ConvNet9: A Cutting-Edge Customized Convolutional Neural Network Model to Identify Potato Leaf Disease with Web Application

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Abstract

Potato Cultivation is globally significant because it ensures food security, farmer's economic stability, and adaptability to diverse climates. Potatoes provide vital nutrients, serve as a versatile staple food, and contribute to agricultural diversity, making them a cornerstone of global agriculture. Numerous leaf diseases drastically lower the yield of potato crop production, impacting the production of agriculture worldwide both in terms of quantity and quality. Thus, an accurate classification of potato leaf illness is needed to solve the problem. Convolutional Neural Network has the potential to revolutionize agricultural health monitoring by analyzing enormous amounts of data to detect crop diseases, pests, and nutrient deficiencies rapidly and accurately. In this research, a deep-learning methodology was suggested to recognize and categorize potato leaf illnesses using the famous PlantVillage Dataset of potato leaf images. Using the photos, we proposed ConvNet9 a CNN based model to detect healthy and infected potato leaves. As for our findings, our proposed ConvNet9 model achieved the 99.30% highest accuracy in identifying potato leaf illness. Therefore, the proposed ConvNet9 model was selected to create an intelligent website for crop disease detection. We have demonstrated the reliability of our proposed web application in addressing potato leaf diseases and diagnosing diseases of potato leaves.

Keywords: Convolutional Neural Network, Deep Learning, ConvNet9, Potato Leaf Diseases, Potato Leaf Illness, Classification, Agriculture.

1. Introduction

Agriculture is acknowledged as the foundation of any country. The industrial and agricultural revolutions are happening at the same time. Our ability to survive depends on crops [1]. In the agricultural tapestry of Bangladesh, where the rhythm is intertwined with the cultivation of crops, the potato holds a place of profound significance [2]. As a staple food and a vital contributor to the nation's agricultural economy, the potato is a source of sustenance and a symbol of resilience and agricultural ingenuity [3].

People worldwide are familiar with potatoes, which are a staple diet in almost every nation [4]. As is already well known, Bangladesh is an agricultural nation that cultivates a variety of commodities, with potatoes making up a sizable portion of the national economy [5]. Bangladesh is a small country, but it is regarded as the seventh-largest potato-producing nation as of February 2024. According to the Department of Agricultural Extension (DAE), potatoes are grown on over 500 thousand hectares of land and produce more than 11 million metric tons per year [6]. However, a silent threat lurks amidst the verdant fields and bustling markets; potato leaf diseases [7].

Deep Learning's Convolutional Neural Networks shine as a hope for technological innovation in difficult agricultural conditions [8]. These sophisticated algorithms were motivated by the complex neural networks seen in the human brain, have revolutionized field image analysis, and hold immense promise for identifying plant leaf diseases [9]. However, Numerous researchers in the past used CNN to detect Potato leaf diseases; for example, [10] proposed a DL method to identify potato leaf illness. This was discovered by the Convolutional Neural Network architecture, which produced 97% training and 92% validation accuracy. [11] Presented a deep learning system for identifying several types of illness in potato plants using VGG19 and VGG16 CNN architecture, achieving an average accuracy of 91%. [12] Presented a potato leaf illness detection method using deep CNN such as ResNet-152 and InceptionV3 and achieved 98.34% and 95.24% accuracy. [13] Used pre-trained VGG19 for fine-tuning, extracting relevant features, and using multiple classifiers, logistic regression outperforms others with 97.8% classification accuracy. [14] Introduced A deep learning system that classifies potato plant diseases using GoogleNet, Resnet50, and VGG16 and achieved 97% accuracy. [15] Presented a DL model for identifying potato leaf illness using optical potato leaf images, and achieved 97.89% accuracy after fine-tuning. [16] Utilized CNN to classify plant leaf diseases and achieved an excellent 98.029% for testing across all datasets. [17] Suggested a model for detecting leaf illness and taking preventative action using CNN models ResNet-50 and AlexNet. To detect potato leaf illness, the suggested method met the overall 97 % highest accuracy for ResNet-50.

According to the literature above, most of these works employed Convolutional Neural Network to detect potato leaf diseases. There is a need for more study and development because the accuracy of these suggested solutions is not high enough. This research aims to build a deep learning-based detection framework to generate extremely accurate results and provide farmers with preliminary recommendations. Additionally, a website has been created specifically for farmers, allowing them to upload photographs of potato leaves; the website then uses those images to identify diseases and provides possible recommendations.

In this research, we embark on a journey to explore the transformative potential of CNN in mitigating potato leaf disease's impact on Bangladesh's agricultural landscape. Leveraging cutting-edge deep learning techniques, Particularly CNN, we aim to develop a robust framework for accurately and efficiently classifying potato leaf diseases, thereby empowering farmers with actionable insights and enhancing crop management practices. The major contributions of our research are as follows:

- We Introduced an improved comprehensive deep-learning framework to identify potato leaf illness.
- Designed a customized 9-layer based ConvNet9 model for potato leaf disease detection, which involves structuring layers for classification and feature extraction, alongside using several CNN models such as MobileNetv3, VGG-19, VGG-16, ResNet-50, and Efficient-Net to benchmark and performance evaluation.
- Developed a user-friendly web application allowing users to identify potato leaf illness by uploading photos of potato leaves.
- The integration of the customized 9-layer trained CNN model into the backend of the web application enhances its capability for leaf disease detection.
- This web Application analyzes real-time potato leaf disease and displays the outcome.

The rest of the section of our research is represented by the headings: Section 2 – Related Work shows the literature review from existing research based on Potato leaf diseases. Section 3 – Methodology This section explains the system architecture, related diagrams, and requirements. Section 4 - Experimental Result shows the results with different tables, graphs, and figures. Section - 5, Proposed Web

Application, presents the proposed website's working principle. Section - 6, Conclusion and Future Prospect presents the article's core idea, which is concluded in this section and discusses potential future applications.

2. Related Work

The primary aim of this study was to build an revolutionized computerized model for detecting potato leaf disease. Several previous studies, especially those that used the PlantVillage Dataset, have been investigated and presented here to understand the current state of this topic. *Erlin et al.* [18] presented a multi-architecture CNN approach to detect potato leaf disease. After carefully analyzing the dataset acquisition, data augmentation, hyperparameter tuning, model selection, and assessment, this research thoroughly analyzed training efficiency, detection accuracy, and model convergence. According to their findings, ResNet50 performed exceptionally well, as seen by its astounding 97% testing accuracy and 98% specificity for PlantVillage Dataset. *A. Abbas et al*. [19] employed Deep learning methods to classify and identify potato leaf illness using the PlantVillage dataset. Plant leaf diseases were categorized into 15 classes using Convolutional Neural Network (CNN) methods. comprising classes for various plant illnesses, such as bacterial and fungal infections, in addition to three classes for healthy leaves. After training and testing, the suggested models had 98.29 and 98.029% accuracy scores, respectively. *D. Murtaza et al.* [20] presented an enhanced CNN Architecture for detecting potato leaf diseases. To train this suggested model an open-source plant leaf dataset called PlantVillage Dataset was used. Data augmentation techniques are utilized with the "Keras" TensorFlow library to expand the dataset size. In their experimental result, the model achieved 98.14% highest accuracy. *N. Rohila et al.* [21] categorized diseases affecting potatoes in their research. The widely recognized PlantVillage Dataset, which is available to the public, was considered in this instance. K-means were assessed for image segmentation; PCA and GLCM ideas were used for feature extraction, and detection and classification; OMFA-CNN research methodology was employed for detection and classification. The research approach yielded an MSE of 4.0, a recall of 99%, and a precision of 99.3%. *M. Iftikhar et al.* [22] investigated deep learning based potato leaf disease diagnostic techniques. More specifically, it classifies and detects the illness using the CNN technique. This research looks at the effects of data augmentation while performing a thorough analysis of the hyper-parameter's performance to identify potato leaf illnesses, specifically concentrating on potato leaf disease. The experimental results showed 98% accuracy using the PlantVillage Dataset. *A. Ghosh et al.* [23] introduced a method for detecting illness of potato leaves. Samples of healthy and infected potato leaves have been examined. To improve accuracy, techniques including image segmentation and data augmentation have been applied. The features recovered from the photos include Wavelet features, fractal dimension, SURF, and Gabor Filter. To train and assess the approach, the popular PlantVillage Dataset was employed. The model has achieved a 95.97% accuracy rate. *D. Rohit et al*. [24] utilized the PlantVillage Dataset from Kaggle, a well-known dataset with over 2000 images of infected and healthy potato leaves. CNN models were used to identify and categorize the health state of leaves. The findings show that the suggested technique achieved a remarkable 99.01% accuracy. *S. Anand et al.* [25] suggested a method for categorizing illnesses that impact potato leaves by employing picture segmentation and deep learning techniques. The main goal is to identify sick potato plants in the PlantVillage Dataset by applying image processing techniques. Potato leaf diseases are categorized using a deep neural network (DNN) model with Adam and are categorized as cross-entropy hyperparameters. The suggested method achieves a 98% classification accuracy for identifying potato leaf illness. *Bania et al*. [26] have employed computational models based on deep transfer learning to identify early-stage potato leaf diseases. They have successfully classified potato leaf diseases using a combination of PCA and ResNet101. Before putting the photos into the model, they used the Contrast Limited Adaptive Histogram Equalization (CLAHE) approach to improve the contrast of the potato leaf images. Their architecture has identified potato leaf diseases with an amazing 95.13% accuracy using the PlantVillage Dataset. *T. Nazir et al.* [27] presented a training-oriented, end-to-end technique for recognizing different potato leaf illnesses, utilizing the EfficientNet-V2 network. PlantVillage Dataset is an open dataset that is used to test the model. When tasked with identifying different potato leaf illnesses, the model achieved 98.12% accuracy. *Y. Khaparde et al*. [28] introduced an automated model for identifying diseases affecting potato leaves, based on ML and image processing. Their goal was to identify potato diseases by analyzing leaf photos with a CNN system. The dataset used to identify potato diseases came from the well-known public data repository Kaggle, named PlantVillage Dataset, which has over 2000 photos of healthy and infected potato leaves. After extensive testing, showed an amazing 91.41% accuracy rate. *N. Chowdhury et al.* [29] created an ensemble model for diagnosing potato leaf diseases utilizing the transfer learning algorithms ResNet50V2 and DenseNet201. More than 5,700 photos were gathered for this research from PlantVillage and potato leaf disease dataset. Potato leaf stages are identified with accuracy and appropriateness by the proposed ensemble averaging model. Thus, the proposed ensemble model's accuracy is attained precisely.

