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Article

Image-based diagnosis of potato leaf diseases using shallow-CNN design

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Abstract: Precision agriculture endures significant hurdles in accurately identifying and classifying plant diseases. Since different plant diseases display subtle and varied symptoms, traditional procedures involving manual inspection are time-consuming and result in high false positives. To overcome these obstacles, a lightweight Shallow-CNN classification framework tailored specifically to potato leaf disease was proposed. The proposed framework is further combined with formidable ensemble learning methods, Random Forest and XGBoost, to ensure better classification of potato leaf disease and reduce overfitting. The proposed algorithm was trained and evaluated on the benchmark Plant Village dataset and real-world images taken from the crop fields. The experimental results show that the proposed framework achieves better accuracy, precision, F1-score and recall when compared with several state-of-the-art approaches. This shows that it is particularly effective and scalable for real-time agricultural disease surveillance systems.

Keywords: Potato leaves disease, classification, Shallow-CNN, Random Forest, XGBoost, hybrid method and agriculture

1. Introduction

Agriculture remains a cornerstone of many economies, providing employment, income, and food security for billions of people globally. Continuous monitoring of the crop field is inevitable for increased productivity. However, a vast range of spreader by bacteria, viruses, and fungi constantly threaten the quality and yield of crops like potatoes. These illnesses resulted in significant yield losses and financial loss if they are not identified or misdiagnosed/treated. The visual evaluation of farmers on defective crops of potatoes leads to misclassification, is unreliable and time-consuming for large-scale farming operations. [1–3].

The production of potatoes (Solanum tuberosum), a crop of global significance, is hindered by several diseases caused by various pathogens. For crop defense and disease management to be effective, these pathogens must be accurately classified, each having distinct traits. **Figure 1** displays the various classes of potato leaf images. The manual inspection of these images is more tedious and time consuming and leads to lack of productivity. Hence, intelligence based models were implemented to identify the faulty leaves. However, traditional Machine learning models failed to discriminate the infected leaves and resulted in high false positives. Particularly successful in image-based classification tasks, convolutional neural networks have demonstrated exceptional performance in early disease diagnosis. The deepness and computational complexity of many of the CNN models in use today, however, make them difficult to implement in real-time or low-resource settings, such as farms in underdeveloped nations [4,5]

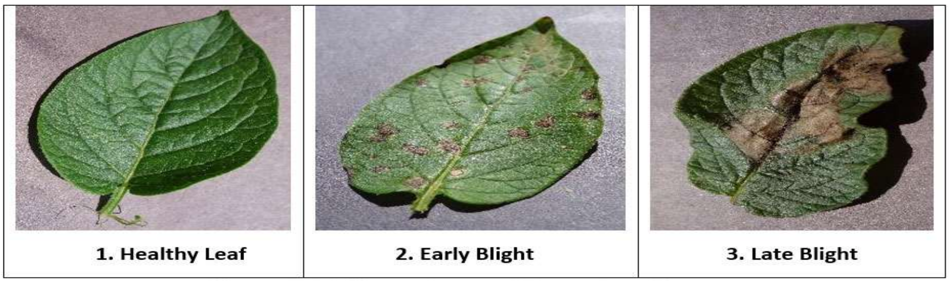


Figure 1. Different classes of potato leaf image.

The development of deep learning techniques based on convolutional neural networks is of special importance to the agriculture industry. CNN automatically extracts features using a stack of convolutional layers. The CNN models' initial layers extract important features like color, edge, and texture. The extracted attributes will be better the more layers the CNN model has. Overfitting of the training set may result from increasing the CNN's layer count. A network that has several layers and a complicated topology also needs a lot of memory and processing power. Numerous CNN models are used in agricultural domains, including pest identification, weed identification, disease detection, and plant identification [6,7].

The first stage of separating potato leaves from a complex background is depicted in **Figure 2**. The process of extracting individual leaves comes next. Based on the segmented individual leaves, the classification system was utilized to differentiate between the healthy, early blight, and late blight leaves. Semantic segmentation served as the training model. The disease discovered during the semantic segmentation stage served as the disease recognition index for the classification step.

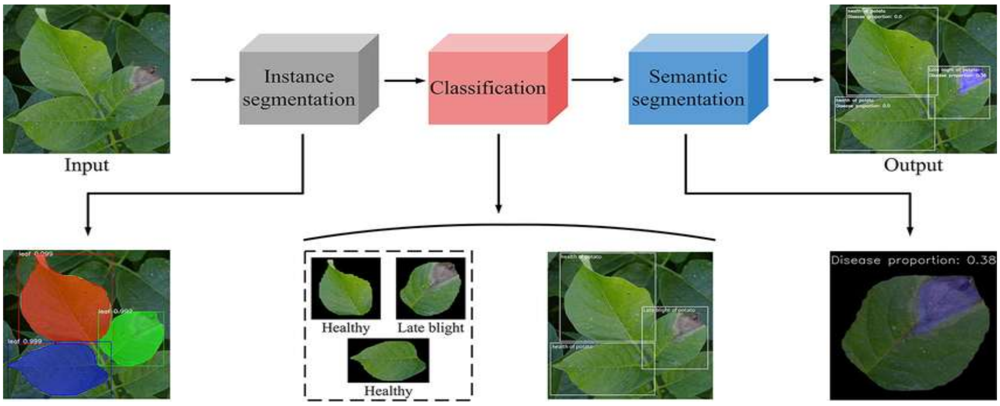


Figure 2. Classification of potato leaf disease.

