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Pigeon Pea Leaf Illness Identification and Categorization Using Bayesian Optimizer Deep Hybrid Learning Approach

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***Abstract:** The pigeon pea, or Cajanus cajan, is a significant legume crop valued for both its commercial value and high nutritional content. However, there are certain diseases that could impact its output and quality. Accurate and quick identification is essential for managing and controlling these disorders. Without expert help, the time-consuming and tedious method of manually identifying pigeon pea leaf disorder could produce unreliable findings. For them to guarantee the purity and quantity of pigeon pea production by offering prompt treatments to reduce disease transmission, farmers must have an automated, early, and accurate leaf disease recognition system. A Bayesian optimized deep hybrid learning system evolved for identifying and classifying damages in pigeon pea leaves. Standardizing the data through substantial preprocessing is necessary to build a custom dataset pigeon pea leaf. To improve the model's speed and accuracy, leaves are separated from its complex background using a modified U-Net segmentation technique. Features are extracted from CNN to get relevant features and then various machine learning classifiers are used for classification. On an unseen dataset, this model achieved accuracy values of 99.5%. The results reveal that the suggested model provides an effective solution for detection and classification in agricultural application in identifying illnesses in pigeon pea leaves.*

Keywords: Pigeon pea leaves Disease detection, Image classification, segmentation, Agricultural applications

1. Introduction

India's economy is based primarily on agriculture. One of the primary legume crops grown in the tropics and subtropics are pigeon peas (Cajanus cajan (L.) Mills.), which are rich in protein, fiber, and all of the essential amino acids [3]. Since plants are the primary source of food for humans, it is imperative that we take care of them. An essential step in the establishment of a successful agricultural industry is the analysis of healthy and ill plants. To keep uninfected plants safe from infected ones, it's critical to identify the diseased plants [1]. Because most disease indicators are evident on the leaves, plants' leaves are the primary source for identifying infections [2]. Hence the most advised method for identifying plant diseases is leaf disease detection, which involves identifying the signs of various illnesses. The most common diseases of pigeon pea leaves are curling, sterility mosaic disease (smd) and leaf spot disorder [4]. Low detection efficiency, reliability and generality are the results of conventional plant disease detection systems that mostly rely on human observation. Farmers who lack agricultural specialists and technological expertise are unable to serve the field constantly, which leads them to miss the opportunities for prevention. Recent years have seen rapid advancements in image processing, pattern recognition, and computer vision, which includes picture or video analysis. An intelligent disease detection method based on machine learning or deep learning offers a way to efficiently address agricultural issues [5].

In this paper, an innovative method to leaf classification is presented by developing seven hybrid models using CNN as a feature extractor and machine learning techniques such as XGBoost, RF, Gaussian Naïve Bayes (GaussianNB), KNN, SVM, Multinomial Logistic Regression, and a Stacking ensemble method. In order to achieve high classification capabilities and good generalization, the hybrid models take full advantage of the unique characteristics of both Deep learning and Machine learning models. The effectiveness of these hybrid models has been confirmed by comparisons with cutting-edge techniques in the literature.

2. Related work

Many studies in recent years have concentrated on using deep learning techniques, including Convolutional Neural Networks (CNNs) and transfer learning methodologies, to increase the efficacy of plant disease identification systems. These methods have demonstrated significant improvements in automated disease detection by learning discriminative features directly from leaf images. Furthermore, several researchers have employed ensemble learning strategies that combine predictions from multiple models to enhance classification accuracy and robustness during the disease detection process [22]. A few representative studies are outlined below.

Memon, M.S. et al. [19] presented comparison of pre-trained models like VGG16 and ResNet50 for cotton leaf disease identification. Cotton plants are prone to many kinds of diseases, including powdery mildew, target spot, leaf curl, bacterial blight, and nutritional deficiencies. A dataset of 2,385 photos of both healthy and sick cotton leaves was gathered from the field. Proposed meta deep learning-based leaf disease identification model. 98.53% classification accuracy was attained by the meta-learning method.

