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Potato Leaf Disease Classification using PoLIVR Model: A Novel Approach

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ABSTRACT

Background: India is among the world's largest producers of the potato. However, early blight and late blight caused by biotic stresses can result in considerable potato yield loss. Traditional methods of leaf disease detection are cumbersome, inefficient and take a long time. Timely and accurate classification of leaf disease can play a major role in increasing crop yield and agricultural sustainability.

Methods: This study proposes an advanced PoLIVR approach for potato leaf illness classification using VGG-19 and Random Forest. This research used potato leaf images from a publicly available dataset. The raw images are pre-processed using grey scaling, denoising and bilateral filtering. VGG-19 is utilized to extract features from the pre-processed output of the pictures.

Result: The proposed PoLIVR approach achieved 95.59% accuracy for illness classification with 96.41%, 91.44% and 93.64% precision, recall and F1-score. The obtained AUC values for the three classes were higher than 0.90, which suggests a strong positive power. The proposed approach also has a higher performance than the compared state-of-art work. These results highlight the potential of PoLIVR approach for timely and accurate leaf illness classification. Overall, the study will also serve as a reference tool for potato grower industry workers to identify diseases in different agricultural settings and facilitate crop protection decision-making.

Key words: Detection, Leaf illness, Potato blight disease, Random forest, VGG.

INTRODUCTION

Potato is the major vegetable crop, often referred to as vegetable's king and a powerhouse of energy and ranks 3rd in terms of human consumption, following wheat and rice in India (Anonymous, 2020). In India, it is cultivated on 2.15 million hectares with 48.53 million tonnes of production, accounting for about 12% of gross produce globally (FAOSTAT, 2018). In various Indian states, 80-85% of potatoes are planted in the winter season, whereas 12% are cultivated in the rainy season (Arya and Joshi, 2019). However, potato cultivation is susceptible to numerous diseases, particularly leaf diseases, which can severely affect yield, quality and profitability. Infestation of early blight in potato due to the fungal pathogen *Alternaria solani,* can reduce 50-75% of the annual output of the crop (Murmu *et al*., 2017). The oomycete *Phytophthora infestans*, which causes late blight, has been reported to be the most significant disease affecting solanaceous crops. If not treated timely, the infestation may entirely ruin the crop (Chowdappa *et al*., 2015). Timely identification and accurate classification of these illnesses are essential for reducing the loss of crop and ensuring the sustainability of agriculture. Conventional approaches to identifying pests and diseases in crops require field sampling and chemical analysis, which can be time-consuming, labor-intensive, slower to yield results and restricted in detecting extent (Kang *et al*., 2023).

In-time automated crop leaf disease detection is the most important step to save crops from major loss. These systems can assist in rapid disease detection, enabling timely intervention and reducing the reliance on traditional disease detection techniques. As the agricultural sector increasingly adopts precision farming technologies, the development of automated, accurate and cost-effective crop leaf disease detection systems can significantly ensure sustainable agriculture and food security (Prakash *et al*., 2023). Machine learning (ML), considered part of artificial intelligence, can acquire knowledge and enhance its conclusions through computational approaches. The researchers are applying various ML techniques, including Support Vector Machine (SVM), Logistic-Regression (LR), Random Forest (RF) and Decision Tree (DT) efficiently to detect and classify crop leaf diseases (Goel and Nagpal, 2023). The extensive application of deep learning (DL) techniques for feature extraction can significantly enhance

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the classification accuracy of leaf diseases in agricultural crops (Mehta *et al*., 2025a). Mathew *et al*. (2025) demonstrated the utilisation of DL models in picture-based plant disease detection, showcasing the potential of CNNs for identifying a wide range of plant diseases. To detect and categorise illness in leaves of potato, Krishnan and Julie (2023) implemented the advanced CNN model, achieving higher accuracy than conventional CNN models. Moreover, DL models have been used extensively for crop leaf disease detection and classification, but certain complexities may restrict their applications. Researchers enlisted some of the limitations, such as DL models require significant efforts to annotate the data, complex integration of DL models with current processing systems of computers, comparative higher computational time and require larger datasets (Wani *et al*., 2022; Kashyap and Kashyap, 2025; Mehta *et al*., 2025b).