The illness causing the leaves to deteriorate is depicted in **Figure 3**. These illnesses cost growers a lot of money in addition to lowering the production and quality of potato crops. Therefore, safeguarding potato crops and boosting agricultural productivity depend heavily on the early detection and efficient treatment of these illnesses. The instance segmentation and classification models were also used to identify the healthy, early blight, and late blight leaves. Captioner, DenseNet, VGG, ResNet, AlexNet, and GoogleNet are among the deep learning architectures used. The additional layers in these deep learning models, greater quantities of parameters are produced. High-end machines with GPUs are usually used to create deep learning models [8–10].

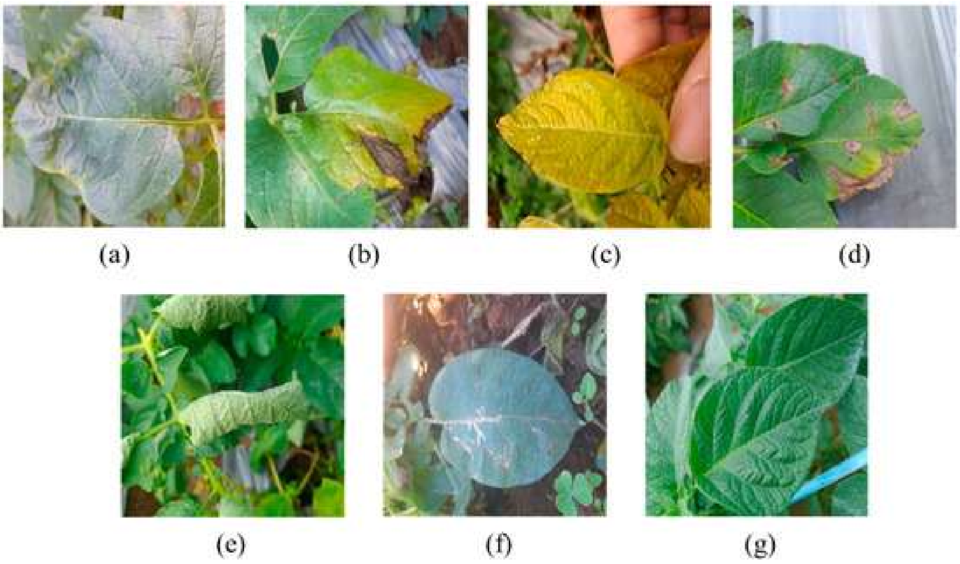


Figure 3. Illustrations of seven potato leaf diseases. (a) Viruses; (b) Phytophthora; (c) Nematodes; (d) Fungi; (e) Bacteria; (f) Pests; (g) Healthy plants.

A novel disease classification method utilizing a Shallow-CNN, a lightweight convolutional architecture modeled after the VGG network but with less depth to increase performance and decrease overfitting, is proposed in this research to overcome these drawbacks. Because Shallow-CNN uses fewer layers to capture key spatial data than typical deep CNNs, it is more computationally efficient and simpler to train on constrained hardware. Additionally, by including Random Forest and XGBoost as downstream classifiers, the model improves its ensemble learning decision-making capacity, which raises classification robustness and accuracy. The diversity of datasets is further demonstrated in this study by combining high-resolution images from the Plant Village dataset with real-world photographs obtained in natural environments. This hybrid dataset makes it easier to train algorithms that can generalize well outside of confined laboratory environments.

Considering all these related works, this article presents a lightweight Shallow CNN framework for potato plant disease detection. The major highlights of the proposed framework:

- Shallow-VGG is efficient in extracting the diseased spot accurately for increased accuracy.
- The integration of ensemble learning combines the deep feature extraction process with ensemble classifiers to enhance the accuracy and robustness in potato leaf disease detection.
- The deployment of a lightweight Shallow-CNN architecture suitable for resource-constrained devices for effective discrimination of infected potato leaves.
- The proposed lightweight framework supports sustainable agriculture through optimized yield management, reduced usage of pesticides and cognizant decision making.

The paper is organized as follows, Section 2 briefly discusses the previous works, Section 3 elaborates on the working of the proposed model. Section 4 presents the simulation results along with the performance metrics, Section 5 analyzed the results obtained for the validation of the proposed model. Section 6 concludes the paper with the future work.