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Liu, H. et al. [20] presented a deep learning-based technique for identifying the three main rice diseases- bacterial blight, rice blast, and rice fake smut. The algorithm was trained on a dataset of 2,000 annotated photos of rice illness that was produced using data augmentation techniques. By adjusting variables including the number of iterations, learning rate, batch size, and optimization procedure, a CNN model was presented. The VGG16 and ResNet50 architectures were compared with the suggested model. According to experimental findings, the optimized model identified rice diseases with a high recognition accuracy of 98.64%.

Pawar, S. Y. et al. [21] pre-trained VGG16 deep learning model was employed. Sterility Mosaic Disease (SMD) is a disease that spreads quickly and can create epidemics, seriously impeding the cultivation of pigeon pea (Cajanus cajan) in the Indian subcontinent. Author examined SMD in pigeon pea fields. Classifiers were trained on a dataset of both healthy and ill leaves gathered from field. The average accuracy for recognizing SMD in pigeon pea crops was 88%.

Rajshekar Gaithond et al. [7] presented a CNN-based method for identifying pigeon pea leaf disease. Leaves were classified as either healthy or afflicted with Sterility Mosaic Disease using the VGG16 architecture. The proposed model reached 82% classification accuracy.

Sandesh Bhagat et al. [23] presented a real-time plant disease diagnosis approach. Using a lightweight Lite-MDC model with multi-kernel depthwise separable convolutions (MDsConv) to effectively capture multi-scale information, The suggested Lite-MDC model obtained an accuracy of 94.14% on a new pigeon pea dataset. Additionally, the model showed promise for real-time illness identification by performing well on public datasets such as PlantVillage (99.78%), Cassava (86.4%), and Apple Leaf (97.2%).

Chao, X. et al. [24] presented a deep learning-based technique for identifying apple leaf illnesses. Utilizing photos taken in a lab and in the field, including healthy leaves and disease. A novel model called XDNet was suggested that combines DenseNet and Xception properties. The XDNet model had the greatest classification accuracy of 98.82%.

Malik et al. [25] proposed a hybrid model that uses deep learning methods to identify and categorize sunflower illnesses. The study examined sunflower leaf diseases, including Verticillium wilt, Phoma blight, Alternaria leaf blight, and downy mildew. Two transfer learning–based models, VGG16 and MobileNet, were combined using a stacking ensemble learning approach to form a hybrid classification model, which attained an accuracy of 89.2%.

The reviewed studies demonstrate the effectiveness of deep learning–based systems for detecting plant diseases. These findings motivate the development of the proposed framework described in the following section.

3. Methodology

We outline the preprocessing and data preparation procedures followed by leaf region extraction to eliminate unwanted background from the images. Subsequently, we present the Bayesian-optimized hybrid CNN methodology. Figure 1 and 2 provides a comprehensive illustration of the proposed framework.

3.1 Input pigeon pea Leaf Image Dataset

Representative data is essential for constructing efficient and improved models for the detection and categorization of plant diseases. In the proposed methodology, we employ the open-access *Pigeon Pea Leaf Disease Dataset (PPLD)* for pigeon pea leaf disease classification. This dataset comprises 1,000 images categorized into four distinct leaf types [6].

The most common diseases in pigeon pea leaves are leaf spot, curling of leaves and sterility mosaic disease [9]. Leaf spot is caused by Cercospora species. Cercospora cajani Hennings is a fungus that can cause diseases in pigeon peas [8]. Initially appearing as brown spots, the symptoms progressively turn dark brown [9]. Aphids, leaf webbers, and pea leafminers are tiny larval insects that burrow into pea plant leaves. This might cause the leaves to curl and become deformed [10]. The pigeon pea sterility mosaic virus, which causes sterility mosaic disease (SMD), is conveyed via the eriophyid mite vector [4]. Common indications of SMD infection in plants include diminished leaves, yellow mosaic, partial or complete sterility, chlorotic places, and increased vegetative growth [7].