3. Methodology

The objective of this research was to build a model that can precisely identify potato leaf diseases early and benefit farmers. We aimed to control the spread of potato leaf disease and stop it from spreading further by early detection. The methodology diagram of the proposed approach to identify potato leaf illness is displayed in Fig. 1 below.

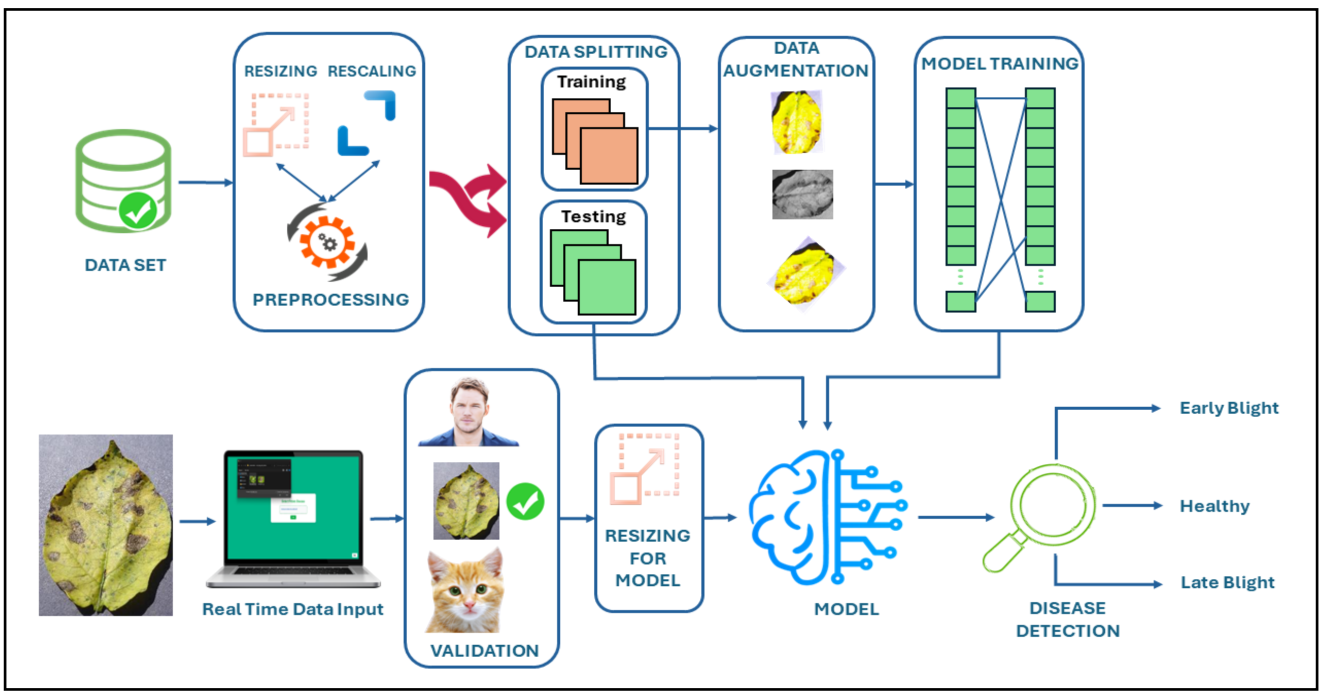


Fig. 1: Proposed Architecture for Potato Leaf Disease Detection

Our Methodology involves the utilization of high-resolution imagery from the dataset we have collected. Through a process of data preprocessing, feature extraction, and model training, we harness the power of CNN to analyze intricate patterns and subtle variations in leaf morphology associated with early and late blight. By evaluating the outcome of the suggested model against ground truth data collected from the dataset and expert assessments, we seek to demonstrate its efficacy in accurately identifying and categorizing potato leaf illness into early and late blight. Furthermore, we aim to assess the scalability and practical feasibility of deploying such technology within the context of Bangladesh's agricultural sector, considering factors such as cost-effectiveness, accessibility, and user-friendliness. Ultimately, our research endeavors to bridge the gap between cutting-edge technology and on-the-ground agricultural realities in Bangladesh. By harnessing the power of CNN, we aspire to empower farmers with the knowledge and tools necessary to combat potato leaf diseases effectively, thereby fostering resilience, sustainability, and prosperity within Bangladesh's agricultural community. The complete procedures to create this model are demonstrated below.

3.1 Data Acquisition:

A suitable and valid dataset is essential to assess the effectiveness of ML and DL models. To detect potato leaf diseases, we collected a dataset named "PlantVillage Dataset" from a public source to detect Potato leaf illness. The PlantVillage Potato Dataset contains a total of 2152 images. All the images are divided into three classes. These are Early Blight, Late Blight, and Healthy. The dataset includes 152 photos of healthy leaves and 1000 for each Early Blight and Late Blight.

Table 1: The PlantVillage Dataset

Class	Samples
Early Blight	1000
Late Blight	1000
Healthy	152
Total	**2152**

3.1.1 Early Blight:

The fungus Alternaria Solani caused early blight, is a common and destructive disease affecting potato plants. It usually appears as black patches on the leaf's stems and sometimes the tubers of potato plants. These lesions often start as small, dark spots with a bullseye pattern, eventually enlarging and merging to form larger, irregularly shaped lesions [30]. Fig. 2. Shows Early blight potato leaves.

Fig. 2 Early Blight Potato Leaves

3.1.2 Late Blight:

Phytophthora infestans is the culprit behind late blight, among the deadliest illnesses that damage potato plants globally. The characteristic appearance of late blight is dark, wet spots on the leaves and stems, and sometimes the tubers of potato plants. These lesions can rapidly expand under favorable conditions, causing the affected tissue to become necrotic and eventually collapse [31]. A sample of late blight potato leaves is Shown in Fig. 3.

Fig. 3: Late Blight Potato Leaves

3.1.3 Healthy Leaf: A leaf that does not hang, curl, or discolor is known as a Healthy leaf. A healthy leaf is not affected by early or late blight and looks fresh, as shown in Fig. 4.

Fig. 4: Healthy Potato Leaves

3.2 Data Preprocessing

Before fitting the raw images into the DL module, they must be preprocessed because the image might contain noise. In addition to leaf sand, there can be dust and other noises in plant leaves. It is important to eliminate the noisy data from plant photos using preprocessing techniques to get high training accuracy performance. Preprocessing is essential for increasing efficiency because training a convolutional neural network directly with raw pictures could result in poor classification performance. Several preprocessing techniques have been used before the photos are inputted into the model. The images of the PlantVillage dataset are by default 256x256 sizes. To adjust various aspects like brightness, contrast, sharpness, and color balance, make the image more visually pleasing, or highlight specific details We use Enhancement, which is the process of improving the quality or appearance. Then we use Resizing an image to change its smaller or larger dimensions.