2. Related works

This section contains an extensive discussion on various machine learning and deep learning models pertaining to potato leaf disease detection. Followed by the limitations posed by the previous works and the research solutions proposed in this article. Dubey et al. [11] proposed Multiclass Support Vector Machine (SVM) to detect the contaminated potato leaf parts, Yun et al. [12] proposed SVM and K-means clustering model as a base model for the Probabilistic neural Network (PNN) for effective leaf disease detection. Li G et al. [13] proposed backpropagation Neural Network model for plant disease detection. Deep learning based detection framework failed to achieve less false positives [14,15]. Hassan et al. [16] proposed shallow CNN model for the plant disease detection however the necessary preprocessing was not properly implemented and it resulted in high computation power. Mohanty et al. [17] proposed GoogleNet and AlexNet model for the identification of 26 different illness presented in the potato leaf disease and 14 distinct plant species. Both the models exposed transfer learning mechanism and produced better results in the classification of affected leaves with an accuracy of 90.34%. Ferentinos et.al [18] proposed five pretrained deep learning models such as VGGNet, AlexNet, ResNet, Overfeat and GoogleNet for the detection of various elements of potato leaf disease. Though, these models presented a deep analysis of detection framework, it fails to address the computational time. Geetharamani et al. [19] presented a model composed of nine layers of Deep CNN for the identification of plant disease with the accuracy of 89.46%. Liu et al. [20] proposed GoogleNet and used inception layer and identified the infected apple plant leaf disease. Ashourloo et al. [21] proposed a model to differentiate spectral information presented in the various plant images and discussed the identification of spectral indices to track and classify the evolution of disease from the remote sensing data.

Zhang et al. [22] proposed various enhanced CNN architectures for automating the disease detection processes and highlighted the importance of sophisticated neural network models for the accurate categorization of diseases [22]. Das presented an assessment of leaf-disease diagnosis using SVM. SVMs are one of the robust classifiers that can employ leaf image features for distinguishing different classes of disease [23]. For the identification and classification of plant leaf diseases, an integrated approach was presented that combined multiple digital image processing techniques with deep learning techniques. After the feature extraction through image processing techniques, the extracted features were then used for classification purposes through algorithmic approaches. This hybrid methodology produced promising results in the accurate identification and classification of plant leaf diseases [24]. Nandhini and Bhavani [25] proposed a spectrum of machine learning techniques to extract features from the images of damaged leaves. Feature extraction is one of the most important steps for revealing salient characteristics associated with a certain type of leaf disease. This research work focused on the importance of feature engineering by exploring various feature extraction strategies with the aim of improving disease classification. Gobalakrishnan et al. [26] performed a systematic review on image-based plant disease detection methodologies and highlighted the diversity of various techniques and algorithms used in the field. Their review can be seen as a rich resource for understanding existing disease-detection methodologies. Suitable deep learning approaches such as convolutional neural networks were used by Sholihati et al. [27] for classifying potato leaf diseases. They showed that deep learning algorithms can help in detecting diseases of potato leaves and go a step further in the automation of agricultural disease management. Their program utilized photographic data to classify healthy and diseased leaves. Charisma [28] asserts that in order to effectively control diseases, early disease detection is essential. It is possible to classify potato leaf disease directly. However, because there are numerous illnesses with similar symptoms, the symptoms may not always be able to identify the specific disease affecting potato leaves. Additionally, human beings are not very good at identifying potato leaf disease. It is anticipated that using deep learning to classify potato leaf disease will speed up the procedure and increase classification accuracy. In comparison to more conventional classification methods, it sought to assess how well the transfer learning strategy utilizes the DenseNet architecture, which increased the classification accuracy of potato leaf disease.

The segmentation and detection accuracy of potato diseases during the learning phase is greatly improved by Fu et al. [29], which permits the network to selectively stress pertinent information characteristics and suppress those that are not. The enhanced RS-UNet network model outperforms the conventional UNet algorithm by 8.96% and 6.33%, respectively, in order to prevent plant illnesses and increase output, it is essential to diagnose them early and use fertilizers and pesticides appropriately. Without giving careful consideration to the health of the plants, most farmers treat all fields with the same fertilizers and insecticides. Consequently, production costs often increase, which sometimes results in a decrease in yield. Deep learning models have been found to be highly effective at automatically recognizing plant diseases from plant photos, hence removing the need for human experience [30]. Though these papers discussed the detection it failed to address the computational efficiency of the model.

3. Proposed method

This section elaborates on the working of the proposed lightweight Shallow-CNN framework. The process begins with the data collection followed by necessary preprocessing and feature extraction using Shallow-VGG, ensemble learning by Random Forest and XGBoost model then classification using the Shallow-CNN for effective potato leaf disease detection.

