Convolutional Neural Network Based Approach for Potato Leaf Disease Detection

Mamta Bisht, Kumud Kundu, Gourav Tyagi, Anshul Sharma, Hardik Soni, Harsh Gupta

Department of Computer Science and Engineering (AIML), Indraprastha Engineering College, Ghaziabad, India

bishtmamta29@gmail.com

Abstract:

In India, agriculture accounts for about 17–18% of the Gross Domestic Product (GDP), and potatoes are among the most important and widely recognised staple foods worldwide. Nonetheless, the ongoing threat of potato diseases poses significant challenges to both the quantity and quality of harvests, hindering their increasing importance. Identifying diseases in crop leaves manually is both labor-intensive and inefficient. To tackle these issues, there has been a growing trend toward utilizing advanced technologies, such as image processing, machine learning, computer vision, and deep learning, for the effective diagnosis of plant diseases and pests. The adoption of these automated techniques greatly improves the efficiency of monitoring extensive farms in shorter periods. This study examines one such effective technique: a Convolutional Neural Network (CNN)-based method for detecting diseases like early and late blight on potato plant leaves. The PlantVillage dataset, obtained from Kaggle, was employed in this research, achieving a classification accuracy of 99.61%.

Keywords: *Plant disease detection, convolutional neural network, deep learning techniques, machine learning techniques, image classification.*

1. Introduction

Agriculture is the most prevalent occupation globally and plays a crucial role in the Indian economy, despite the presence of other sectors of employment. In global potato production, India ranks second, with an estimated annual output of 60.1 million metric tons in 2023. This places it behind China, which produced around 93.5 million metric tons. [1]. Globally, potatoes are an incredibly adaptable crop, ranking fourth among agricultural crops after rice, wheat, and maize. According to the 2nd Advance Estimates from the National Horticulture Database released by the National Horticulture Board, India produced 204.96 million metric tons of vegetables in FY24. Among these, potatoes are one of the major crops, ranking second in production among vegetables grown in India, as per the database. Potatoes are utilised for purposes other than food. In the textile industry, cotton and worsted fabrics are sized by using potato starch or farina. Potatoes are nutrient-dense foods that also offer health benefits, such as lowering cholesterol and reducing the risk of high blood pressure, cardiovascular disease, stroke, and osteoporosis. [2].

For a country's growth, rising demand for the agricultural sector is crucial, and there is a need to enhance traditional farming methods and techniques. In this context, this study focuses on potato, a versatile root vegetable that serves as a staple food in many households. The primary objective of this project is to classify images using Convolutional Neural Networks (CNN) to diagnose diseases in potato plants. The PlantVillage dataset, sourced from Kaggle, was used for classification. Sample images of each class (early blight, healthy, and late blight) are shown in Figure 1.

Early Blight Healthy Late Blight

Figure 1: Sample images of each class

2.Literature Survey

Research on detecting potato leaf diseases is documented in the literature, with a summary of several studies provided in Table 1. Researchers have investigated various methods using machine learning and deep learning for this purpose. Convolutional Neural Networks (CNNs) have demonstrated promising outcomes in classifying potato leaf diseases. Many studies have employed datasets like PlantVillage to train and evaluate models for identifying diseases such as early blight and late blight. Recent studies have reported accuracy rates between 95% and 99%. To enhance model robustness and performance, data augmentation techniques have been applied as shown in Table 1.

Table 1: Literature Survey

Author	Dataset	Sample size	Accuracy	Method Used
Tiwari et al., 2020 [3]	-	2152	97.8%	pretrained VGG19 model and logistic regression
Nishad et al., 2022 [4]	PlantVillage and Mendeley	2580	97%	VGG16, VGG19, ResNet50
Singh and Kaur, 2021 [5]	PlantVillage	300 (Training-210 and testing -90)	95.99%	image segmentation -the K-means methodology feature extraction - grey level co-occurrence matrix concept classification - support vector machine

Kothari et al., 2022 [6]	PlantVillage	1200 (Training-900 and Validation - 300)	97%	VGG16, GoogLeNet, ResNet50
Gaikwad and Musande, 2023 [7]	Kaggle	-	96%	CNN

3. Proposed Methodology:

Figure 2 presents a block diagram illustrating the proposed methodology. This section outlines the dataset, preprocessing steps, model development, and image classification employed in the proposed approach.