3.3 Data Partitioning

To train the proposed model, we split the dataset into testing, validation, and training sets. The training set is used to train the model to identify features from images, such as curves, lines, textures, and other elements. The validation set was used for the model selection, hyperparameters selection, and assess the model. Finally, the suggested model's performance with unseen data is assessed using the test set. Initially, 80% of the data is utilized for training. Ultimately, the dataset division procedure is finished when the remaining 20% is divided equally between testing and validation. Fig. 5 shows data partitioning.

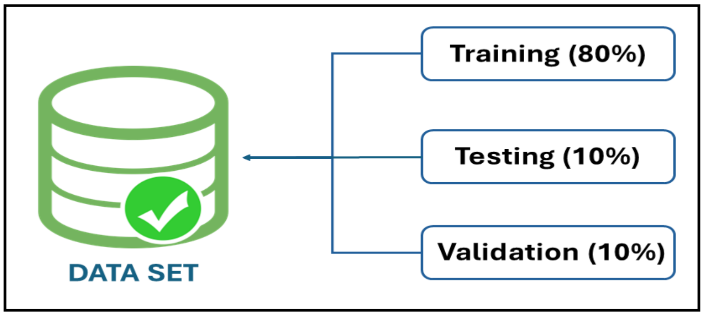


Fig. 5: Data Partitioning

3.4 Cross Validation

Cross Validation assesses a model's outcome. It is a Machine Learning method. The provided data is divided into several folds, or subsets, of which one is utilized as a validation set and the others to train the model. The K-Fold cross-validation method was used in the proposed approach, it involves dividing the dataset into k folds, or subsets. Then trained on each fold and reserved a fold for the trained model's assessment. Using this strategy, we iterate k times using a different subset for testing each time. In this proposed model, to increase the model's efficacy 5-fold cross-validation was utilized. Fig. 6 displays the process of 5-fold cross-validation.

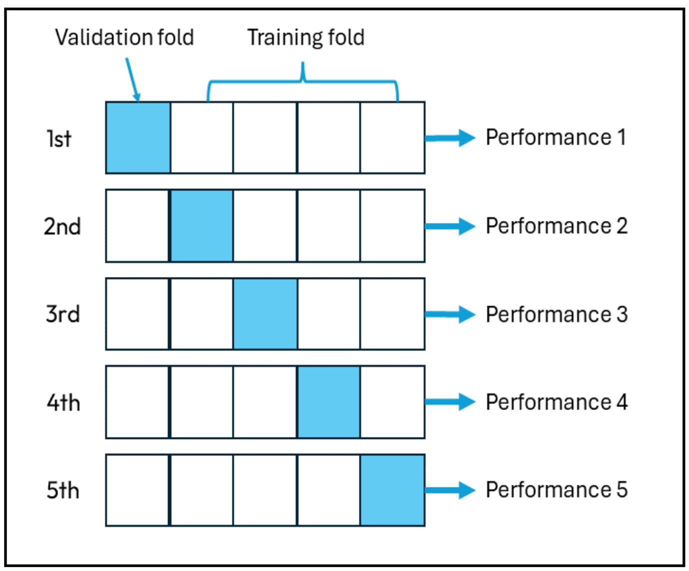


Fig. 6: Process of 5-Fold Cross Validation

3.5 Data Augmentation

Compared to machine learning's shallow network, deep learning requires vast data. Common issues in ML and DL are the deficiency of training data and the distribution of data across classes [32]. Data augmentation is the strategy used to solve this issue. Modifying data while retaining its essential qualities is known as data augmentation. Applying a range of changes to pre-existing data samples improves the flavor of collection by altering an image's color, scaling, flipping, or rotation [33]. Data Augmentations diversity reduces the likelihood that the model will be confused by variants it hasn't encountered before, making it more flexible and efficient in addressing real-world circumstances.

3.6 Image Classification

Deep Learning is a subset of Machine Learning. The adjective "deep" refers to the fact that deep learning is more complicated than machine learning. DL methods have raised the bar in numerous fields, including object detection, image classification, speech recognition, visual object recognition, and many more [34]. CNN is one of the most often used classes in DL. CNN is one kind of neural network that is frequently applied to image data. CNN falls under the category of Deep Neural Networks and is frequently applied to image data due to the depth of the network level [35]CNN is an extended form of Artificial Neural Networks primarily utilized for feature extraction from grid-like matrix datasets. CNN is composed of several layers, including input, pooling, fully connected, and convolutional layers. The pooling layer downsamples the picture to reduce processing, the convolution layer applies filters to the input image to extract features, and the fully connected layer makes the final prediction.

Numerous investigations have employed the convolutional neural network technique to detect illnesses in potato leaves mentioned in the related work chapter. In this research, a customized 9-layer-based ConvNet9 model was proposed to identify potato leaf diseases. Additionally, five distinct CNN pre-trained models MobileNetV3, VGGNet16, VGGNet19, EfficientNet, and ResNet have been implemented. All of these models are outlined below.

3.6.1 MobileNetV3

MobileNetV3 was invented by Google researchers [36]. The work process of MobileNetV3 encompasses several key stages. It begins with the design of an efficient convolutional neural network architecture, tailored specifically for embedded and mobile devices, focusing on optimizing both performance and computational efficiency. The model undergoes training on massive datasets like ImageNet to learn and recognize patterns and features within the input data. Finally, the trained and optimized MobileNetV3 model is deployed for real-time inference on embedded and mobile devices, enabling tasks such as object detection and image recognition in our application.

3.6.2 VGGNet16 - Visual Geometry Group Network 16

CNN using the VGG16 architecture is well known for being simple and efficient in image classification applications. VGGNet16 was introduced by Simonyan and Zisserman [37]. It comprises 16 layers, 13 convolutional layers, and 3 fully connected layers. Its distinguishing features are max pooling layers and tiny (3x3) convolutional filters. VGG16's straightforward architecture and uniform design make it easy to understand and implement, facilitating widespread adoption and serving as a baseline model for many computer vision applications. Despite its simplicity, VGG16 performs strongly on benchmark datasets like ImageNet, achieving high accuracy rates in image classification tasks.

3.6.3 VGGNet19 - Visual Geometry Group Network 19

VGG19 is an extension of the VGG16 architecture, featuring 19 layers instead of 16 like its predecessor, VGG19 is well known for being easy to use and efficient at image classification. It has the same max-pooling layers and tiny (3x3) convolutional filters as VGG16, with 16 convolutional layers and 3 fully connected layers. The additional layers in VGG19 allow for a deeper network architecture, potentially capturing more intricate features for input images. Despite its increased depth, VGG19 retains the straightforward design principles of VGG16, making it easy to understand and implement. Similar to VGG16, VGG19 achieves strong performance on image classification benchmarks such as ImageNet, demonstrating a high accuracy rate across various datasets and tasks.

3.6.4 EfficientNet

EfficientNet is a family of CNN architectures developed to surpass standard models in terms of processing resources and parameter counts, while still achieving cutting-edge performance. EfficientNet was Developed by Google researchers [38]. It uses a compound scaling technique to optimize efficiency by balancing the model's resolution, depth, and width while maximizing accuracy. The architecture consists of a baseline network, EfficientNet-B0, scaled up to create larger variants such as EfficientNet-B1, B2, B3, B4, B5, and B6. Each Variant performs progressively better by scaling the baseline network's resolution, depth, and width. Across a range of image classification benchmarks, EfficientNet has proven to perform better, including ImageNet, with significantly fewer parameters and FLOPs (floating-point operations) compared to other models, making it highly efficient for deployment on resource-constrained devices.

3.6.5 ResNet - Residual Network

A deep CNN architecture called ResNet was developed to address the vanishing gradient problem that comes up during the training of incredibly deep neural networks. The Residual Network was introduced by Microsoft researchers [39] in 2016, Resnet Introduced skip connections or shortcuts that let gradients to pass across the network more directly learning residual functions specifically, the distinction between a layer's input and output, which facilitates training of deeper networks with improved performance. ResNet designs usually have many residual blocks, with numerous convolutional layers in each block, with skip connections connecting input and output across blocks. ResNet has demonstrated exceptional performance on various computer semantic segmentation, and it has become a fundamental building block for many state-of-the-art neural network architectures.