Key contribution

The rapid and accurate detection of leaf diseases allow for timely interventions, potentially increasing crop yield and profit of the farmers. The proposed PoLIVR approach comprises feature extraction using VGG-19 for automatic learning, extracting relevant features from raw image data and classification using the Random Forest (RF), which are the major key objectives of this research. The combination of DL for feature extraction and ML for classification leads to a highly efficient pipeline that enhances the precision of disease diagnosis. The ML models benefit from the rich feature set produced by the DL model, improving the overall classification accuracy. The notable contributions of the planned study are encapsulated as follows:

- Enhancement of colors, resizing of pictures, bilateral filtering in pre-processing.
- The pre-processed output is used in VGG-19 for extraction of features.
- The classification of leaves to distinct three groups of early blight (EB), late blight (LB) and healthy leaves.

This research study consisted of the subsequent sections. Section 2 comprised a thorough investigation of distinct ML and DL techniques employed in the agricultural sector for the detection of leaf illness in potato. Section 3 describes the dataset, its acquisition and pre-processing of the pictures, extraction of features and proposed model for classifying leaf diseases. Section 4 contains the results, discussion, graphical representation of the outcomes and conclusions.

Recent development in potato leaf disease detection

This section explores existing ML and DL techniques used for leaf disease identification and classification. The review literature highlights advancements in computational models, identifies gaps in current research and provides insights into the challenges and opportunities for improving automated systems in agricultural disease management.

To detect leaf disease in various plant species, Ganatra and Patel (2020) implemented ML techniques. The researchers created the two datasets of leaf images gathered from available on online platform. The raw images were pre-processed, followed by segmentation and extraction of features, including shape, texture and color, using traditional techniques. Different ML methods, *i.e*. RF, SVM and KNN, were applied for the classification of the leaf diseases. Among the classifiers, RF achieved 62.50% average accuracy in the dataset-15, which has fewer images. Raigonda *et al*. (2022) created a open weather picture dataset of the breeder seed and leaves of the potato. The procedure started with resizing, followed by enhancement of contrast, shape, texture and intensity features extraction using traditional methods. The classification was done by SVM, LR, DT and KNN algorithms. The DT model achieved the highest accuracy of 74.64% for leaf illness identification and 81.05% for tuber illness identification.

Gupta *et al*. (2023) aimed to use CNN to extract features and use the RF algorithm to detect and categorise potato leaf illnesses applying a combined approach. The researchers created the image dataset of 3400 images using a camera and categorised them into eight types of disorders. The model attained an overall 89.92% accuracy for classifying potato leaf diseases. Kiran and Chandrappa (2023) focuses on developing a robust method for detecting plant leaf diseases using histogram equalization, denoising and feature extraction, such as Haralick textures and Hu moments. The research utilizes various machine learning algorithms for illness classification. The findings show that RF model achieved a high accuracy rate of 94.43% for detecting 40 classes of 10 plant species of non-segmented leaf images. A study was conducted on potato leaf images to classify leaf illness using ML models with enhancement in selected features. The features were enhanced by optimizing binary features onto the pre-processed images. The highest accuracy of 94.89% was achieved using the LR model with no enhancement of features (Radwan *et al*., 2024).

In another research, Husna *et al*. (2024) utilized traditional techniques to extract color, shape and texture features and classification by SVM for disease classification in Potato. The proposed method achieved 87.17% overall accuracy in disease classification. Talab *et al*. (2024) focused on detecting leaf illness in potato using Random Forest (RF) on a total of 1900 potato leaves, including 1000, 350 and 550 LB, EB and healthy, respectively. The dataset was split into the ratio 80:20 for training and testing. Three combinations of datasets were evaluated, *i.e*. under-sampled, over-sampled and unbalanced raw data. After initial pre-processing, the features (shape, color and texture) were extracted by conventional techniques and selected by relief techniques. The results reveal that the original images dataset had 87.89% accuracy. Ramu *et al*. (2025) investigated ML techniques for identifying and categorising two major leaf illnesses of potato and tomato plants: EB and LB. The researchers used images of potato and tomato from the online platform PlantVillage. In the pre-processing

phase of the procedure, the set of pictures data was split into testing and training groups, followed by normalization, augmentation, feature extraction using ResNet, Inception and VGG-16 and classification using RF, K-NN and ANN. The highest accuracy of 98.5% was achieved by DL model ANN. The authors discuss how modern hybrid and advanced technologies, specifically machine learning, can play a critical role in disease manage-ment by improving early detection and implementing prevention strategies.