3.2 Data preparation and preprocessing

3.2.1 Data Preprocessing

Preparing and pre-processing images is a crucial stage in classification model's pipeline. Before submitting the raw images to any deep learning models, pre-processing is required since they may differ in size, contain noise, or have uneven illumination. The effectiveness of the model is also impacted by appropriate data preprocessing. Applied hybrid image enhancement strategy by integrating Contrast Limited Adaptive Histogram Equalization (CLAHE), Retinex, Fast Fourier Transform (FFT), and Gaussian filtering techniques [17].

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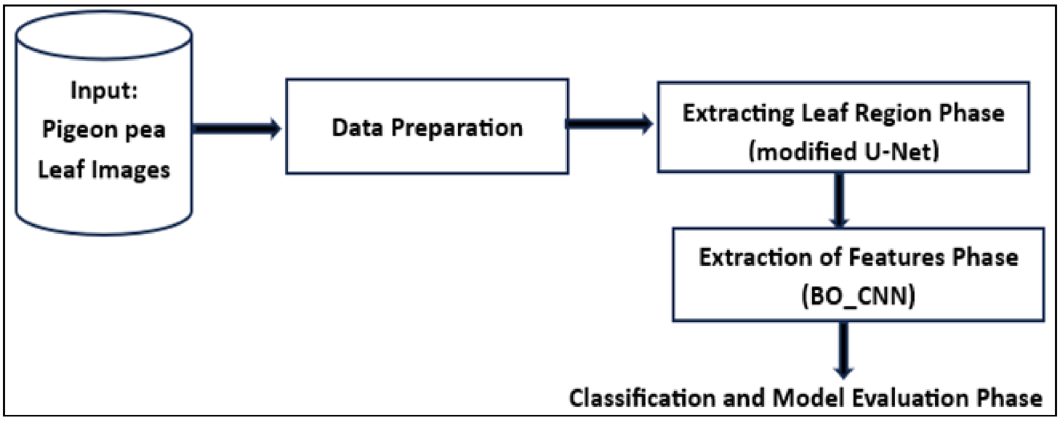


Figure 1: Proposed model for leaf disease classification

Algorithm 1: Categorization of Pigeon pea Leaves
Input: Database of Pigeon pea Leaf Image
Output: Prediction of pigeon pea leaf image class

Phase 1: Data preparation
— Load images from the dataset, standardize and augmentation of image
Phase 2: Leaf area separation from its background
— Utilization of modified U-Net architecture which is a light weight model for separating leaf region and exclude unwanted portion of image
Phase 3: Feature Extraction
— The outcome of phase 2 is used here to extract features by adopting proposed CNN model with Bayesian Optimization (BO) then save extracted features for further phase.
Phase 4: Classification
— Machine learning classification techniques such as SVM, KNN, RF, XGBoost etc. are considered for plant illness classification. Train each classifier performance hyper parameter tuning to improve model performance.
Phase 6: Model evaluation
— Trained models are now undergoing testing phase on test dataset to predict the leaf class, model are evaluated by metrices such as accuracy, f1-score, recall, precision to access the performance of each classifier.