3.6.6 Proposed ConvNet9 Model

To identify potato leaf disease, we proposed a 9-layer-based CNN model, ConvNet9. The semantic architecture of ConvNet9 is displayed in Fig. 7. This proposed model takes 256 × 256 size images as input. The proposed CNN model starts with a custom resizing and rescaling layer that adjusts input images to a fixed size and scales pixel values to a standardized range, typically between 0 and 1. The input image is subjected to 32 filters using a 3x3 kernel by the first convolutional layer (Conv2D), which recognizes edges and textures, among other fundamental features. The model may learn more complex patterns because of the non-linearity introduced by the ReLU activation function. Subsequent convolutional layers with 64 filters and a 3x3 kernel extract more intricate features from the input data. Interspersed between these convolutional layers are max-pooling layers (MaxPooling2D) with a 2x2 window, which reduces spatial dimensions while preserving essential information. After convolution and pooling operations, 2D feature maps are converted to 1D vectors using a flatten layer, making the data suitable for fully connected layers. Using the ReLU activation function, the first fully connected layer, including 64 neurons, introduces non-linearity and learns intricate patterns. The output layer creates a probability distribution over classes using the softmax activation function to enable the model to generate predictions.

Fig. 8 demonstrates the inside architecture of the proposed ConvNet9 model, starts with an input layer that accepts images, followed by preprocessing to standardize their size and pixel values. Convolutional layers (Conv2D) extract features from the images using ReLU activation. MaxPooling layers reduce spatial dimensions while retaining important features, effectively downsampling the input. The flatten layer creates a 1D vector from the 3D feature maps in order to prepare the data for fully connected layers

(Dense) with ReLU activation. Class probabilities are produced by employing a softmax activation function on the output layer, with the number of neurons equal to the output classes.

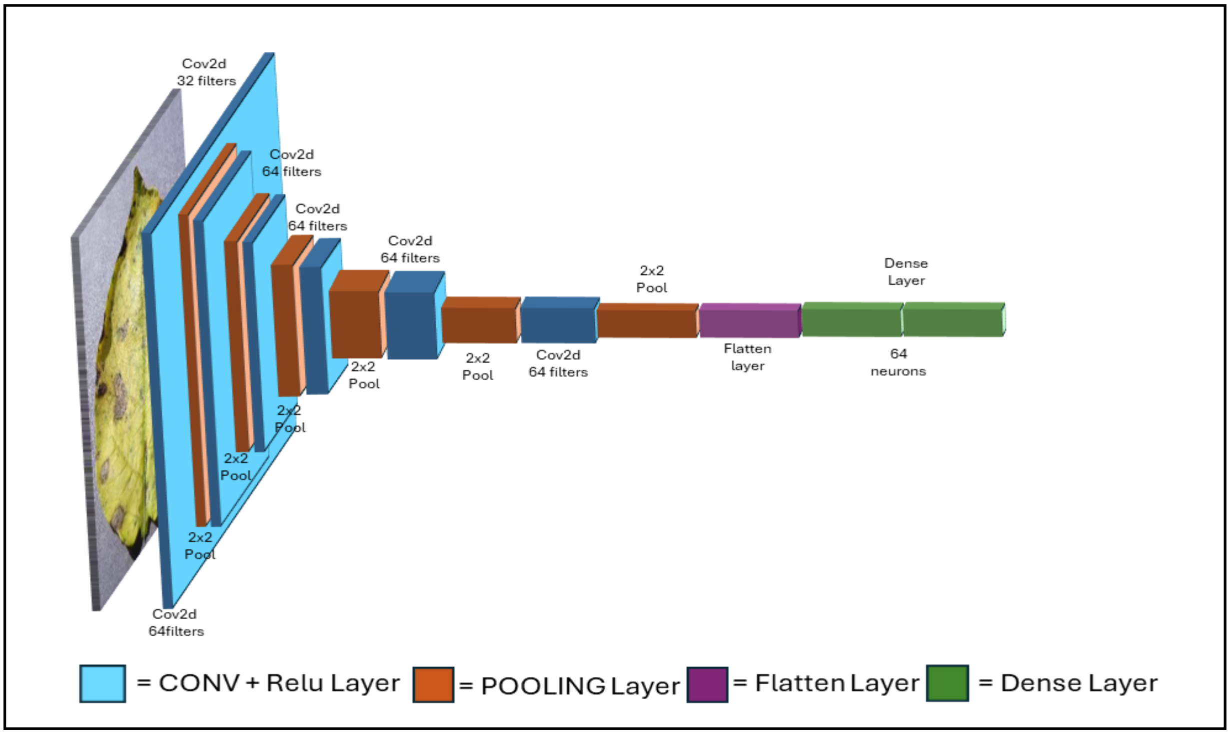


Fig. 7: Semantic Architecture of Proposed ConvNet9 Model

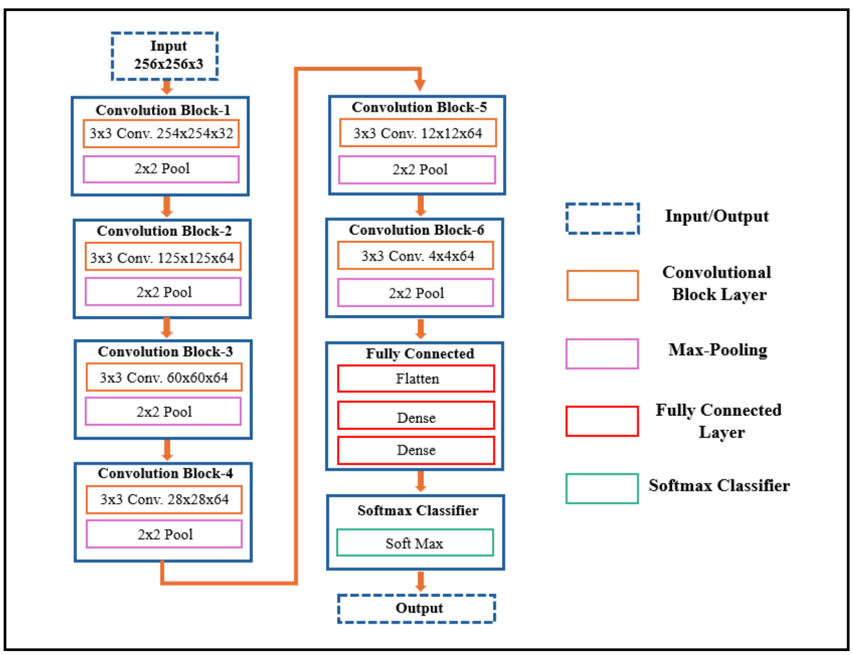


Fig-8: Inside Architectural Model of Proposed ConvNet9

3.7 Experimental Setting

3.7.1 Parameter Setting

The suggested model was trained with 50 epochs and a minimum batch size of 32 to identify the potato leaf blight area. A standard dimension of 256 x 256 pixels is applied to all photos of the potato leaves dataset. The training size of the suggested approach was 0.8 and the validation size was 0.1. For K-fold cross-validation, 5-fold is used. Furthermore, Adam Optimizer was chosen to build this model. It takes 8 hours for training and 2 hours for testing the model. Table 2 displays the values of the parameters utilized while training.

Table 2: Experimental Parameters Setting

Parameters	Values
Batch Size	32
Image Size	256*256
Classes	3
Epochs	50
K_fold	5
Optimizer	Adam
Train size	0.8
Validation size	0.1

3.7.2 Environmental Setting

The experimental study was conducted using a Windows 10 operating system on a ×64 processor, intel(R) core i5 CPU running at 2.60GHz to 2.71GHz with 8 GB of RAM. Anaconda Navigator was used with the Jupiter Notebook for image processing applications. Here, the flask serves as the server. TensorFlow was our model exponent. We utilized the Adam optimizer for optimization.

3.7.3 Performance Evaluation Metrics

The primary evaluation metrics accuracy, recall, precision, and F1-score are used to assess the suggested framework.

An evaluation of the model's prediction ability overall for every class is provided by accuracy.

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{(\text{FN}+\text{TN}) + (\text{TP}+\text{FP})} \quad \text{---}(1)$$

The precision determines the ratio of true positives to the total of false positives and true positives and assesses the model's capacity to prevent misinterpreting a negative instance as positive.

$$\text{Precision} = \frac{\text{TP}}{(\text{FP} + \text{TP})} \quad \text{---}(2)$$

The ratio of true positives to the total of true positives and false negatives indicates recall, which measures the model's capacity to detect positive occurrences.

$$\text{Recall} = \frac{\text{TP}}{(\text{FN} + \text{TP})} \quad \text{--}(3)$$

Lastly, the F1 score is a weighted harmonic mean of recall and accuracy, representing the percentage of accurate positive predictions.

$$\text{F1 Score} = 2\, x \frac{Recall\ x\ Precision}{Recall + Precision} \text{--(4)}$$

3.7.4 Confusion Matrix

Confusion matrix is utilized to assess a model's outcome, graphically displayed as a table. It is used to display the prediction summary in matrix form. For each class, it displays the percentage of accurate and inaccurate predictions. It facilitates comprehension of the classes that the model misinterprets for other classes. Confusion matrices are necessary to create other performance evaluation matrices.