MATERIALS AND METHODS

The proposed framework (PoLIVR) comprises Potato leaf Illness classification using VGG-19 and Random Forest hybridisation. The approach generates efficient classification of illness of leaves in potato through the use of PoLIVR, which integrates transfer learning. Initially, raw pictures were acquired from PlantVillage followed by pre-processing, feature extraction using VGG-19 and leaf disease classification using RF. The entire procedure for classifying illnesses in the leaves of potato is illustrated in Fig 1.

Dataset and acquisition of images

In the first phase, 2152 leaf pictures of potato from the publicly available dataset, *i.e.* PlantVillage were acquired, which comprises 1000, 1000 and 152 pictures of early blight, late blight and healthy (https://github.com/spMohanty/PlantVillage-Dataset). Further, the set of raw pictures was split into training, testing and validation sets in a 70:20:10 ratio.

Pre-processing

Initially, the images are transformed to grayscale, followed by normalization in which the pixel values lie between 0 and 1. Normalizing images helps distinguish subtle features like discoloration or spots that may represent disease symptoms and enhances the contrast between healthy and diseased parts of the leaf, which improves the extraction of relevant features for further process. Then, the images were resized to 64×64 (width, height) using area interpolation, reducing the classification's computing work. The raw images may commonly have noise from external sources such as camera, change of weather and lighting conditions. Therefore, the images were denoised using Non-Local Means (NLM) denoising. NLM denoising was done by averaging similar pixels from the whole image. Further, the images were smoothened using a bilateral filter while preserving edges and maintaining the boundaries of the image. The parameters control the diameter of the pixel neighbourhood during filtering and the standard deviations for color and spatial details. In conclusion, the pre-processing for picture classification tasks has been done to prepare the dataset for further analysis, which helps improve the efficiency of model to recognise and classify the leaf disease in potato as shown in Fig 2.

Feature extraction and classification

The leaf disease classification of potato has been done using the proposed model approach (PoLIVR) comprised VGG-19 for feature extraction and RF for classification. The outcome of the pre-processing was utilized as input for feature extraction, which has been done using VGG-19 architecture represented in Table 1. VGG-19 is a deep convolutional neural network (CNN) that has 19 layers with 16 convolutional layers and three fully connected layers. A convolutional layer (Conv2D) is added next to the model. The convolutional (Conv2D) layer consists of 3 filters with a 3×3 size to the input. The ReLU serves as the activation function, introducing non-linearity to the computational framework of the model. The resultant data of the convolutional layer is transit through the pre-trained VGG19 model, which is already trained on ImageNet. In this step, the model extracts useful features from the input images. In the final step, the model applies a flattened to convert the multi-dimensional tensor output to a 1D vector, which is easier to process in further layers or for tasks like retrieval or comparison.

The output from the feature extractor fed to the RF classifier. This classifier is a potent and adaptable data mining algorithm frequently used for regression and classification due to its simplicity and versatility (Talab *et al*., 2024).

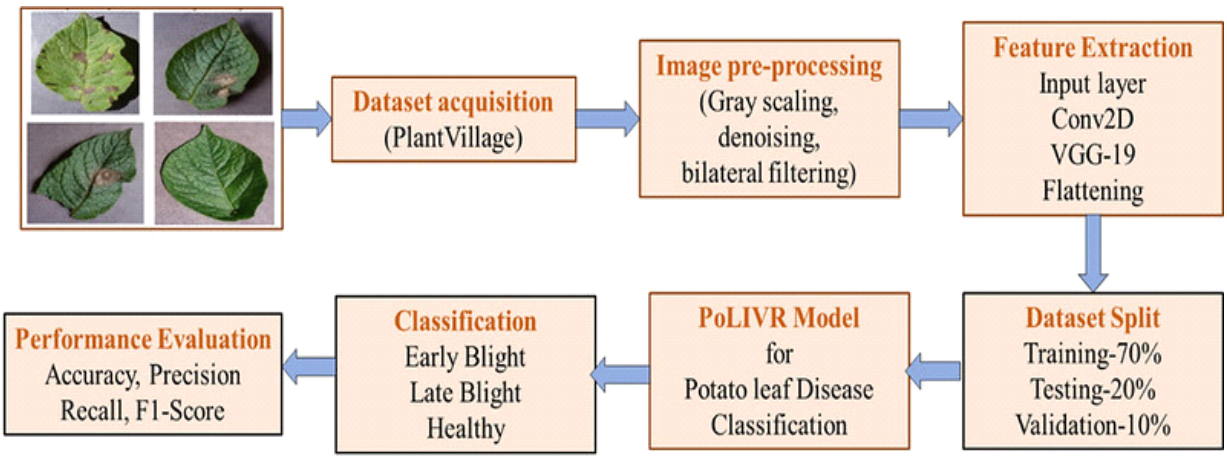


Fig 1: Flow diagram of proposed model (PoLIVR) for plant disease classification.

