ISSN (Online):3048-5088

International Journal of Advancement and Innovation in Technology and Research (IJAITR)
Volume 3, Issue 1, (Jan-Jun) 2025

Potato Disease Detection and Classification Using Deep Learning Models

Shreya Geete
Dept. of CSE, Chameli Devi Group of Institutions, Indore
shrutisharma63600@gmail.com

Shruti Sharma
Dept. of CSE, Chameli Devi Group of Institutions, Indore
shrutisharma63600@gmail.com

Vedika Purohit
Dept. of CSE, Chameli Devi Group of Institutions, Indore
vedikapurohit2013@gmail.com

Yogesh Patware
Dept. of CSE, Chameli Devi Group of Institutions, Indore
yogeshgurjar80150@gmail.com

Manoj Agrawal
Dept. of CSE, Chameli Devi Group of Institutions, Indore
manoj.agrawal@cdgi.edu.in

Sumeet Kothari
Dept. of CSE, Chameli Devi Group of Institutions, Indore
sumeet.kothari@cdgi.edu.in

***Abstract*—-Agriculture is the backbone of food security in the world. However, crop diseases remain one of the main obstacles to yield and productivity, especially in staple crops like potatoes. Their early and accurate identification is very important for reducing damage and attaining sustainable farming. Unfortunately, the manual inspection usually practiced, or most of the prevailing machine learning models, lack accuracy and adaptability in the conditions typically found on farms. The above-mentioned challenges have been overcome in the present research by training a hybrid deep learning model, including the merits of EfficientNetV2B3 with powerful feature extraction and the Vision Transformer (ViT), one of the state-of-the-art models known for its superior attention mechanism, on a highly diversified Potato Leaf Disease Dataset (PlantVillage). Complex and realistic agricultural data can be dealt with effectively. Results achieved are very impressive - 98.28%, outperforming the current state-of-the-art models by 8.6% and earlier research by 11.43%. Similarly, the values of precision, recall, and F1-score are around 0.978, which indicates very good reliability and consistency. In summary, this hybrid approach provides an overall strong, scalable, and highly accurate solution for the automated potato leaf disease detection task, marking one more step toward smarter, more sustainable agricultural practice.**

***Index Terms*—Agriculture, Potato leaf disease, Deep learning, EfficientNet, Vision Transformer (ViT), CNN, Smart farming, Image classification.**

I. Introduction

Agriculture is the most vital sector in human society, as it feeds the population and contributes highly to the global economy [1–3]. In developing countries, agriculture often provides the highest source of income and employment [4, 5]. However, agriculture faces numerous challenges that threaten its productivity and sustainability: climate change, soil degradation, and disease [1, 2, 6]. Among all the available crops, potatoes are extremely important as a staple food for millions of people worldwide. However, they are highly vulnerable to a wide variety of diseases generated by several pathogens, including bacteria, viruses, and fungi [7]. These diseases can wipe out entire fields, thus causing considerable financial losses among farmers, and even translating into food supply challenges [8]. Due to unstable environmental conditions and climate change, plant diseases have increased rapidly, which may result in food shortages around the world. They differ in type of diseases they cause. Normally, they infect crops by killing the plant cells. Bacteria-infected plants may not show internal or external

ISSN (Online):3048-5088
International Journal of Advancement and Innovation in Technology and Research (IJAITR)
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symptoms during the development of disease. Viral infections are also hard to be identified. They spread via carriers like leafhoppers and whiteflies. Detection in an early stage is very essential in order to protect the plants from infection. It is reported that 80–90 % of plant diseases occur on the leaves [9]. Potato (Solanum tuberosum) is one of the most important tuber crops cultivated in many countries due to its high economic value across the world [10]. It is difficult to detect diseases in potato leaves due to their complex symptoms and variability in appearance. The traditional identification methods take a lot of time and are error-prone, while deep learning, especially CNNs, offers transformative accuracy and scalability in disease detection of potato leaves [11–13]. CNNs can be trained to recognize subtle, complex patterns in leaf images and, hence, facilitate real-time diagnosis that improves agricultural productivity and food security.