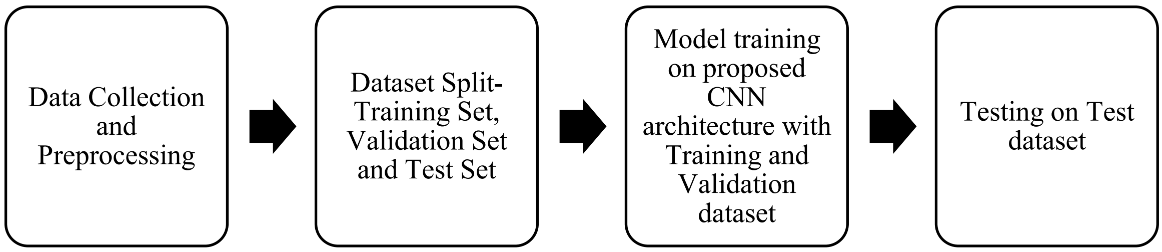

Figure 2: Proposed Methodology

a) **Dataset collection:**
The project involved categorising a collection of potato leaf images into three distinct groups: healthy leaves, early blight, and late blight. This dataset, referred to as the "PlantVillage Dataset," was sourced from the Kaggle website. Table 2 provides details on the volume of data utilised in this project.

Table 2: Dataset sample

SAMPLES	NUMBER
Healthy Leaf	152
Early Blight	1000
Late Blight	1000
TOTAL	2152

b) **Dataset Preprocessing:**
Data augmentation is the first step in increasing the amount of data and reducing overfitting. The training dataset was artificially expanded by this process, which produced realistic and varied variations in each training sample. Every image in the training set underwent a variety of transformations during data augmentation, such as small shifts, rotations, and resizing, by varying percentages. The training set was then

updated using the augmented images produced. This method improves the model's ability to adjust to changes in the orientation, position, and size of objects within the images. To further diversify the dataset, adjustments were made to lighting and contrast, and images were flipped both vertically and horizontally. Sample Augmented Images are presented in Figure 3.

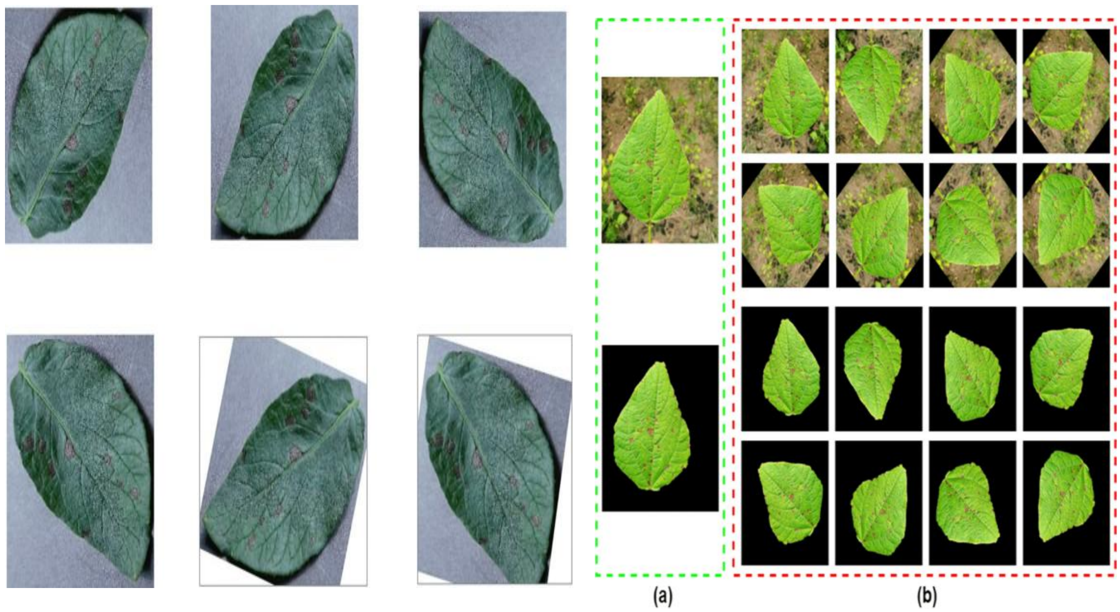

Figure 3: Sample Augmented Images

c) **Model Building and Image Classification**
The description of the proposed Convolutional Neural Network (CNN) model for the classification of images into healthy leaves, early blight, and late blight is presented in Figure 4. The input to the proposed model was a potato leaf image with dimensions of 256×256×3. After preprocessing, this input image was fed to the CNN layers.

A description of each layer and the number of parameters trained in each layer are presented in Table 3. The model consisted of 290,211 trainable parameters. This architecture enables the model to achieve high accuracy with minimal loss, while remaining computationally efficient. The framework was implemented using the Python software.