Figure 2: Methodology for categorization of Pigeon pea Leaves

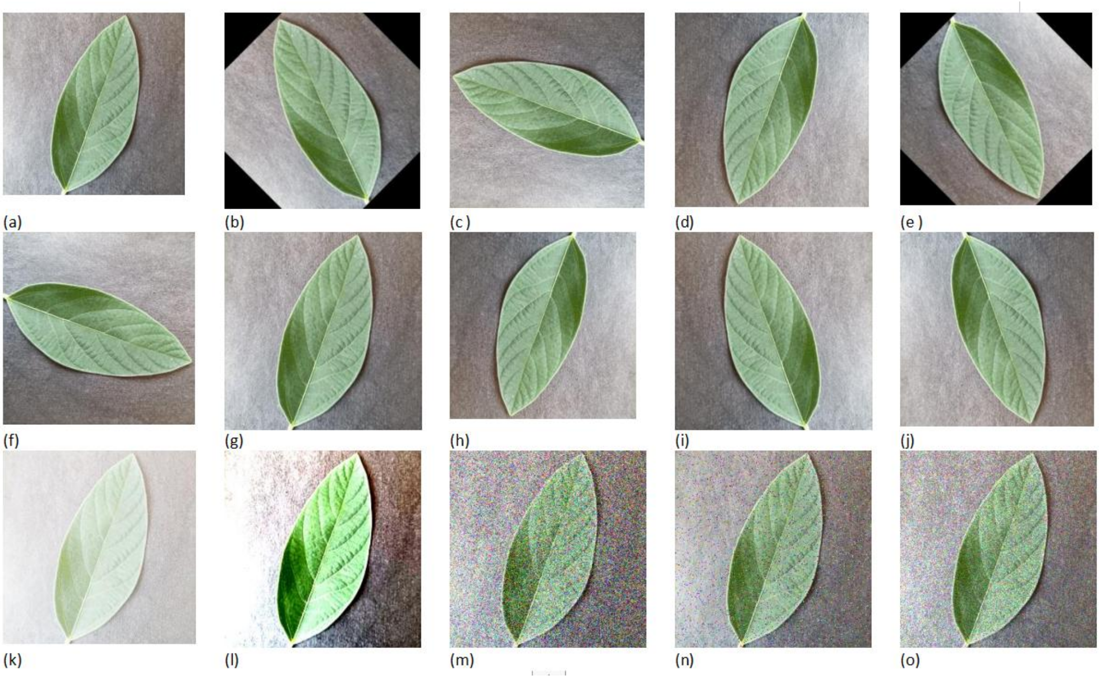


Figure 3: Data augmentation (a) original picture (b) 45 °, (c) 90 °, (d) 180 °, (e) 225 °, (f) 270 °, (g) 315 ° rotations (g) vertical alignment (h) horizontal symmetry (i) & (l) modifying different picture intensity values (m) Noise types: Gaussian (n), salt and pepper (o), and speckle

3.2.2 Data augmentation

To improve smaller datasets by extending them into larger datasets, the field-collected pictures were submitted to data augmentation. The accuracy of a deep learning model is strongly influenced by the amount of the dataset; larger datasets typically yield more accurate and dependable models. Data augmentation is the most effective and successful approach to solving this problem [11]. Numerous data augmentation methods, including rotation, translation/shifting, noise injection, mirror symmetry, and illumination correction, were used in this work. They rotated at 45^0, 90^0, 180°, 225^0, and 270^0 degrees. Figure 3 displays the example of various data augmentation techniques used to enlarge the dataset. and table 1 provides the number of samples before and after the data augmentation.

3.2.3 Resizing and rescaling

Generally speaking, CNNs use low to mid-level image resolutions, usually falling between 64 × 64 and 256 × 256. Several research have demonstrated that the deep learning model performs better at 224 x 224 & 256 × 256 visual resolutions than at other resolutions [12,13].

Therefore, here, the photos were resized to the appropriate resolution of 256 × 256 pixels using the "flow_from_directory" procedure from the "ImageDataGenerator" component from the "Keras" API. ImageDataGenerator (rescale = 1/255) from the tf.keras.preprocessing was used after resizing.image module to perform a normalization, or rescaling, operation on the photos.

The pixel values in the input photos were rescaled using this method from Numpy arrays of [0,255] to Numpy arrays of [0,1]. For numerical calculation, model training, and evaluation, Numpy arrays provide a quicker and more memory-efficient data structure. The custom CNN model was fed these numpy arrays as input in order to extract features.

3.2.4 Dataset splitting

Training and testing datasets were the sub-datasets created from the main dataset. Eighty percent of the data was chosen at random for training, and twenty percent was set aside for testing. The test data set was used to evaluate the models' performance following training, while the training dataset was utilized for training.