Table 3: Confusion Matrix

	Actual Positive	Actual Negative
Predicted Positive	TP	FP
Predicted Negative	FN	TN

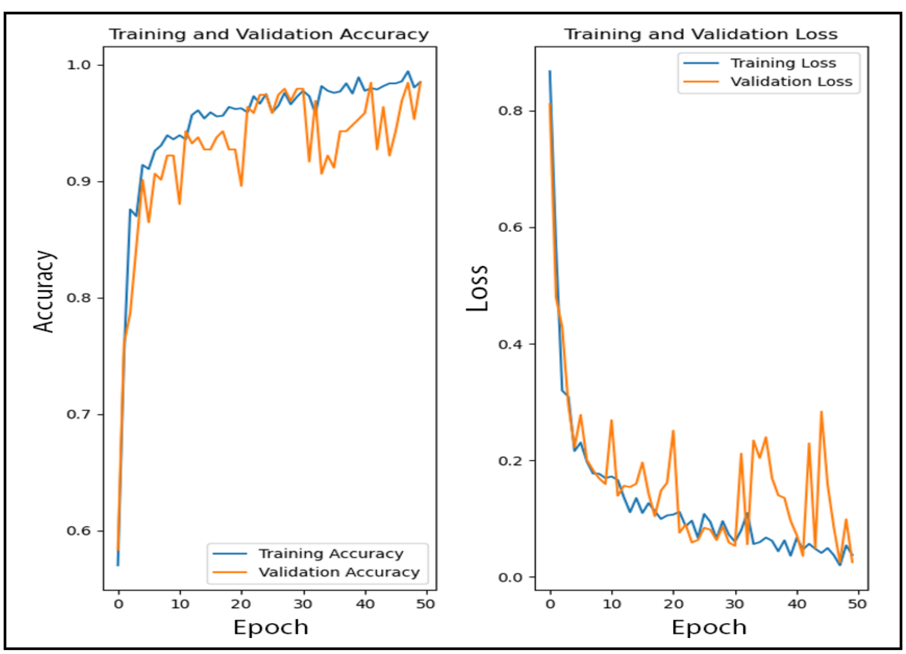
The values in the confusion matrix denoted by the letters TP, FP, FN, and TN, respectively, are the true positive, false positive, false negative, and true negative.

4. Experimental Result and Discussion

The learning experiment for the model was carried out utilizing the Convolutional Neural Network technique. The outcomes of the suggested work were presented in this portion of the study.

4.1 Training and Validation

The proposed approach was trained with 50 epochs, a minimum batch size of 32, and a 0.01 learning rate to boost the model's performance. The value of the taught picture must match exactly at every step of the epoch. The outcomes of the epochs were noted to calculate the accuracy and loss value. Accuracy value is a measure of the system's degree of success in classifying objects, and loss is an indicator of a low value on the model. The value of the loss achieved must be either zero or very close to it. Fig. 9 shows the accuracy and loss values for 50 training and validation epochs for ConvNet9 model.



(a) Accuracy Curve (b) Loss Curve

Fig. 9: Training and Validation (Accuracy and Loss) Curve for Proposed ConvNet9

We randomly picked nine photos to assess the suggested model's outcome and look into its categorization accuracy. The findings of the three classes of potato disease categorization are displayed in Figure 14. The PlantVillage dataset has been partitioned into training, testing, and validation sets. More than 4 hours are typically spent training the model, and around 1 hour is spent testing it. Table 4 displays a comparison of the Accuracy and Loss of different models and the proposed ConvNet9 model.

Table 4: Comparison of Different CNN Models and Proposed ConvNet9 Model

Model	Epochs	Accuracy	Loss	Validation Loss	Validation Accuracy
MobileNetv3	50	0.4844	4.0498	2.67858	0.472668
VGG16	50	0.4181	0.9152	0.902974	0.451604
VGG19	50	0.95	0.1924	0.317162	0.905202
EfficientNet	50	0.50	0.8854	0.88469	0.451068
ResNet	50	0.8519	0.3899	0.517174	0.814246
Proposed ConvNet9	**50**	**0.9930**	**0.0735**	**0.0613**	**0.9930**

Fig. 10 indicates the comparison of five different CNN models and our proposed ConvNet9 model. It is evident that our suggested ConvNet9 model obtained the highest Accuracy and Validation Accuracy and the Lowest Loss and Validation Loss, which indicates that our proposed model performed very well and also surpassed other CNN models in identifying potato leaf diseases.

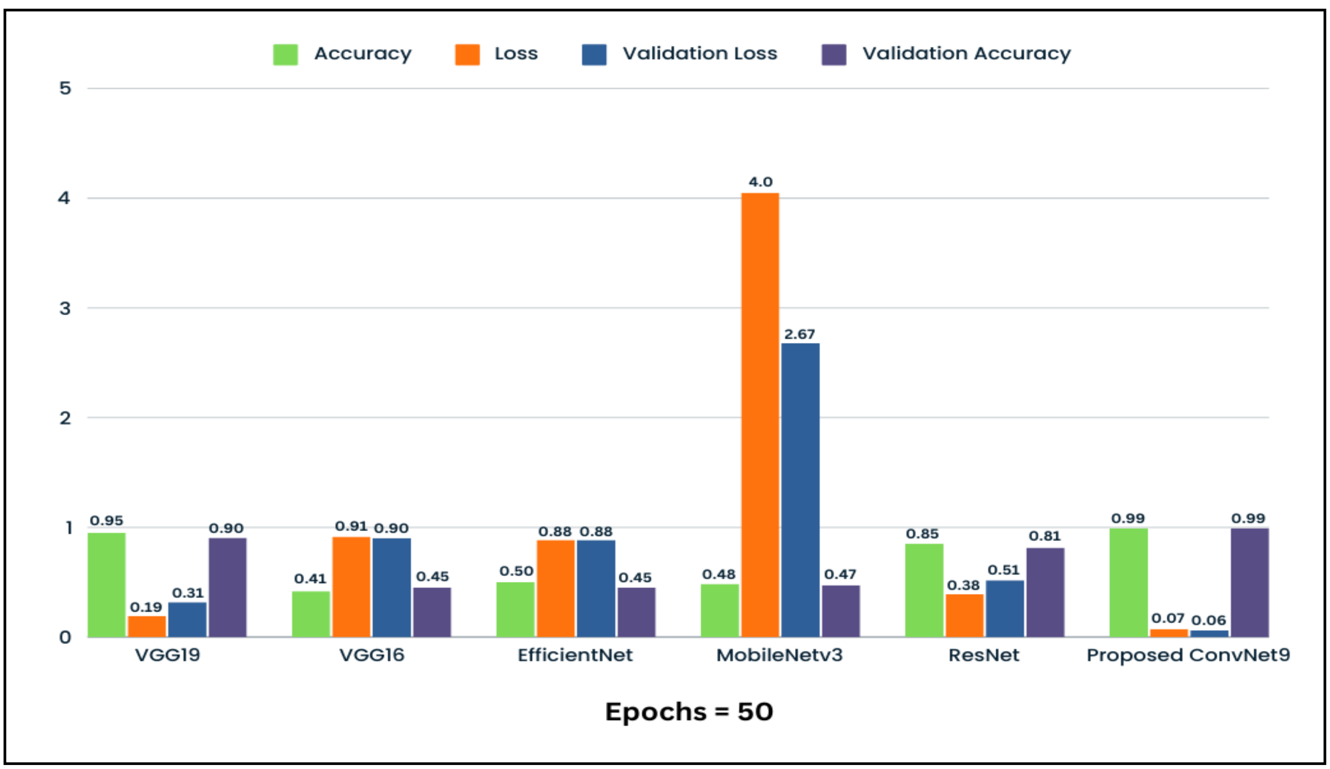


Fig-10: Comparison of Different CNN Models with the Proposed ConvNet9 Model

4.2 Result Analysis

Our objective was to identify potato leaf illnesses utilizing the CNN. The findings of the CNN models in identifying potato leaf illness from images of the PlantVillage Dataset are presented in this part of the paper. The dataset comprises 2152 images in three different classes: Early Blight, Late Blight, and Healthy. We employ accuracy, F1-score, precision, and recall to evaluate the efficiency of our suggested approach. Table 5 shows the outcome of different CNN models and our proposed ConvNet9 model. The proposed ConvNet9 achieved the 99.30% highest accuracy for identifying potato leaves with early and late blight disease.