RF classifier emerges from combining decision trees to deliver enhanced classification results and reduce overfitting. The parameters that have a direct effect on model performance patterns and functioning are explained.

Key parameters and their role

Estimators

This parameter calculates the total number of trees composing the forest model. The model implementation includes 12 trees as a part of its structure. More trees in the model lead to stronger performance as averaging predictions of multiple trees, which reduces the variance and enhances generalizing outcomes.

Gini criteria

The function is used to evaluate split quality at each node of the tree. Its measurement tracks the purity level of nodes by determining the frequency of incorrect classifications when picking random elements. The objective focuses on minimizing Gini impurity using the following calculation formula:

$$\text{Gini} = 1 - \sum_{i=1}^{n} P_i^2$$

Where,

P_i = Proportion of class' *i'* in the node.

Maximum depth

The parameter functions to establish the maximum permissible depth for trees to grow. Tree growth under a max depth of none continues until perfect data fit or leaf node formation occurs. The resulting tree structures can become excessively complex because this practice increases the risk of memorizing training data samples. The overfitting problem can be managed through limiting the maximum depth value of trees.

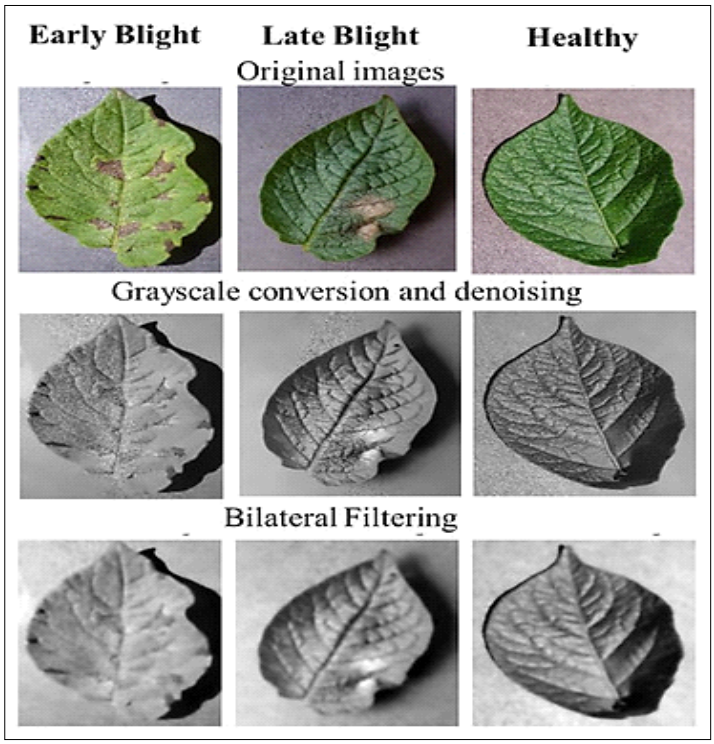


Fig 2: Preprocessing of the raw leaf images of potato.

Table 1: Feature extraction using VGG-19.

Layer (Type)	Description
Input layer	Accepts grayscale images with dimensions 64×64 pixels.
Conv2D	Applies three 3×3 filters to the input images to generate processed feature maps.
VGG-19 (Functional)	The three-dimensional feature maps are passed through pre-trained convolutional neural network for high-level extraction of features with output of dimensions (2,2,512)
Flatten	The flatten layer reshapes the output from VGG-19 into a single vector of 2048 elements.

The model uses a total of 20,024,414 trainable parameters for the extraction of features and these features are then forwarded to the ML model Random Forest for classification.

Number of minimum sample

The minimum number of required samples for splitting internal nodes. Each split attempt by the tree proceeds according to the value of min_samples_split=2, including nodes with just two remaining samples. The combination of this parameter with min_samples_split=2 liberates models to build extensive trees consisting of numerous small leaf nodes yet escalates the risk of overfitting. Overfitting prevention can be achieved through min_samples_split values that require enough instances at nodes before allowing splits.

Maximum features

The number of characters to evaluate for the best split at each node is set by max_features='sqrt.' This parameter selects a randomly chosen subset of features that matches the square root of the dataset's total feature count. Randomness is used during this step to decrease the correlation between trees and increase forest diversity. Random Forest achieves better generalization and avoids overfitting by using this method.