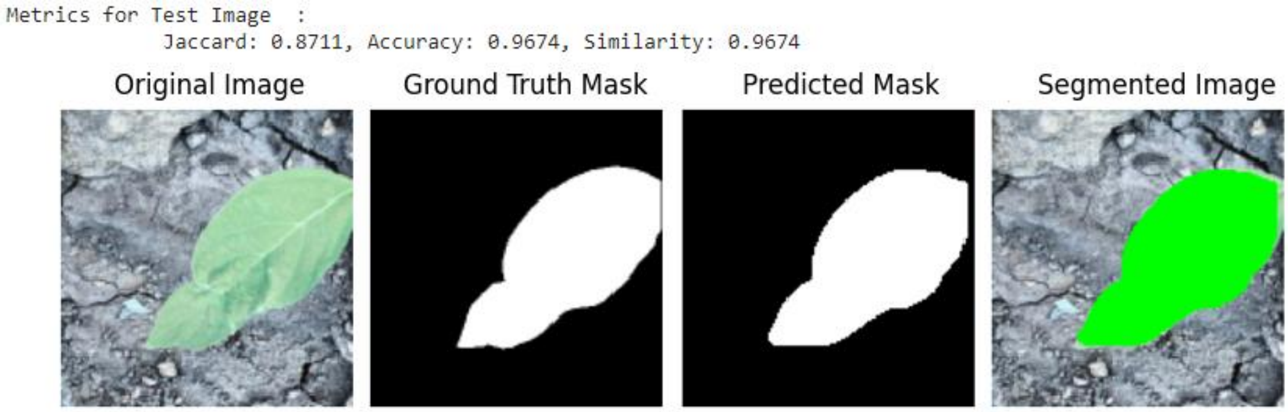
Table 1: No. of samples before and after the data augmentation

Condition of Leaf	No of samples before Data Augmentation	No of samples after Data Augmentation
Healthy	195	2925
Cercospora Leaf spot	336	5040
Leaf webber	146	2190
Sterilic Mosaic	292	4380
Total Number of Images	1000	14556

3.3 Extraction of Leaf Region

The modified U-net model [18] constituting two convolutional layers make up the encoding subnetwork. Maxpooling is used to reduce the dimension of extracted input features, 128 filters are then used for additional processing.