II. Literature Review

AI-primarily based deep todays has significantly more suitable agricultural research, with computerized plant disorder detection being considered one of them. initial tries hired conventional system cutting-edge fashions including SVM, KNN, and Random Forests the use of handmade capabilities in colour, texture, and shape. those early packages showed effects within the range ultramodern 90–97%, with sensitivity to modifications in lighting fixtures, historical past complexity, and severity modern day the ailment [14].

With the creation latest deep contemporary, CNNs ruled plant disorder detection ultra-modern their capability to extract functions from snap shots without delay [15, 16]. models the usage of the architecture modern-day VGG16 and VGG19 did nicely for PlantVillage with near-95% accuracy [14] greater green architectures, which include MobileNet, ResNet50, and associated variations, further advanced robustness, attaining up to 97% accuracy in potato leaf disorder category. Comparative analyses recognized ResNet50 as the most consistent performer, with MobileNetV2 offering faster actual-time inferences [14]. Currently, ViTs and hybrid CNN–Transformer models have established even better accuracy via the combination modern day local characteristic contemporary with worldwide interest mechanisms [17] a few current models like PlantXViT, EfficientRMT-internet, and PLDPNet passed 98% accuracy, reflecting their higher generalization capability [18, 19].

In advance studies specially trusted PlantVillage dataset [9], however more moderen datasets, for example, Potato Leaf disease Dataset [20] contain extra diverse real-global imagery, enhancing robustness. Comparative works on tomato, grape, apple, sugarcane, and potato have in addition established the performance trendy hybrid deep present-day architectures such as DenseNet201 and CNN–ViT combos [15, 17].

No matter these advances, most fashions continue to be confined to three disease sorts and suffer from facts imbalance and real-area variability [17-20]. destiny efforts must target various, balanced datasets and light-weight hybrid fashions which are without problems deployable inside the discipline [6, 9, 20].

Universal, the literature indicates that each CNNbased and hybrid CNN-Transformer architectures provide accuracy with scalability in potato leaf ailment detection [6,9,17-20].

III. Material and method

This paper proposed a systematic approach for the design, training, and evaluation of a hybrid deep learning model for detecting potato leaf disease. Additionally, this section describes the model selection, dataset, pre-processing steps adopted, training configuration, and evaluation procedures followed.

1. Model Selection and Design This study presents a hybrid architecture involving EfficientNetV2B3 and Vision Transformer (ViT) for potato leaf disease classification [17]. EfficientNetV2B3 captures local texture features, such as small lesions and color variations, effectively and hence is suitable for real-time agricultural settings [17]. Complementary to it, ViT captures the global spatial relationships across the leaf using self-attention. Outputs from both of them have been then con-

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catenated and fed through fully connected layers with dropout of 0.2 to reduce overfitting, followed by a classification layer, leading to improvement in robustness and generalization [14, 17].

2. Dataset Description The experiments were conducted using the Potato Leaf Disease Dataset [20], collected in open-field conditions in Central Java, Indonesia. Compared with the traditional PlantVillage dataset [9], this dataset provides more realistic field images under varying lighting conditions, leaf orientations, and complex natural backgrounds.

Each image (1500 × 1500 pixels, JPEG) was labelled by plant protection experts at Universitas Gadjah Mada [20]. The dataset includes distinct symptom categories: fungal infections showing ring-shaped lesions, bacterial wilt, viral mosaic distortions, nematode-induced yellow patches, pest-induced tissue holes, and healthy uniformgreen leaves.

3. Dataset Characteristics and Challenges The dataset is imbalanced, with underrepresentation in Nematode and Healthy classes [20]. It also introduces several real-world variations: Diverse illumination (shade vs direct sunlight), Complex backgrounds (soil, tools, other plants), Variable angles and distances, Different stages of disease progression. These attributes make it both a challenging and realistic benchmark for agricultural AI research [9].