Bootstrapping

The Bootstrap method uses data sampling with replacement to produce each tree in the decision forest. Using the bootstrap=True, results in different random data subsets for each tree where duplicate original dataset instances might be included. The bootstrapping allows each tree in a random forest model to analyze a distinct subset of data, resulting in diversity because each version shows a slightly different perspective of the information. Bootstrapping improves generalization because each tree analyses a distinct subset of data, which results in reduced overfitting risks when collective predictions of multiple trees are aggregated.

Table 2: Performance metrics.

Metrics	Equation
Accuracy (A)	$A = \frac{TP + TN}{TP + TN + FP + FN}$
Precision (P)	$P = \frac{TP}{TP + FP}$
Recall (R)	$R = \frac{TP}{TP + FN}$
F-1 score (F)	$F = 2 \times \frac{(Recall \times Precision)}{(Recall + Precision)}$
TPR	$TPR = \frac{TP}{TP + FN}$
FPR	$FPR = \frac{FP}{FP + TN}$

Table 3: Performance for classifying illness in leaves of potato.

Classes	Precision	Recall	F1-score
Early blight	95.59	97.60	96.59
Late blight	95.23	95.80	95.51
Healthy	98.40	80.92	88.81
Accuracy			95.59
Macro average	96.41	91.44	93.64
Weighted average	95.62	95.59	95.54

Performance evaluation

To assess the disease classification model, standard mathematical equations were used, which are given in Table 2. In the equations, TP, TN, FP and FN represent true positives, true negatives, false positives and false negatives, respectively. The trade-off between true positive rate (TPR) and false positive rate (FPR) at various threshold values is used to represent the performance utilising Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC) curves.

RESULTS AND DISCUSSION

Random Forest functions as an ensemble technique by crafting numerous decision trees which are then aggregated for prediction purposes. This model accomplishes bagging (Bootstrap Aggregating) through the generation of multiple different models built from random dataset samples. The final prediction emerges by conducting an aggregate calculation of the majority vote to classify potato leaf illnesses, including EB, LB and healthy leaves. The efficacy of the PoLIVR model employed in this work was juxtaposed with contemporary methodologies used by the different researchers to extract features and classify the leaf disease in potato. The results were drawing from the classification of leaf illness from the PlantVillage dataset, having 2152 images of potato leaves. The performance of the PoLIVR approach has been examined for classification efficiency to detect EB, LB and healthy leaves. The model's performance was determined by examining different performance indicators for each class depicted in Table 3. The results on precision show that model predicted 95.59, 95.23 and 98.40% for EB, LB and healthy classes. However, the recall means model identified the 97.60, 95.80 and 80.92% of the classes. Moreover, the model reflects a fair performance and balance between recall and precision, which the F1-score had shown. The F1-score varied from 96.59, 95.51 and 88.81% for EB, LB and healthy classes. However, Ganatra and Patel (2020) used the RF model for potato leaf disease classification with 62.50% accuracy. The feature extraction using traditional methods may be the reason for low accuracy. Whereas Gupta *et al*. (2023) had an accuracy of 89.92% using CNN model for feature extraction and RF model for classification.

The proposed PoLIVR approach attained a classification accuracy of 95.59%. The macro average precision is the

average value of precision scores for each class. Since healthy class has the highest precision, it pulls the macro average closer to its value. The macro average F1-score was 93.64%, showing adequate yet somewhat diminished performance due to the issues with recall for healthy class. The weighted average precision is slightly lower than the macro average due to the class imbalance, as class EB and class LB have more instances than healthy class. The weighted average recall is almost the same as precision, showing that the model performs consistently well in terms of identifying true positives when considering the class distribution. The weighted average F1-score is 95.54%, reflecting the model's good overall performance, considering the class imbalances. Moreover, Gupta *et al*., 2023 observed 90.50, 89.14 and 89.91% of macro average precision, recall and F1-score. The weighted average precision, recall and F1-score were 90.59, 89.26 and 89.92 respectively. More recently, the researchers used traditional feature extraction techniques (GLCM), Husna *et al*. (2024) and Talab *et al*. (2024) found 87.17 and 87.89% accuracy in potato disease classification (Table 4). Hence, employing novel feature extraction techniques can substantially enhance illness classification accuracy.