The model decoder upscales the features using upsampling layers, which are followed by the convolution layer. Additionally, skip connections are used to combine feature maps from the encoder with the decoder, preserving important details. The leaf segmentation mask is created by the last output layer. Figure 4 displays the results of the leaf area separation task.



```
Metrics for Test Image  :
          Jaccard: 0.8711, Accuracy: 0.9674, Similarity: 0.9674
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Figure 4: Displays the results of the leaf area from its background

3.4 Extraction of Features from proposed model CNN with BO

Machine learning is used for feature categorization, and CNN with a Bayesian optimized deep hybrid approach to learning is used for feature extraction. An exclusive CNN model serves as the deep learning framework along with seven powerful supervised learning algorithms are utilized for classification. The Bayesian optimization method is used to optimize the hyperparameters of the machine learning and deep learning models. Finding the optimal hyperparameters by hand requires a significant amount of time, effort, and domain expertise. In comparison to Bayesian optimization, random search & grid search are similarly time-consuming procedures [42]. A iterative technique that is widely recognized for its efficacy is Bayesian optimization (BO).

Each hyperparameter tuning technique is tested using test data and applied to the training dataset. For feature extraction, last four layers of convolutional neural network from the framework is eliminated. With remaining 14 layers, i.e., 1 input, 4 MaxPooling2D, 4 conv2D, 1 flatten layer & 4 batch normalization and, feature extraction is done for training and testing datasets. Table 2 presents the detailed parameters of CNN framework employed.

Table 2: CNN Model Hyperparameters from Bayesian Search.

Layers	Hyperparameters	Input / Output
Conv2D	filters: 32, kernel size: (2, 2), activation: "relu", strides: (1, 1), padding: "same", kernel regularizer (l2): 0.0001282	256, 256, 3 256, 256, 32
Batch Normalization	momentum: 0.99, epsilon: 0.001	256, 256, 32 256, 256, 32
MaxPool2D	pool size: (3, 3), padding: "same", strides: (3, 3)	256, 256, 32 86, 86, 32
Conv2D	filters: 64, kernel size: (2, 2), activation: "tanh", strides: (1, 1), padding: "same", kernel regularizer (l2): 0.0004593	86, 86, 32 86, 86, 64
Batch Normalization	momentum: 0.99, epsilon: 0.001	86, 86, 64 86, 86, 64
MaxPool2D	pool size: (3, 3), padding: "same", strides: (3, 3)	86, 86, 64 29, 29, 64
Conv2D	filters: 16, kernel size: (3, 3), activation: "relu", strides: (1, 1), padding: "same", kernel regularizer (l2): 0.01	29, 29, 64 29, 29, 16
Batch Normalization	momentum: 0.99, epsilon: 0.001	29, 29, 16 29, 29, 16
MaxPool2D	pool size: (2, 2), padding: "valid", strides: (2, 2)	29, 29, 16 14,14, 16