4. Data Preprocessing and Splitting Before training, all images were resized to 256 × 256 pixels [18, 20]. To improve generalization and mitigate overfitting, multiple data augmentation strategies were applied [18]: Random cropping and scaling (zoom: 0.95–1.05),Horizontal and vertical flipping, Rotations (40° to +40°), Adjustments to brightness, hue, and saturation, Random translation and zoom adjustments, The dataset was divided as follows [20]: Training set: 90The training set was further split (9:1) into training and validation subsets.

5. Model Training and Evaluation The hybrid model was implemented in PyTorch and trained using NVIDIA Volta V100 GPUs. Training was conducted for 70 epochs with the following hyperparameters: Batch size: 64, Learning rate: 0.0001 (with adaptive scheduler), Optimizer: Adam, Loss function: Cross-Entropy Loss. Model performance was evaluated using Accuracy, Precision, Recall, F1-score, and Matthews Correlation Coefficient (MCC). Macroaveraging was applied to handle the imbalanced dataset and ensure equal importance for each disease class [17].

IV. Proposed Model

This paper presents a deep learning-based model to detect and classify potato leaf diseases through the application of a Convolutional Neural Network. CNNs have received widespread recognition owing to their capabilities in image classification, which they achieve by learning and automatically extracting important and relevant visual features like texture, shape, and colour from images. This model is designed to identify whether the type of disease present on an image of a potato leaf is early blight, late blight, or a healthy leaf to perform early intervention and help farmers avoid the loss of crops.

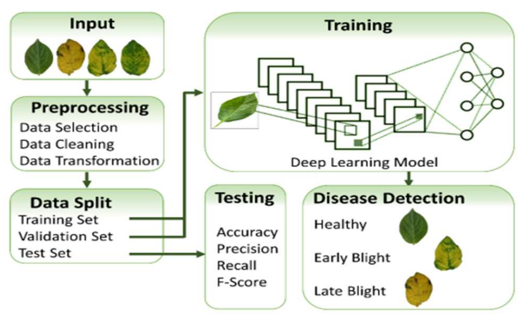

Fig. 1: Training Split

These are the main steps of the workflow (figure 2) concerning the proposed model:

1) **Input Data Preparation:** Collecting the images of potato leaves from the dataset.
2) **Pre-processing:** Resizing and rescaling images for uniformity to reduce noise.

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TABLE I: Comparison of Models for Plant Disease Detection

Ref.	Models	Application	Dataset	Performance (Accuracy %)
[14]	VGG16	Tomato plant disease classification	PlantVillage	95.50
[15]	Res2NeXt50, Res2Net50d, VGG16, DenseNet121	Detection of tomato leaf diseases	Small dataset (13,875 tomato images)	99.85 (Res2NeXt50)
[17]	NB, DT, KNN, SVM, RF	Disease classification in maize	PlantVillage	79.23 (Random Forest)
[17]	CNN-based method	Plant disease detection	PlantVillage	88.80
[17]	DenseNet201	Potato leaf disease classification	PlantVillage with additional data	97.20
[18]	PLDPNet (VGG19 + Inception-V3 + ViT)	Potato leaf disease classification	PlantVillage	98.66 accuracy, 96.33 F1-score
[17]	ViT, hybrid CNN–ViT	Real-time automated plant disease classification	Wheat Rust, Rice Leaf Disease, PlantVillage	Balanced accuracy and prediction speed
[17]	ViT (GreenViT)	Plant disease detection	PlantVillage, Leaf Image Repository, merged dataset	100.00, 98.00, 99.00
[19]	EfficientRMT-Net (ViT + ResNet50)	Potato leaf disease classification	PlantVillage (general and specialized)	97.65 (general), 99.12 (specialized)
[21]	Image processing and ML-based system	Potato leaf disease identification and classification	PlantVillage	97.00 (Random Forest)