In **Figure 4**, the suggested Shallow-CNN combines the advantages of ensemble classifiers and shallow learning architectures to represent a major advancement in plant disease classification. It presents a viable precision agricultural solution that will help farmers, agronomists, and legislators make prompt, well-informed decisions about crop management and disease prevention. The following subsection 3.1 presents the data collection and data preprocessing images. 3.2 presents the feature extraction process using shallow-VGG architecture, 3.3 and 3.4 defines the classification part using XGBoost and Random Forest model and finally the detection process is performed by Shallow-CNN model.

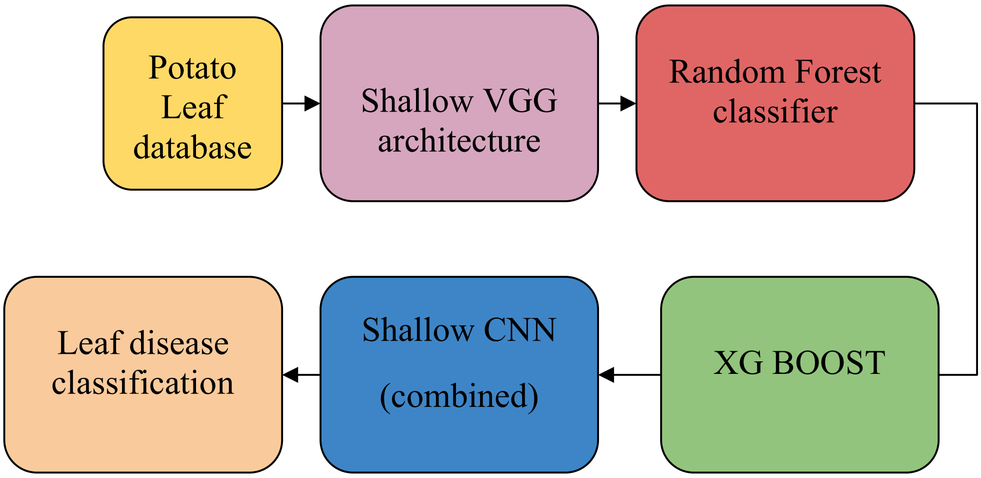


Figure 4. The proposed method.

3.1. Data collection and preprocessing

Plant Village dataset [31] is used for the validation of the proposed lightweight potato leaf disease detection model. It is a comprehensive open resource image dataset for leaf disease detection process. The dataset comprises of nearly 54,000 images across the multiple crops such as potato, tomato and corn. 36 different classes were included for both healthy and infected leaves. The images were pertained from the various crop fields and used for observations. Specifically, tailored to this research article, potato leaves are observed with the specification of classes in the format of early bright, late blight, infected leaf, healthy leaf and so on. Apart from this dataset, the real time images were captured from the both infected and the healthy leaves of the potato plant in crop fields. The processing of these raw images is tedious as it contains the RGB format and leads to more computation power. Initially, the process begins with the preprocessing methods such as binary lesion, contrast, segmentation and resized images. a crucial role in potato leaf disease identification. Binary lesion conversion highlights damaged areas, making disease spots stand out. Contrast enhancement makes subtle symptoms more visible, aiding detection. Segmentation isolates relevant leaf areas, reducing noise. Resizing images standardizes them for faster processing and better model performance. Together, these techniques boost accuracy in identifying diseases in potato leaves.

3.2. Feature extraction – shallow-VGG architecture

The shallow-VGG architecture is represented by it, which is distinguished by the unique configurations of its convolutional layers. The first step of feature extraction is the extraction of hierarchical features from input photos. A condensed variant of the original VGG neural network, the Shallow VGG architecture for potato leaf disease detection is made to be portable and effective for smaller-scale picture classification applications like recognizing plant diseases. A ReLU activation and max pooling layer come after a few convolutional layers, usually two to four each, in the shallow version of the VGG16 or VGG19 models, which have 16 or 19 layers, respectively. The VGG model's fundamental idea of using tiny (3 × 3) filters to extract fine-grained spatial characteristics from input images is preserved in this architecture.

Prior to the final softMax output layer, which categorizes the image into predetermined illness categories, the model flattens the output after feature extraction and runs it through one or two fully connected layers. This shallow form is particularly helpful for agricultural applications with limited resources or smaller datasets because it provides quicker training durations, uses less processing power, and lowers the chance of overfitting.

3.3. Classification model - XGBoost

Regression and classification problems are its main uses. It makes use of a gradient boosting architecture. When it comes to unstructured data prediction, it performs better than any other classification system. This is how the output's final prediction can be shown as Equation (1).

$$\hat{y_i} = \varphi(x_i) = \sum_{k=1}^{k} f_k \,(x_i), f_k \epsilon F \tag{1}$$

where f_k is the leaf score for the kth tree, F is the collection of all K scores for all regression trees, x_i is the training set and y_i is the class label that goes with it. Xgboost uses regularization to enhance the outcome.