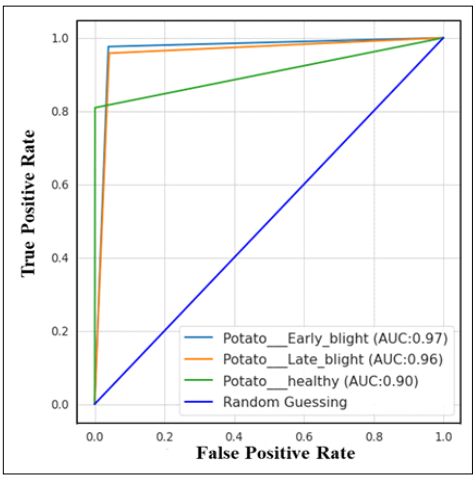


Fig 3: ROC curve for proposed approach.

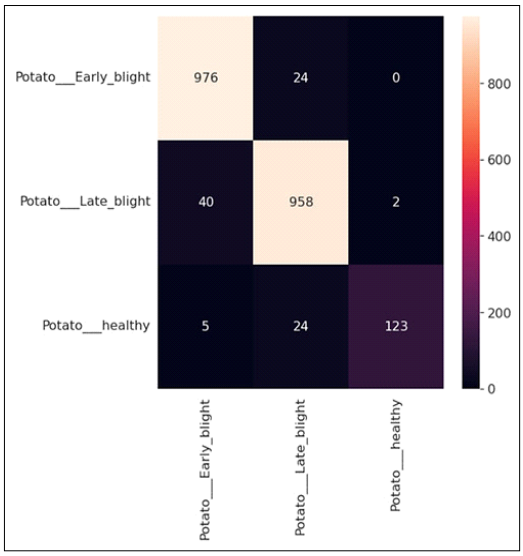


Fig 4: Confusion matrix.

The ROC graph illustrates the distinct performance of three classes, EB, LB and healthy, as observed in potato leaf images in leaf images of potato (Fig 3). The vertical axis (y) shows the TPR, whereas the horizontal axis (x) denotes the FPR. The proximity of the curve reaching the left corner of the upper side shows the capability of the model. The proposed approach demonstrated AUC of 0.97, 0.96 and 0.90 for early blight, late blight and healthy leaves. Since the computed AUC values of the three classes were above 0.90, the proposed PoLIVR approach performed strongly and positively. Fig 4 represents the confusion matrix, which depicts the performance of the proposed model in distinguishing between three studied classes potato leaves. The column of the matrix represents the predicted classes, while the rows show the actual classes. Out of 152 images of healthy leaves, the models correctly classified 123 samples. The proposed study correctly classified 976 and 958 samples as early blight and late blight. Overall, the proposed approach correctly classified the high number of samples, representing its generalization capabilities.

Table 4: Comparative analysis of potato leaf disease classification.

References	Feature extraction	Classifier	Accuracy	Precision	Recall	F1-score
Ganatra and Patel (2020)	GLCM, Zernik Moment, Vein and Gabor texture	Random Forest	62.50	62.62	62.50	61.26
Gupta *et al*. (2023)	CNN	Random Forest	89.92	90.50	89.14	89.81
Husna *et al*. (2024)	GLCM	SVM	87.17	-	-	-
Talab *et al*. (2024)	GLCM	Random Forest	87.89	82.76	68.57	75.00
Proposed PoLIVR approach	VGG-19	Random Forest	95.59	96.41	91.44	93.64

CONCLUSION

The model performs exceptionally well overall with high precision, recall and F1-scores for EB and LB classes and a slightly lower performance for healthy class, mainly due to the class imbalance. The elevated ROC AUC score (0.9435) demonstrates the model's strong capacity for class discrimination, while the accuracy rate of 95.59% implies its overall effectiveness. However, the lower recall for healthy class highlights areas for improvement, especially in dealing with imbalanced data. The macro and weighted averages provide a balanced view, reflecting the model's strengths and areas for refinement. The machine learning and deep learning techniques have greatly improved the disease detection in plants. With the introduction of AI techniques in agriculture, many researchers have contributed to the early disease detection of plants utilizing various machine and deep learning techniques. However, the gap in AUC values suggests potential improvements in identifying healthy plants with better feature extraction or data balancing. Overall, the model is reliable for detecting potato diseases but could benefit from refinements in differentiating healthy plants. In future, various intelligence approaches for the extraction of significant features can be used to improve accuracy. Moreover, subsequent research could focus on enhancing the efficacy of deep learning in identifying plant diseases within a multiclass framework.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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