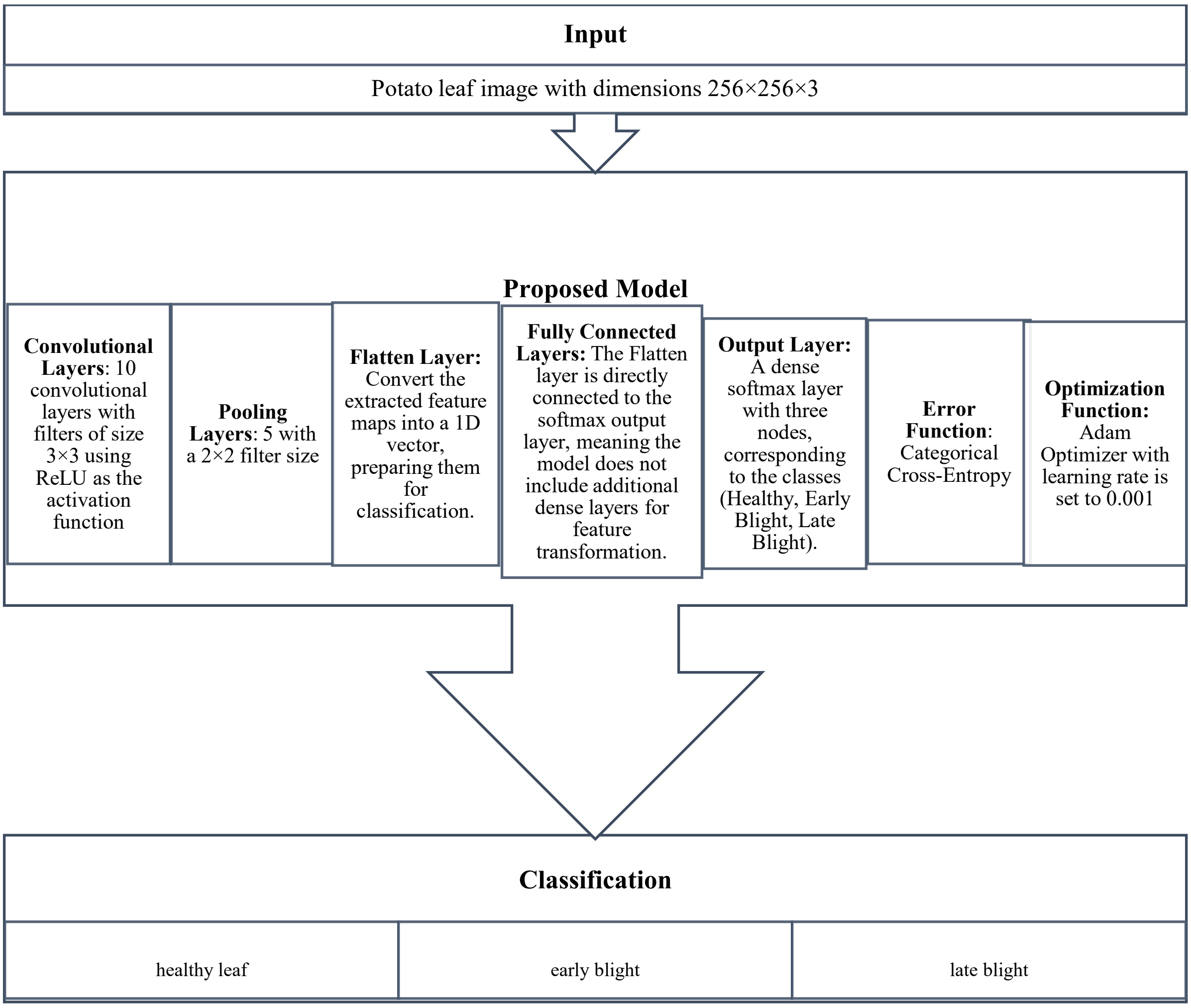

Figure 4: Proposed model

Table 3: Parameters in the proposed model

Layers	Output Shape	Parameters
Input	None, 256, 256, 3	0
Conv2D	32, 254, 254, 32	896
Conv2D	32, 252, 252, 32	9248
MaxPooling2D	32, 126, 126, 32	0
Conv2D	32, 124, 124, 64	18496
Conv2D	32, 122, 122, 64	36928
MaxPooling2D	32, 61, 61, 64	0
Conv2D	32, 59, 59, 64	36928
Conv2D	32, 57, 57, 64	36928
MaxPooling2D	32, 28, 28, 64	0
Conv2D	32, 26, 26, 64	36928
Conv2D	32, 24, 24, 64	36928
MaxPooling2D	32, 12, 12, 64	0

Conv2D	32, 10, 10, 64	36928
Conv2D	32, 8, 8, 64	36928
MaxPooling2D	32, 4, 4, 64	0
Flatten	32, 1024	0
Dense	32, 3	3075
Total params: 290,211 Trainable params: 290,211 Non-trainable params: 0		

4. Results

Our model achieved outstanding results, boasting an overall accuracy of 99.61%. The associated loss was minimal, recorded at 0.0133. The training process involved 50 epochs and took 1.75 hours to complete. During training, a total of 2700 iterations were performed, with 54 per epoch. These results underscore the effectiveness and efficiency of our approach, achieving high accuracy with reasonable execution time and minimal loss. The specifics of the training process are detailed in Table 4.