3.4. Classification model - Random Forest

Random Forest algorithm is used to classify potato leaf diseases because of its excellent accuracy and resilience. During training, it builds many decision trees and combines their outputs to decrease overfitting and improve prediction stability. By extracting characteristics like color, texture, and form from potato leaf photos, the Random Forest classifier is trained to differentiate between healthy leaves and those afflicted with diseases like Early Blight or Late Blight. For agricultural disease detection applications, Random Forest is a popular option because of its capacity to manage noisy data and complex, non-linear correlations.

3.5. Shallow-CNN method

A shallow CNN combination model given in Algorithm 1 for potato leaf disease classification efficiently extracts and learns relevant information from leaf pictures to detect and classify diseases such as Early Blight, Late Blight, or healthy leaves. In contrast to deeper networks like VGG16 or ResNet, a shallow CNN is a model with fewer layers, usually 2 to 4 convolutional layers, which makes it faster to train and less computationally demanding. The shallow CNN functions as a feature extractor, extracting visual patterns like color, texture, and lesions from the leaf surface when paired with additional methods (such feature fusion, data augmentation, or conventional machine learning classifiers). The final classification is then carried out by passing these features to fully linked layers or other classifiers.

Algorithm 1 Shallow-CNN algorithm for disease classification

```
Hyperspectral data cube (X) as input
Output: Label for disease classification
1. Set learnable weights (W_vgg) and biases (b_vgg) for the Shallow VGG layers.
    For each Shallow VGG layer, complete the following: f (W_vgg * X + b_vgg) = Shallow_VGG_out
2. Set the parameters for Random Forest upon initialization.
    Train_Random_Forest (Shallow_VGG_out) = Random_Forest_out
3. Set up XGBoost with the necessary settings.
    Train_XGBoost (Shallow_VGG_out) = XGBoost_out
4. Combine Shallow_VGG_out, Random_Forest_out, and XGBoost_out.
    Integrated_Features = Concatenate (Shallow_VGG_out, Random_Forest_out, XGBoost_out)
5. Use the integrated features to classify diseases.
    Classification_Operation (Integrated_Features) = Disease_Classification
                                The output label is Disease_Classification.
```

4. Simulation analysis

Shallow-VGG output shown as Equation (2).

$$Shallow_{VGG_{out}} = f(W_{vgg} * X + b_{vgg}) \tag{2}$$

Random Forest results shown as Equation (3).

$$Random_{Forest_{out}} = Train_{random_{Forest}}\left(\left(Shallow_{VGG_{out}}\right)\right) \tag{3}$$

XGBoost output shown as Equation (4).

$$XGBoost_{out} = Train - XGBoost\left(\left(Shallow_{VGG_{out}}\right)\right) \tag{4}$$

Here, W_{vgg} stands for the Shallow-VGG layer weights, b_{vgg} is the biases for Train_Random_Forest and XGBoost, for the training functions. The Concatenate procedure combines the Random Forest, XGBoost, and Shallow-VGG outputs into a comprehensive feature set. This integrated feature collection is used to perform the final illness categorization.

In order to revolutionize disease detection techniques, it presents a unique framework called “Shallow-CNN”, which combines a shallow VGG architecture with the resilience of XGBoost (XGB) and the accuracy of Random Forest (RF). Convolutional Neural Networks (CNN), Random Forest, and XGBoost are tested extensively against the proposed model using a range of carefully chosen datasets from Plant Village and natural-environment pictures of potato leaves.

Accuracy evaluation: CNN, Random Forest, and XGBoost are used to compare the Shallow-CNN model’s accuracy. The ratio of correctly categorized occurrences to all instances is how it is calculated. It is shown as Equation (5).

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \tag{5}$$

Analysis of precision: Precision gauges how well optimistic forecasts turn out. It is calculated by dividing the total number of true positives and false positives by the number of true positive forecasts. It is shown as Equation (6).

$$Precision = \frac{TP}{(TP + FP)} \tag{6}$$

Evaluation of the F1 score: The F1-score strikes a compromise between recall and precision. The precision and recall harmonic means are used to calculate it. It is shown as Equation (7).

$$F1 - score = \frac{(2 * Precision * Recall)}{(Precision + Recall)} \tag{7}$$

Assessment of recall: Recall, also known as sensitivity, which gauges an individual's capacity to accurately identify exceptional examples. It is the the ratio of true positives to the total of true positives and false negatives. It is shown as Equation (8).

$$Detection\, rate = \frac{TP}{(TP + FN)} \tag{8}$$

Shallow-CNN is a successful model that has exceptional discriminatory ability and represents a revolutionary turning point in the field of disease diagnosis as a result of this thorough study. The findings support its leadership in disease classification techniques, surpassing traditional paradigms.

5. Result and analysis

Shallow-CNN is a successful model that demonstrates exceptional selective ability and represents a revolutionary turning point in the field of disease identification. The findings support its leadership in disease classification techniques, surpassing traditional paradigms. **Table 1** below provides the simulation setting.