Conv2D	filters: 64, kernel size: (2, 2), activation: "relu", strides: (1, 1), padding: "same", kernel regularizer (l2): 0.0011262	14, 14, 16 14,14, 64
Batch Normalization	momentum: 0.99, epsilon: 0.001	14, 14, 16 14,14, 64
MaxPool2D	pool size: (3, 3), padding: "same", strides: (3, 3)	14, 14, 64 5, 5, 64
Flatten	-	5, 5, 64 1600
Dense	units: 32, activation: "relu", kernel regularizer (l2): $1.35e^{-05}$	1600 32
Batch Normalization	momentum: 0.99, epsilon: 0.001	32 32
Dropout	rate: 0.3	32 32
Dense	units: 4, activation: "softmax"	32 4

3.5 Classification and Evaluation

The optimized feature vectors extracted from the CNN are used as input to six conventional machine learning classifiers for leaf disease classification. These include KNN, SVM, Decision Tree, Random Forest, Naïve Bayes, and Multinomial Logistic Regression. To further enhance performance, a stacking ensemble classifier is employed.

The gathered photos of plant leaves have been used to test the suggested approach. The infected leaf was distinguished from the uninfected leaf using the suggested technique, Bayesian optimization with convolution neural network (BO-CNN). The study assesses four common evaluation metrics, including classification recall, accuracy, precision, and F1-score.

4. Results and Discussion

The optimized feature vectors extracted from the CNN are subsequently used as input to six conventional machine learning classifiers to perform leaf disease classification. The k-Nearest Neighbor (KNN) classifier classifies leaf samples based on similarity measures by considering the distance between feature vectors, making it effective for capturing local patterns in the data. The Support Vector Machine (SVM) is employed because it can create the best separating hyperplanes in high-dimensional feature spaces, thereby enhancing class discrimination. The Decision Tree (DT) classifier provides a rule-based classification mechanism by learning hierarchical decision rules from the data, offering interpretability and simplicity. The Random Forest (RF) classifier, an ensemble of multiple decision trees, improves classification robustness by reducing overfitting and increasing generalization capability. The Naïve Bayes (NB) classifier is based on probabilistic principles and assumes feature independence, enabling fast and efficient

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classification. Multinomial Logistic Regression (Multinomial LR) is employed to handle multi-class leaf disease classification by extending binary logistic regression to multiple disease categories. It models the probability of each disease class using a softmax function, allowing the classifier to assign an input feature vector to one of several mutually exclusive classes.