Table 5: Results of different CNN Models

CNN Type	Accuracy	Precision	Recall	F1 Score
MobileNetv3	0.51	0.51	1.00	0.68
VGG16	0.55	0.54	0.77	0.63
VGG19	0.52	0.51	0.53	0.52
EfficientNet	0.50	0.50	1.00	0.67
ResNet	0.89	0.87	0.92	0.89
Proposed ConvNet9	**0.993**	**0.995**	**0.99**	**0.992**

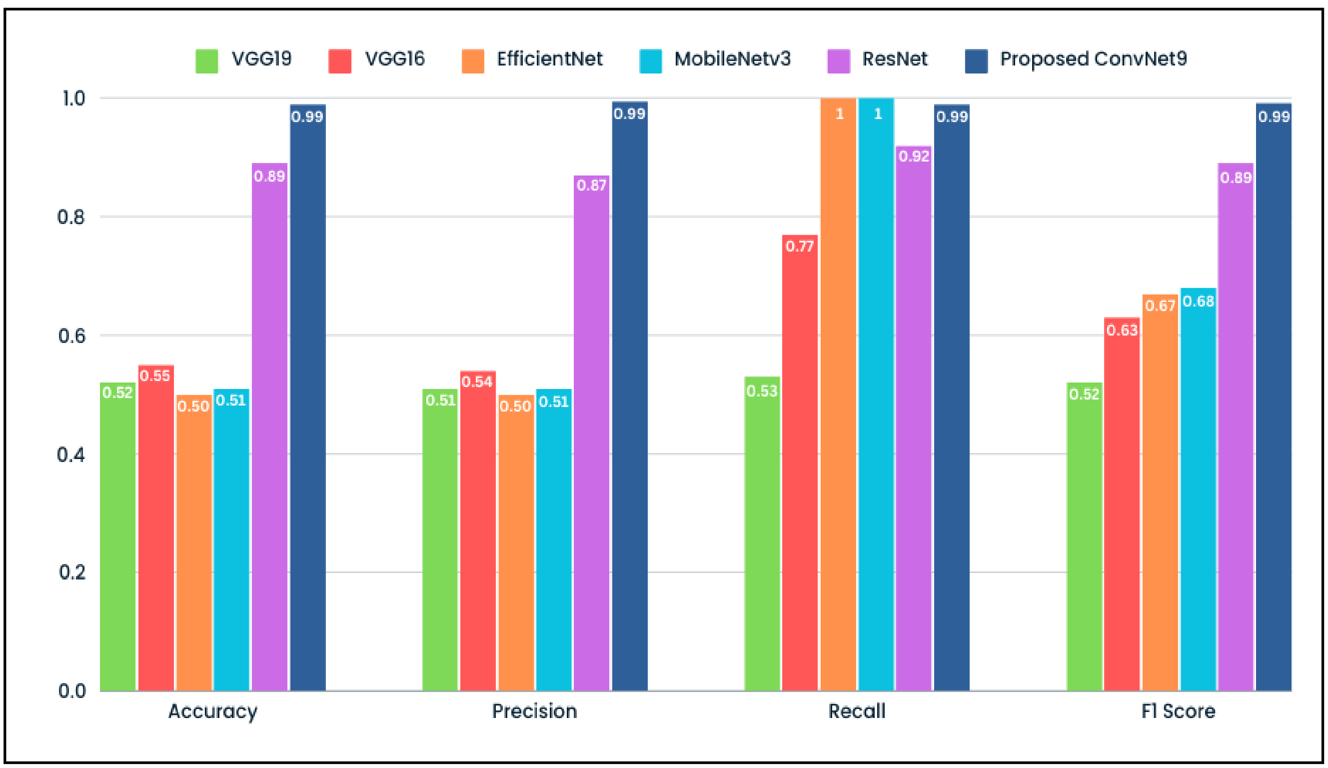


Fig. 11: Results of Different CNN Models

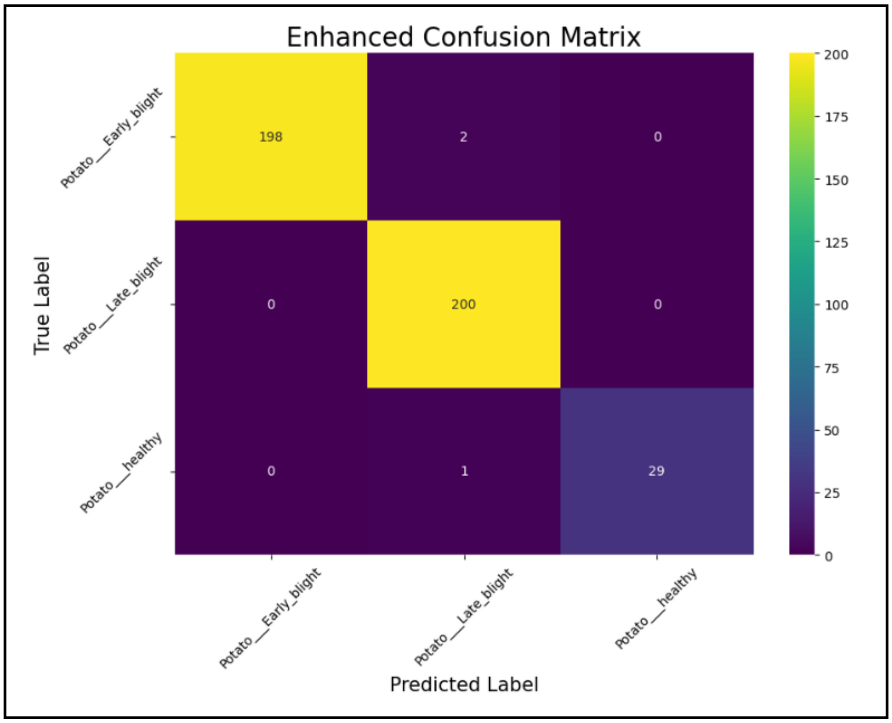
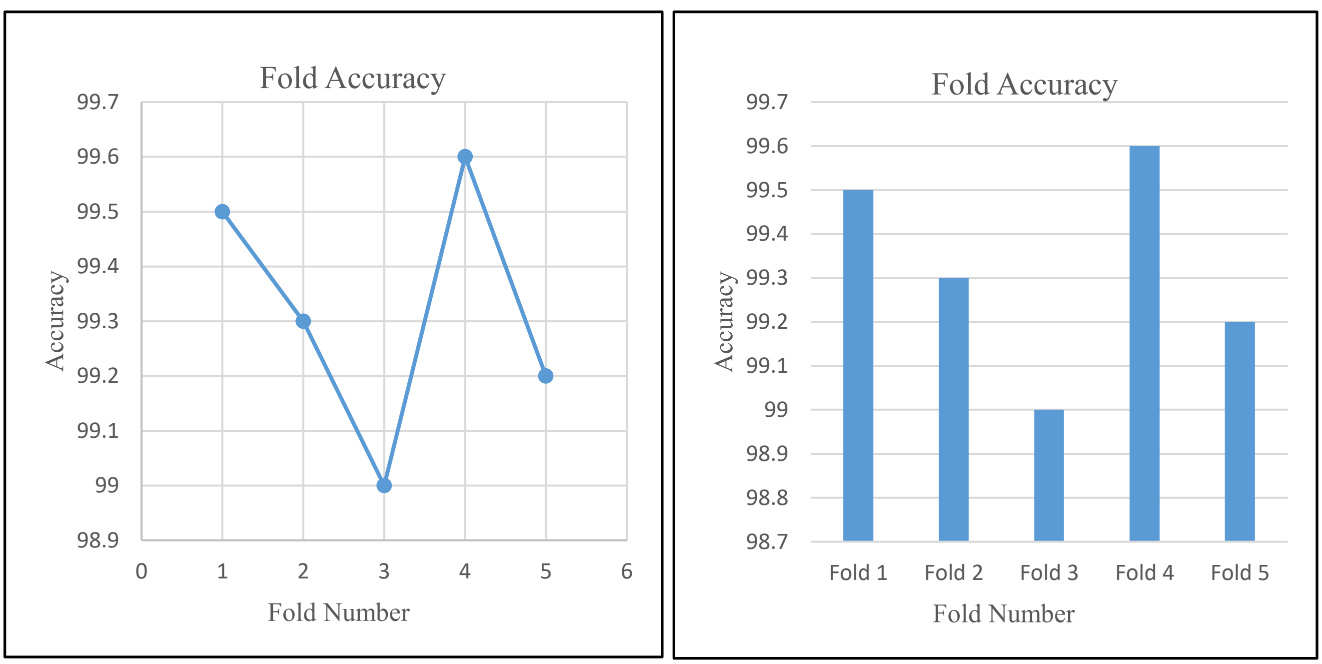


Figure. 12: Confusion Matrix of Proposed ConvNet9



(a) (b)