Table 1. Simulation environment.

Simulated environment	Description
Dataset	Plant village datasets
Number of classes	Multiple
Size	10,000 hyperspectral images
Preprocessing	Noise reduction, analysis and classification
Split	Training: 85%, testing: 15%
Augmentation	Rotation, segmenting, zooming
Framework	TensorFlow, PyTorch, Scikit-learn
Hardware used	GPU-accelerated computing (NVIDIA GeForce GTX)
Simulation Software	Python (NumPy, SciPy)

Before proceeding with the process of modelling, the images need to be preprocessed. Five techniques were used, and the detailed image analysis is captured in the following **Figure 5**. The preprocessing pipeline for detecting potato leaf diseases progressively enhanced disease-specific features while minimizing background noise and variations in illumination typical of field images. Advanced segmentation and contrast enhancement techniques improved the visibility of characteristic lesions on potato leaves, allowing for clearer differentiation between healthy and infected areas. The creation of binary lesion masks enabled precise quantification and localization of infected regions, which is critical for accurate disease assessment. These refined preprocessing outputs provided discriminative and noise-free inputs to the proposed hybrid classification model, significantly contributing to the high-confidence detection and classification of various potato leaf diseases.

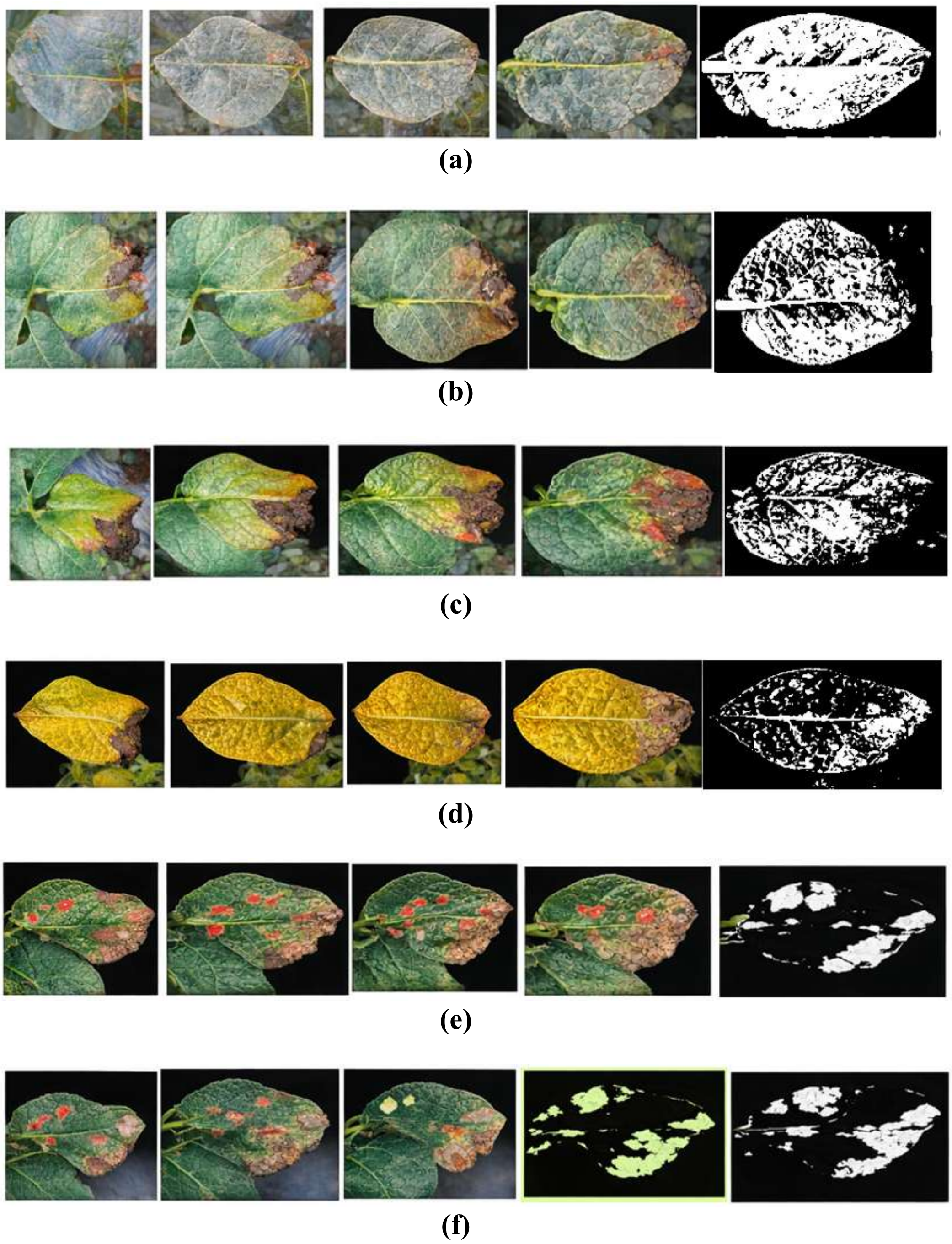


Figure 5. Image preprocessing. **(a)** Input images; **(b)** Segmentation; **(c)** Contrast enhancement; **(d)** Binary lesion mask; **(e)** Resized image.