Each classifier independently predicts whether a leaf is healthy or diseased. To further enhance classification performance, a stacked ensemble classifier is employed, wherein the predictions from all six base classifiers are combined and used as input to a meta-classifier. This stacking strategy exploits the complementary strengths of individual classifiers, leading to improved accuracy and robustness in leaf disease classification.

The figure 5 confusion matrix of the proposed stacking ensemble classifier shows excellent classification performance across all four classes- Cercospora, Healthy, Leaf Webber, and Sterilic Mosaic. The diagonal values indicate that most samples are correctly classified, while the very low off-diagonal values reflect minimal misclassification. This demonstrates the high accuracy, robustness, and reliability of the stacking ensemble approach for leaf disease classification.

The figure 6 represents performance comparison show that the CNN–Stacking model achieves the best results across all evaluation metrics, with the highest accuracy (99.5%), precision, recall, and F1-score compared to other CNN-based classifiers. While individual models such as CNN–SVM, CNN–KNN, CNN–RF, CNN–MLR, CNN–XGBoost, and CNN–GNB also demonstrate strong performance, the stacking ensemble consistently outperforms them. This confirms that combining multiple classifiers enhances robustness and overall leaf disease classification performance.

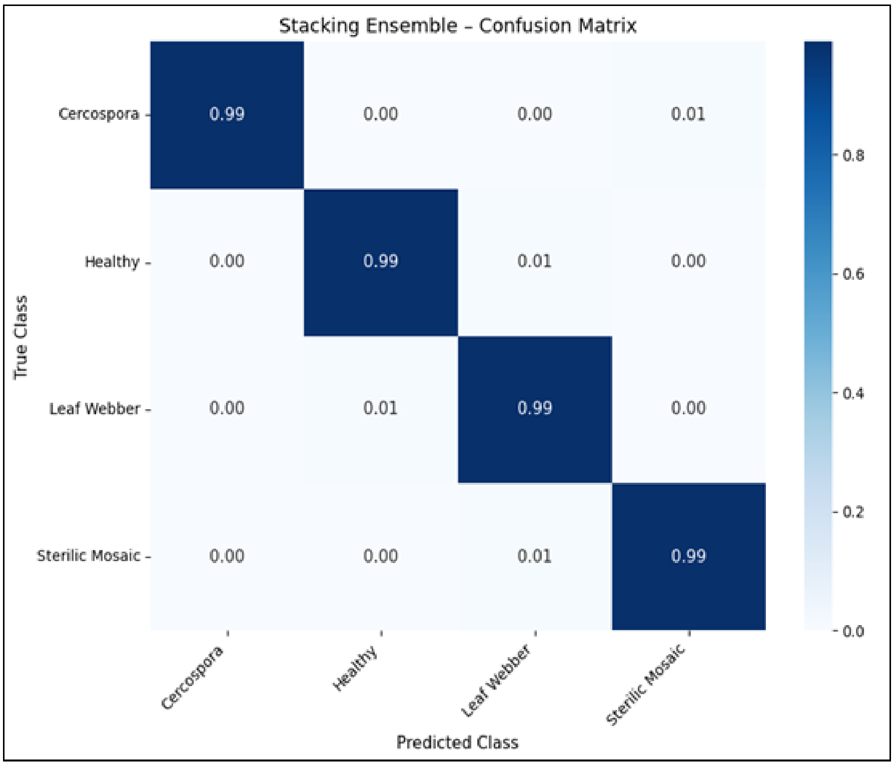

Figure 5: Confusion matrix of different classifier on PPLD

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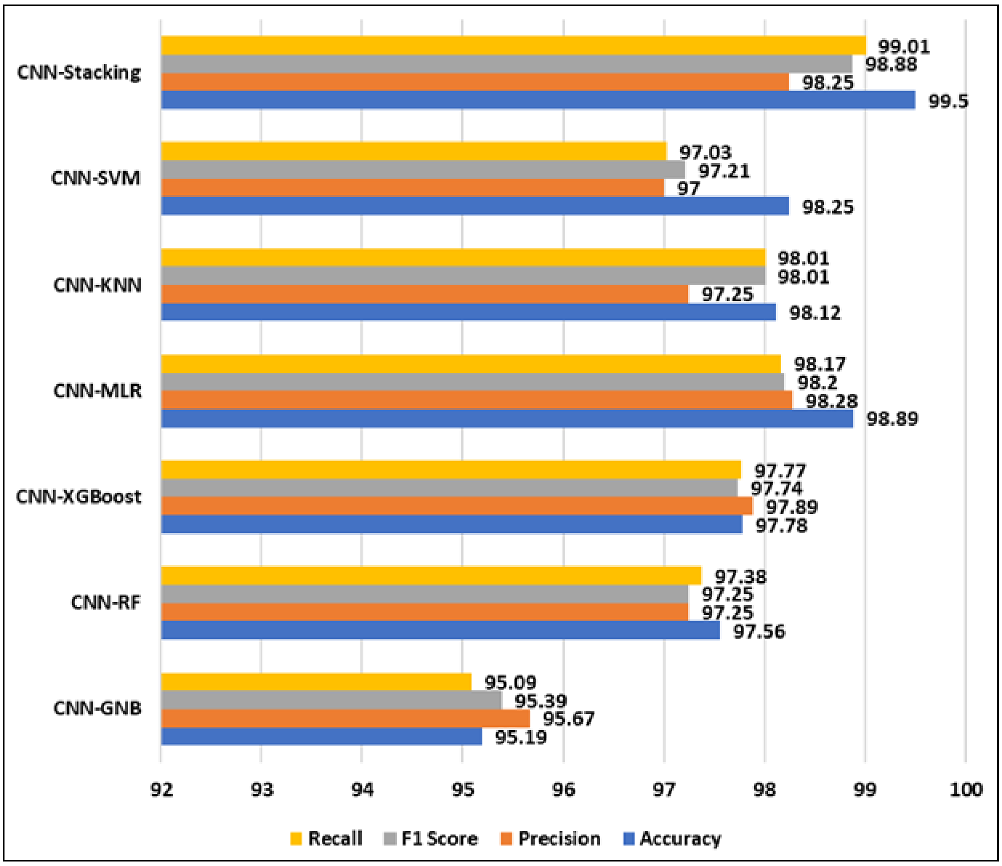

Figure 6: Comparison of performance of various classifiers on PPLD dataset

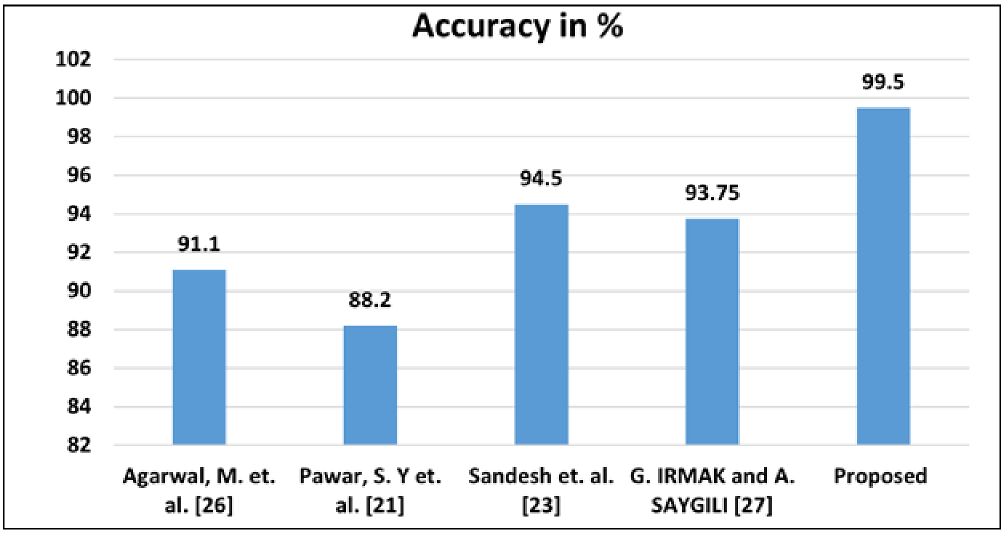

Figure 7: Assessment of results with state-of-the-art systems

The figure 7 compares classification accuracy (%) of existing methods with the proposed approach. While previous studies report accuracies ranging from 88.2% to 94.5%, the proposed method achieves the highest accuracy of 99.5%, demonstrating a significant improvement and confirming the effectiveness of the proposed framework for leaf disease classification.

Conclusion

Crop protection in organic farming is a challenging task that requires comprehensive knowledge of pests, diseases, weeds, and the crops being grown. Early detection of leaf diseases is essential for minimizing yield losses and ensuring sustainable agricultural practices. This work focuses on the fundamental concept of plant leaf disease identification based on visible infection symptoms. Traditional image-based methods are employed to test real-time leaf images for disease identification. The proposed approach provides an effective solution for farmers to detect and recognize plant leaf diseases at an early stage. An BO–CNN optimization framework is introduced for leaf disease detection. The proposed method effectively distinguishes infected leaves from healthy ones, demonstrating its potential for practical agricultural applications.

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