Fig. 13: Result of 5-Fold for Proposed ConvNet9

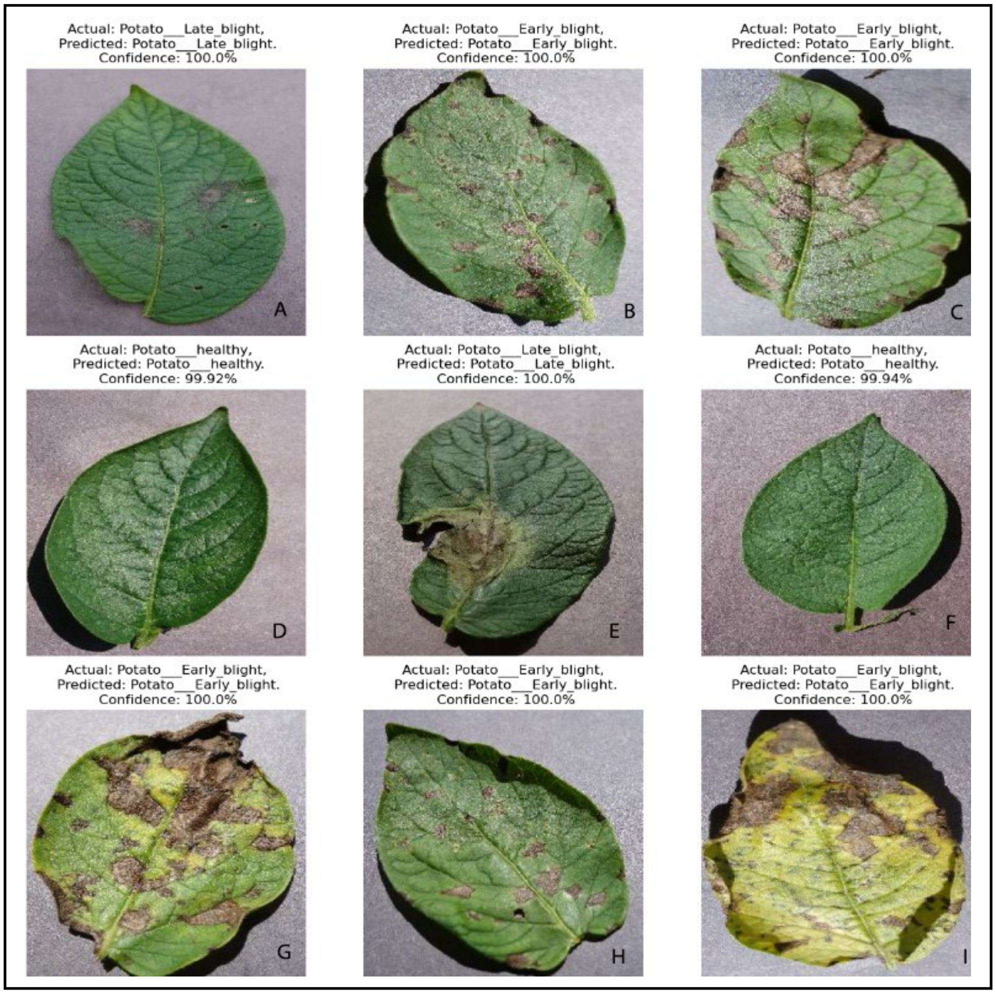


Fig. 14: Result of Proposed ConvNet9 for Healthy, Early, and Late Blight Detection

Fig. 11 shows the overall findings of Convolutional Neural Network models. Five different CNN models MobileNetV3, VGG16, VGG19, EfficiantNet, and Resnet are used, additionally proposed a custom ConvNet9 model. Accuracy, f1-score, precision, and recall were utilized to examine the model's outcome. In this experimental research, ResNet achieved the highest 89% accuracy and F1-Score, but the proposed ConvNet9 model surpassed it with 99.30% accuracy and 99.20% F1-Score to identify potato leaf disease. A 5-fold cross-validation strategy on every experiment was used while dealing with the proposed CNN model to validate the experiment more accurately.

Fig. 12 demonstrates the proposed model's confusion matrix and shows each class's TP, FP, FN, and TN values independently. Where TP and TN values are high, and FP and FN values are nearly zero, this indicates that the proposed model is working well.

Fig. 13 indicates the performance of 5-fold cross-validation for ConvNet9 and shows the accuracy of the 5-fold. The mean accuracy of the 5-fold is 99.30%, showing that the suggested approach worked effectively in identifying early and late blight potato diseases.

Fig. 14 displays an overview of the findings for three classes of potato leaves. The information provided demonstrates how well the prediction algorithm classified potato leaves into three categories based on their health early blight, late blight, and healthy. The image shows that these forecasts are remarkably accurate. The expected label and the actual label coincide in every instance. The model shows high confidence in its predictions, scoring 100% in 7 out of 9 prediction results. In the context of a classification job, the lowest confidence score was 99.92%, which is very high and almost 100%.

4.3 Discussion

Potato leaf illness is a serious threat to global agriculture. Several CNN models have been presented in this research to identify potato leaf illness. We evaluate the effectiveness of five well-known pre-trained CNN models: ResNet, MobileNetV3, EfficiantNet, VGG-16, and VGG-19. In addition, we proposed building a custom CNN to categorize leaf diseases effectively. Our research indicates that, compared to the five pre-trained models, our suggested CNN based ConvNet9 model performs better in diagnosing leaf illnesses effectively. Those five pre-trained models can't alleviate the problem of disappearing gradients, and as a result, they provide accuracy levels that fall short of what's considered acceptable. On the other hand, the Proposed CNN based ConvNet9 effectively solves this issue and lowers testing mistakes in experimental settings. Consequently, the proposed ConvNet9 outperforms the remaining pre-trained models and is selected to identify potato leaf diseases.

Several investigations utilizing deep learning have already been conducted to identify potato leaf illness. In our research, we found that the PlantVillage dataset was utilized by the majority of the researchers to identify crop diseases, especially potato leaf diseases. The nature and results of the leaf disease classifications are very similar. Considering this research, we proposed a model that can precisely identify and be effective for potato leaf diseases. There is research with a similar focus, as we mentioned earlier in the chapter of Related Work. The outcome of the suggested model is shown in Table 6, and a comparison is made to earlier research on the subject of potato leaf disease identification.

Table 6: Comparing Proposed Model with Existing Work

Ref.	Dataset Name	Total Images	Model	Highest Accuracy
[18]	PlantVillage Dataset	2152	VGG16, VGG19, MobileNetV2, ResNet50, and AlexNet	98% highest accuracy with Resnet50
[22]	PlantVillage Dataset	2150+	CNN Based Model	98%
[25]	PlantVillage Dataset	-	Deep Neural Network	98%
[26]	PlantVillage Dataset	2152	ResNet101 with PCA	95.31%
[27]	PlantVillage Dataset	3000	Proposed EfficiantPNet Based on EfficiantNetV2	98.12%
[28]	PlantVillage Dataset	2000+	CNN Based Approach	91.41%
Proposed Model	PlantVillage Dataset	2152	Proposed ConvNet9 Model	99.30%

Ultimately, Table 10 indicates that, in terms of performance, the proposed ConvNet9 model outperformed other cutting-edge approaches.

From Table 6, The authors of references [18] [26] used different pre-trained CNN models, Authors [22] [28] proposed their own CNN based model, Author [25] proposed a Deep Neural Network, Author [27] suggested an EfficiantPNet model based on the efficiantnetv2 framework to detect potato leaf illness. All of this research used the popular PlantVillage dataset. In their experiment, the accuracy of all of this research was pretty good. Still, compared to these studies, our proposed model performed better and surpassed them with an accuracy of 99.30% in identifying early and late blight detection for potato leaf diseases.

5. Implementation of Web Application

Based on the effectiveness results, we also created a web tool to help farmers remotely diagnose illnesses and choose appropriate remedies. To build this website, we used HTML, CSS, and Bootstrap for front-end development. For the backend, we used Flask. Flask is a straightforward Python framework for building web applications. It makes it possible to develop and implement deep learning-based solutions that help end users predict different classifications, such as potato leaf diseases. After gathering and preprocessing the PlantVillage Dataset for potato leaf disease classification, we Train a CNN model using the deep learning framework TensorFlow. After that, we designed a user-friendly interface so that users could input photos of potato leaves and see the categorization results. We have ensured the frontend design is responsive and works on various devices and screen sizes. By continuously updating the website with security patches, performance improvements, and adding new features, our model is also capable of giving a solution to the problem. Our model can suggest supplements for disease based on classification results. The following fig. 15 is our website's workflow diagram.