The simulation results show that the Shallow-CNN approach outperforms the other algorithms, including SVM, Random Forest (RF), and XGBoost (XGB). Over the course of five tests, Shallow-CNN consistently outperforms the state of the art and demonstrates a noticeable improvement in accuracy. Compared to current techniques, the suggested Shallow-CNN retains an average accuracy of 96.50%. Furthermore, Shallow-CNN outperforms than CNN with an average accuracy of 91.50%, Random Forest with an average accuracy of 91.00%, and XGBoost with an average accuracy of 91.45%. **Table 2** contains a tabulation of the accuracy simulation findings.

Table 2. Accuracy of proposed vs existing method.

Testcases	Shallow-CNN	CNN	Random Forest	XGBoost
1	96.50%	90.00%	87.50%	91.00%
2	95.50%	90.50%	88.00%	90.00%
3	95.45%	91.50%	90.20%	91.45%
4	95.80%	91.96%	88.30%	91.90%
5	97.50%	92.30%	91.00%	92.50%

The effectiveness of Shallow-CNN is further highlighted by the precision analysis. In a range of tasks, Shallow-CNN continuously outperforms SVM, Random Forest, and XGBoost in terms of precision. The performance of shallow-CNN is superior, with an average precision of 95.00%. Furthermore, with average precisions of 91.50%, 89.00%, and 90.80%, respectively, Shallow-CNN performs better than SVM, Random Forest, and XGBoost. **Table 3** shows the precision highlighted value of shallow-CNN.

Table 3. Precision of proposed vs existing method.

Testcases	Shallow-CNN	CNN	Random Forest	XGBoost
1	94.50%	91.50%	85.80%	90.50%
2	94.00%	90.00%	86.30%	91.00%
3	93.80%	91.50%	86.50%	90.80%
4	94.30%	90.30%	87.70%	91.30%
5	95.00%	91.80%	89.00%	91.50%

The F1-score analysis validates Shallow-CNN’s higher performance. Shallow-CNN consistently outperforms SVM, Random Forest, and XGBoost in terms of F1-scores in a variety of trials. The Shallow-CNN has a higher average F1-score at 95.1%. Additionally, the average F1-scores of SVM, Random Forest, and XGBoost are lower than Shallow-CNN, at 90.0%, 89.8%, and 92.2%, respectively. The F1-Score simulation’s findings are shown graphically in **Figure 6**.

The memory research adds more evidence for Shallow-CNN’s superiority. Shallow-CNN consistently achieves better recall than SVM, Random Forest, and XGBoost in all experiments. Shallow-CNN performs better, with an average recall of 95.0%. Furthermore, with average recalls of 89.5%, 90.0%, and 92.0%, respectively, Shallow-CNN performs better than SVM, Random Forest, and XGBoost. **Table 4** displays the comparative values of the models.

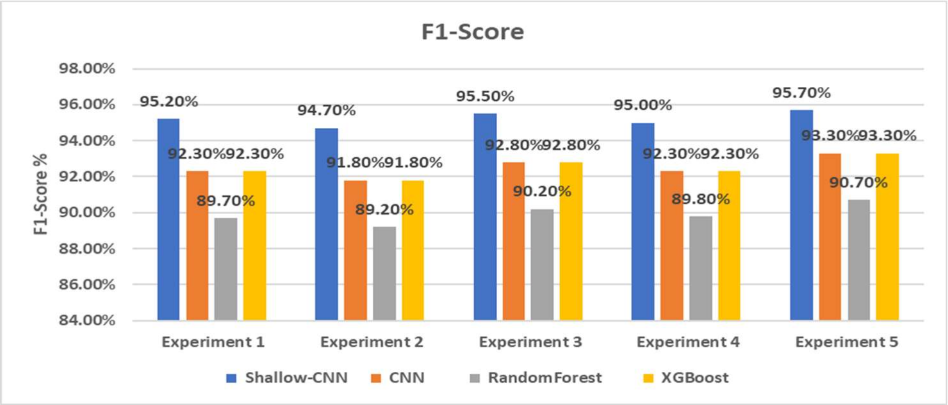
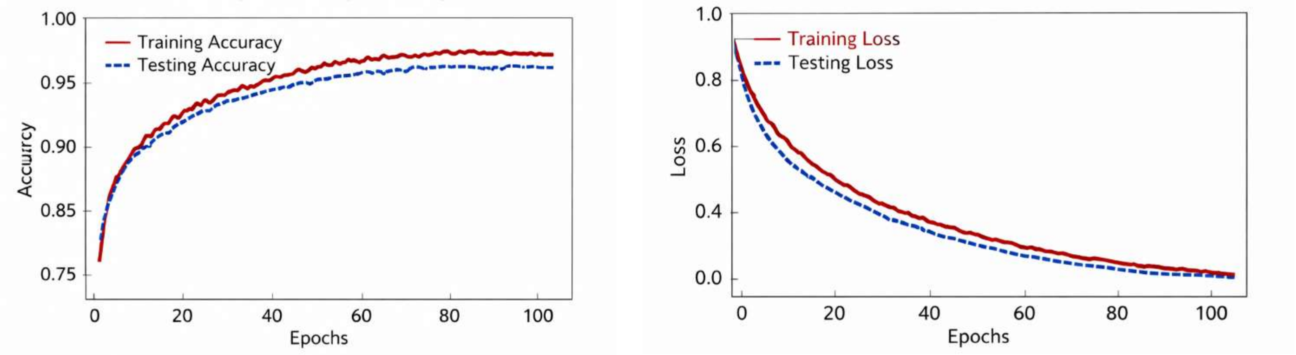