Table 4: Details of the training process

Execution time	1.75 Hours
No. of epochs	50
Total iterations	2700
Iteration per epoch	54
Accuracy	99.61
Losses	0.0133

The dataset utilised for training and testing was divided in an 80:20 ratio, as illustrated in Table 5. Figure 5 presents a graph of both training and validation accuracy and training and validation loss. The blue line represents the accuracy and loss during training, while the yellow line corresponds to the accuracy and loss during validation, as shown in Table 5.

Table 5: Dataset used in training and testing

S.No.	**Category**	**Total Sample**	**Training Sample**	**Testing Sample**
1.	EARLY BLIGHT	1000	800	200
2.	HEALTHY	152	122	30
3.	LATE BLIGHT	1000	800	200
4.	TOTAL	2152	1722	430

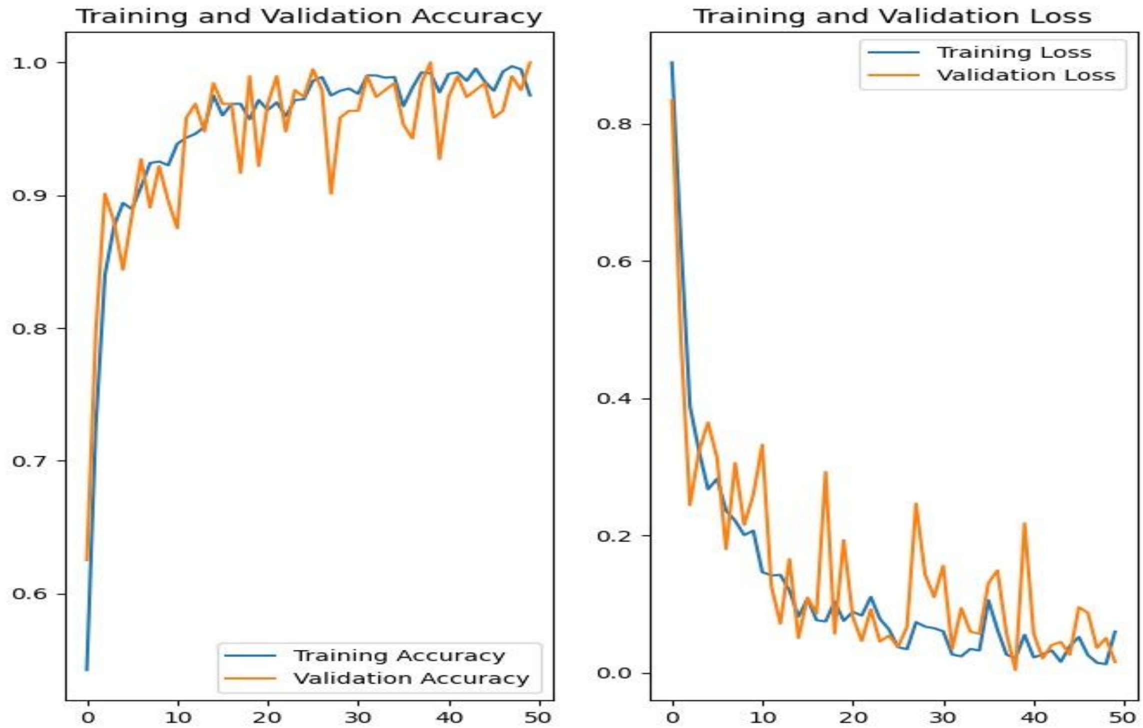

Figure 5: Training and validation accuracy and loss

The achieved results are compared with those of some existing works, as shown in Table 6.

Table 6: Comparison with Existing Results

Author	Dataset	Model	Accuracy (%)
Sofuoğlu and Bırant, 2024 [8]	PlantVillage	CNN	98.28
Lee et al., 2021 [9]	PlantVillage	CNN	99%
Saha et al., 2025 [10]	PlantVillage	CNN	99.3%
Proposed	PlantVillage	Custom 10-layer CNN Architecture	99.61%

4.Conclusion:

In this research, Convolutional Neural Networks (CNNs) were employed to develop a dependable approach for categorising the conditions of potato leaves. Achieving an impressive classification accuracy of 99.61%, our model successfully differentiated between healthy leaves and both late and early blight. Incorporating data augmentation enhanced the model's overall performance by bolstering its resilience. Our approach has significant potential to help farmers detect diseases early, thereby boosting crop yields. Future research could expand this classification method to other vital crops. Moreover, the trained model can be adapted for efficient use on mobile devices, enabling real-time testing.

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