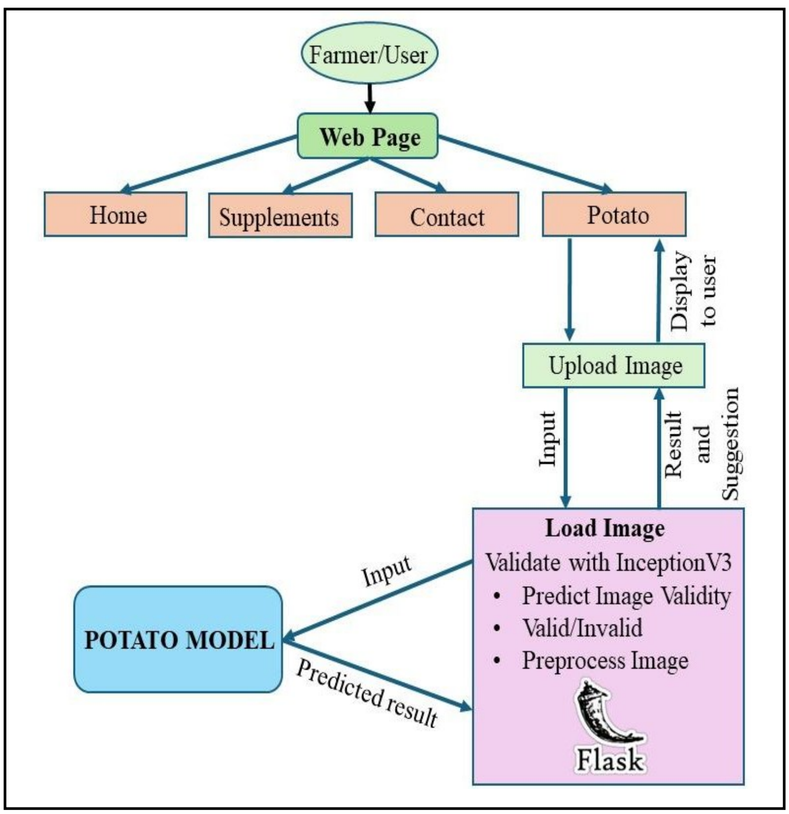


Fig-15: Workflow Diagram of Implemented Web Application

Fig. 16 displays the user interface of the implemented web application. Users begin by interacting with the web page, which features several sections: Home, Supplements, Contact, a specific Potato Plant Leaf section, and more. Users can upload images of potato leaves within the potato plant leaf section, which are then processed by the backend system. The uploaded image is first loaded and validated using the InceptionV3 model to ensure that it is suitable for validation. This validation step includes predicting the image's validity, classifying it as valid or invalid, and preprocessing the image to a specialized potato model designed to analyze potato images. The model returns a predicted result which is feedback into the backend process. Finally, the model not only indicates to the user if the plant in the picture is healthy or infected, but it also offers recommendations for a successful treatment for the sickness in the former case.

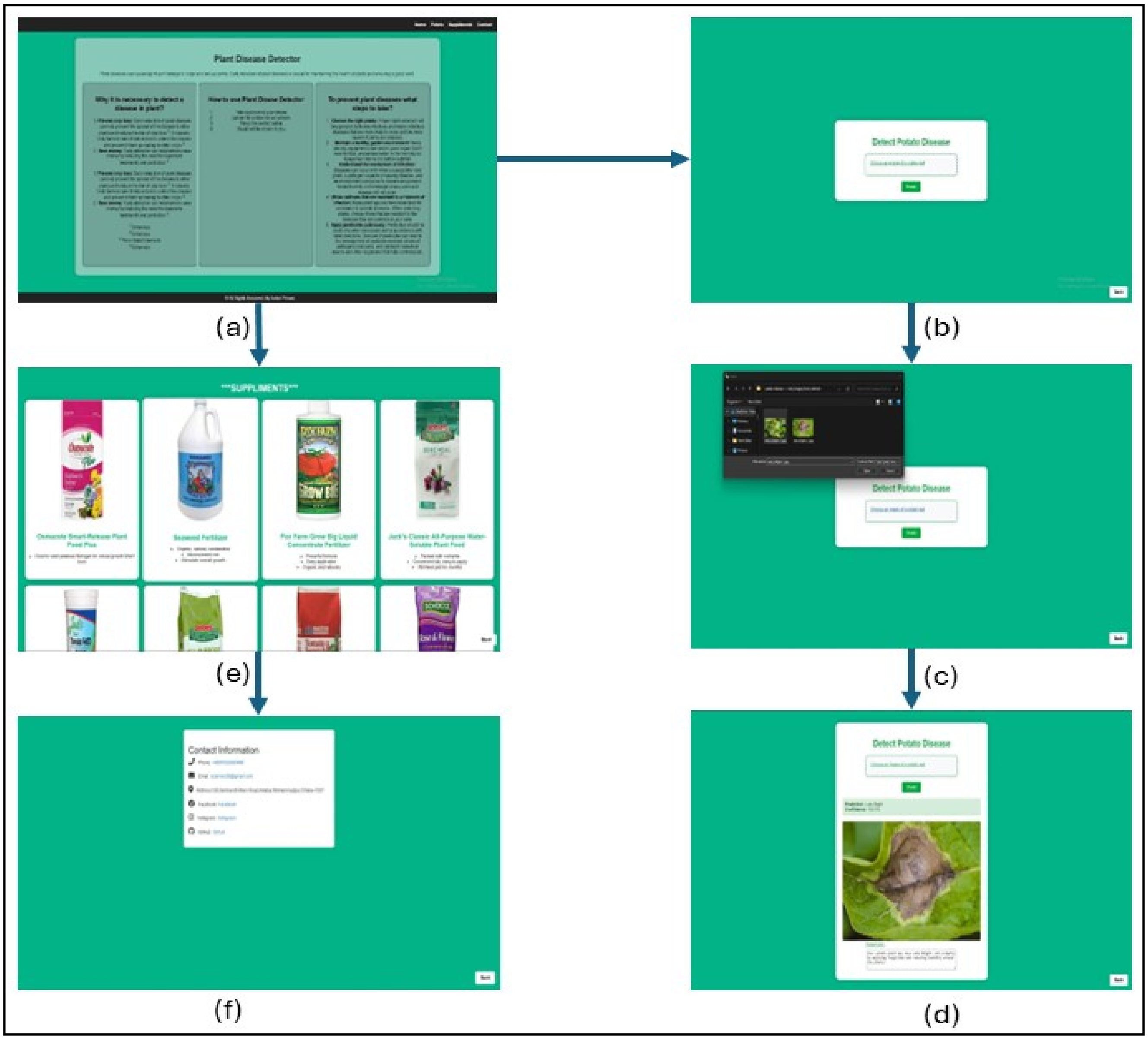


Fig-16: User Interface of Implemented Web Application

Fig. 16 also shows our implemented web application process tailored for farmers or users to upload potato leaf photos for potato leaf illness categorization and get suggestions. Fig. 16(a) shows the home page of the implemented web application. The homepage features several sections like Home, Potato Diseases Detection, Supplement, Contact, and more. Users have to select the "Potato Diseases

Detection” section to upload potato leaf images displayed in Fig. 16(b) to detect potato leaf illness. After clicking on “Choose an Image of Potato Leaf” it will open the user's local drive or gallery to select an image shown in Fig. 16(c). Upon uploading an image, it will be verified by the system; if it is not the potato leaf image, it will indicate that the image is inaccurate. If the image is accurate, the model will provide users with predictions such as "healthy," "early blight," or "late blight," along with accurate results shown in Figure 16(d). The model will also offer recommendations based on forecasts for dealing with the diseases. Users may observe that the website contains a "Supplement" section on the homepage of the website as we describe in Fig. 16(a). Users can view the recommendation provided by the model depicted in Fig. 16(e) by selecting the "Supplement" button on the webpage. Furthermore, the website has a "Contact" page to contact us shown in Fig. 16(f).

6. Conclusion and Future Prospects

Early determination of potato leaf illness is essential to protecting potatoes from disease and improving potato cultivation worldwide. Identifying and classifying potato leaf diseases is a critical and difficult task in global agriculture. This research showcases the promising potential of Convolutional Neural Network in revolutionizing agriculture through precise and efficient disease classification in potato leaves by harnessing the power of convolutional neural networks. By using the Convolutional Neural Network, we have developed this proposed ConvNet9 model and achieved 99.30% accuracy in identifying potato leaf diseases, and the proposed model was selected to build the web application. We have demonstrated not only high accuracy in leaf illness identification but also laid the groundwork for future advancements in automated agricultural diagnostics. As we continue to refine these techniques and integrate them into real-world farming practices, we pave the way for more sustainable crop management strategies, ensuring food security and agricultural prosperity in the face of evolving plant diseases. This research extends the possibilities for diagnosing potato leaf diseases and creates a baseline for future studies. Currently, the web platform is designed for single disease detection (potato leaf). In the future, we aim to develop multiple plant leaf disease detection models and integrate them into the web platform with large amounts of data. Additionally, we aim to create a mobile app version to identify several diseases in agricultural fields.

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