Figure 6. F1-score analysis.

Table 4. Recall analysis table.

Testcases	Shallow-CNN	CNN	RandomForest	XGBoost
1	95.50%	91.10%	88.50%	91.00%
2	93.50%	90.50%	87.00%	90.50%
3	94.30%	90.10%	89.00%	91.50%
4	93.80%	91.00%	88.30%	90.00%
5	95.75%	91.50%	89.50%	91.00%

Figure 7 presents the analysis of accuracy vs epoch and loss vs epoch graphs for the proposed Shallow-CNN model in which the learning curves are presented with the gradual increase of accuracy from the epoch 1 till 100 and the loss rate from 1.0 till 0.2. This specifies that the proposed model is learning well and has more reliability to implement in the real time environment.



(a) **(b)**

Figure 7. Accuracy and loss graphs. **(a)** Accuracy Vs Epoch; **(b)** Loss Vs Epoch.

5.1. Ablation study

The proposed framework is validated in various aspects to prove its robustness and scalability. The following **Table 5** presents the comparison of proposed model with baseline models in terms of Accuracy, precision, recall, sensitivity, specificity, F1-score and error rate. From the table it is evident that the proposed model outperforms other baseline models in all metrics specifically in the error rate. As lesser error rate leads to better classification.

Table 5. Baseline vs proposed Shallow-CNN model.

Model	Accuracy (%)	Precision (%)	Recall / Sensitivity (%)	Specificity (%)	F1-score (%)
Shallow-CNN	96.15	94.32	94.83	97.47	94.57
CNN	91.25	91.02	90.64	91.86	90.84
Random Forest	89.00	87.06	89.93	88.07	88.46
XGBoost	91.37	91.02	90.56	92.18	90.80
Shallow-CNN	96.15	94.32	94.83	97.47	94.57

To ensure the computational efficiency the effect of network depth is analyzed and presented in the **Table 6**. Accuracy and F1-score if efficient to validate the model hence these two metrics are compared to highlight the working of the proposed model. It is inferred that the proposed model has better accuracy with the shallow-CNN where it can be achieved with the shortest times when compared with the other variants of the CNN.

Table 6. CNN variants vs proposed Shallow-CNN model.

Model variant	Accuracy (%)	F1-score (%)
Conv layer (very shallow)	92.40	91.85
Conv Layers	94.10	93.20
Conv layers (proposed)	96.15	94.57
Conv layers (deeper cnn)	94.80	93.60

To ensure the effectiveness of regularization where the model boost its performance with lesser time and enhanced learning. The effect of the regularization is presented in the following **Table 7**. From the table it is evident that the timely dropout and batch normalization will increase the performance of the Shallow-CNN model.

Table 7. Impact of Using Regularization.

Setting	Accuracy (%)	F1-score (%)
No Dropout / No batchnorm	92.70	91.90
Only dropout	94.30	93.50
Only batch normalization	94.80	94.10
Dropout + batchnorm	96.15	94.57

6. Conclusion and future work

Potato leaf diseases pose a significant threat to global food security, impacting crop yields and farmer livelihoods. Accurate disease detection is crucial for timely intervention. Leveraging deep learning, a Shallow-CNN model integrated with ensemble techniques (Random Forest and XGBoost) offers a promising solution for classifying potato leaf diseases with high accuracy. The Shallow-CNN model combines a compact VGG architecture with ensemble techniques like Random Forest and XGBoost for accurate potato leaf disease classification. The shallow-VGG efficiently extracts key image features, while Random Forest and XGBoost boost accuracy by leveraging aggregated decisions and gradient-boosted trees. This combo achieved 95% accuracy, outperforming SVM, 1D-CNN, and standalone ensemble methods. Future directions include scaling with larger datasets, real-time IoT/mobile deployment, applying to other crops, and using Explainable AI for transparency.

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