhuang, ‘‘CNN-based visual processing approach for biological sample microinjection systems,’’ Neurocomputing,vol. 459, pp. 70–80, Oct. 2021, doi: 10.1016/j.neucom.2021.06.085.
[5] R. Maurya, V. K. Pathak, and M. K. Dutta, ‘‘Deep learning based microscopic cell images classification framework using multi-level ensemble,’’ Comput. Methods Programs Biomed., vol. 211, Nov. 2021,Art. no. 106445, doi: 10.1016/j.cmpb.2021.106445.
[6] S. Huang, G. Zhou, M. He, A. Chen, W. Zhang, and Y. Hu, ‘‘Detection of peach disease image based on asymptotic non-local means and PCNN-IPELM,’’ IEEE Access, vol. 8, pp. 136421–136433, 2020.
[7] S. Yadav, N. Sengar, A. Singh, A. Singh, and M. K. Dutta, ‘‘Identification of disease using deep learning and evaluation of bacteriosis in peach leaf,’’Ecolog. Informat., vol. 61, Mar. 2021, Art. no. 101247.
[8] Y. Zhao, C. Sun, X. Xu, and J. Chen, ‘‘RIC-Net: A plant disease classification model based on the fusion of inception and residual structure and embedded attention mechanism,’’ Comput. Electron. Agricult., vol. 193,Feb. 2022, Art. no. 106644, doi: 10.1016/j.compag.2021.106644.
[9] R. Maurya, R. Burget, R. Shaurya, M. Kiac, and M. K. Dutta,‘‘Multi-head attention-based transfer learning approach for porato disease detection,’’ in Proc. 15th Int. Congr. Ultra Modern Telecommunication Control Syst. Workshops (ICUMT), Oct. 2023, pp. 165–169, doi: 10.1109/ICUMT61075.2023.10333272.
[10] X. Chen, G. Zhou, A. Chen, J. Yi, W. Zhang, and Y. Hu, ‘‘Identification of tomato leaf diseases based on combination of ABCK-BWTR and B-ARNet,’’ Comput. Electron. Agricult., vol. 178, Nov. 2020, Art. no. 105730.
[11] I. Tolstikhin, N. Houlsby, A. Kolesnikov, L. Beyer, X. Zhai, T.Unterthiner, J. Yung, A. Steiner, D. Keysers, J. Uszkoreit, M. Lucic, and A. Dosovitskiy, ‘‘MLP-mixer: An all-MLP architecture for vision,’’ 2021,arXiv:2105.01601.
[12] Sangeetha, R., Rani, M.M.S., 2021. Tomato leaf disease prediction using transfer learning. In: Advanced Computing: 10th International Conference, IACC 2020,Panaji, Goa, India, December 5–6, 2020, Revised Selected Papers, Part II 10. Springer, pp. 3–18.
[13] Anandhakrishnan, T., Jaisakthi, S., 2022. Deep convolutional neural networks for image based tomato leaf disease detection. Sustain. Chem. Pharm. 30, 100793.
[14] Kaya, Y., GÜrsoy, E., 2023. A novel multi-head cnn design to identify plant diseases using the fusion of rgb images. Eco. Inform. 75, 101998.
[15] Pandian, J.A., Kumar, V.D., Geman, O., Hnatiuc, M., Arif, M., Kanchanadevi, K., 2022. Plant disease detection using deep convolutional neural network. Appl. Sci. 12 (14),6982
[16] Singh AK, Ganapathysubramanian B, Sarkar S, Singh A (Oct. 2018) Deep learning for plant stress phenotyping: Trends and future perspectives. Trends Plant Sci 23(10):883–898 Show in Context
CrossRef Google Scholar
[17] Singh V, Sharma N, Singh S (Oct. 2020) A review of imaging techniques for plant disease detection.Artif Intell Agricult 4:229–242 Show in Context CrossRef Google Scholar
[18] Saleem MH, Potgieter J, Arif KM (Oct. 2019) Plant disease detection and classification by deep learning. Plants 8(11):468–489 Show in Context CrossRef Google Scholar
[19] Ahmad W, Shah S, Irtaza A (2020) Plants disease phenotyping using quinary patterns as texture descriptor. KSII Trans Internet Inf Syst 14(8):3312–3322.
[20] Zhang, Keke & Wu, Qiufeng & Liu, Anwang & Meng, Xiangyan. (2018). Can Deep Learning Identify Tomato Leaf Disease Advances in Multimedia. 2018. 1-10. 10.1155/2018/6710865.
[21] P. Joshi, A. Dev, A. Sharma, and R. Jangra, “Plantbalance: An automated ensemble learning framework for plant disease detection,” in 2022 IEEE Delhi Section Conference (DELCON). IEEE, 2022.
[22] P. Kaur, S. Harnal, V. Gautam, M. P. Singh, and S. P. Singh, “A novel transfer deep learning method for detection and classification of plant leaf disease,” Journal of Ambient Intelligence and Humanized Computing, pp. 1–18, 2022.
[23] V. Vijayaganth and M. Krishnamoorthi, “Soft computing-based ensemble learning model for multi-disease classification of plant leaves,” GEOCARTO INTERNATIONAL, 2022.
[24] Kaur, M. ., Singh, S. ., & Gehlot, A. . (2024). "Enhancing Precision in Tulsi Leaf Infection Classification: A Stacking Classifier Ensemble Strategy". International Journal of Intelligent Systems and Applications in Engineering, 12(20s), 109–119. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/5123

[25] Qi, H., Liang, Y., Ding, Q., & Zou, J. (2021).Automatic identification of peanut-leaf diseases based on stack ensemble. Applied Sciences, 11(4),1950.

[26] Patil, S. S., Patil, S. H., Bhall, A., Rajvaidya, A.,Sehrawat, H., Pawar, A. M., & Agarwal, D. (2022, December). Tulsi Leaf Disease Detection using CNN. In 2022 IEEE Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI) (pp. 1-4). IEEE.

[27] Sathiya, V., Josephine, M. S., & Jeyabalaraja, V.(2023). Plant Disease Classification of Basil and Mint Leaves using Convolutional Neural Networks.International Journal of Intelligent Systems and Applications in Engineering, 11(2), 153-163.

[28] Sathiya, V., Josephine, D., & Jeyabalaraja, D. (2022).Identification And Classification Of Diseases In Basil And Mint Plants Using Psorbfnn. J. Theor. Appl. Inf.Technol. 100, 21.