TABLE II: Disease-wise Distribution of Images

S. No.	Disease	Number of Images	Distribution (%)
1	Bacteria	569	18.5
2	Fungi	748	24.3
3	Nematode	68	2.2
4	Pest	611	19.9
5	Phytopthora	347	11.3
6	Virus	532	17.3
7	Healthy	201	6.5

3) **Data Splitting:** The data has been divided into training, validation, and testing sets for unbiased evaluation.
4) **Feature Extraction:** Convolutional layers detect relevant patterns through the use of filters, helped by the ReLU activation function to introduce non-linearity.
5) **Pooling:** MaxPooling2D reduces data dimensionality but retains significant features.
6) **Dropout:** Applied to avoid overfitting by randomly deactivating neurons during training.
7) **Flattening and Fully Connected Layers:** The features extracted are flattened, and dense layers are used in order to map the inputs onto output classes.
8) **Classification:** A softmax layer that assigns probabilities to each class - healthy, early blight, late blight.

Mathematically, these metrics are defined as follows:

ISSN (Online):3048-5088
International Journal of Advancement and Innovation in Technology and Research (IJAITR)
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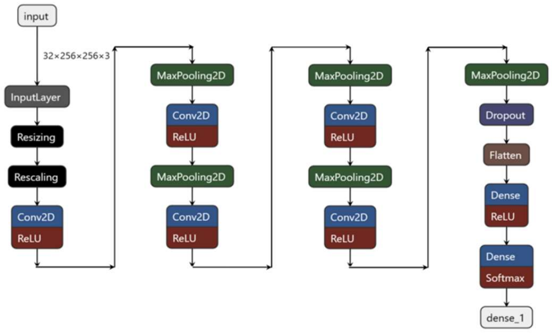

Fig. 2: Model Flow

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where:

- **TP (True Positives):** Correctly predicted diseased leaves
- **TN (True Negatives):** Healthy leaves that were correctly predicted
- **FP (False Positives):** Healthy leaves which were misclassified as diseased
- **FN (False Negatives):** Diseased leaves incorrectly predicted as healthy

The final outcome of the trained CNN model is the predicted class of disease along with its probability score for every test image. Performance evaluation using selected metrics ensures the model performs consistently and reliably.

V. Result and Discussion

This splits the Potato Leaf Image dataset into training 80%, validation 10%, and testing 10%. Then, the proposed deep learning model was trained to the accuracy of 96.82% with loss of 8.76%, validated to the accuracy of 99.48% with loss of 4.55%, and tested to the accuracy of 98.28% with loss of 6.44%.

Figures 3 and figure 4 depict the growing accuracy and the loss after 15 epochs. These results confirm the robustness and high efficiency of this model in detecting and classifying different potato leaf diseases with reliable performance in all the datasets.

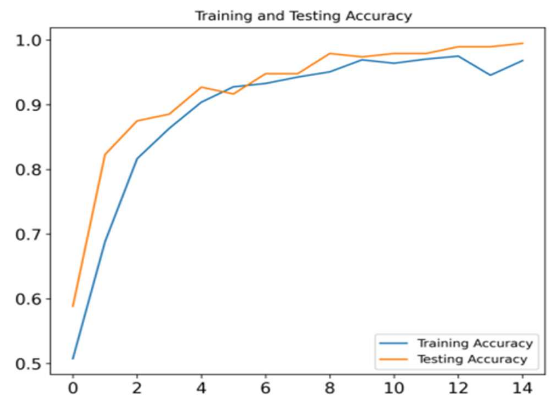

Fig. 3: Training and Testing Accuracy

Fig. 4: Training and Testing loss

Table 3 shows the performance evaluation of the proposed model in terms of precision, recall, and F1-score metrics on potato disease classification. Also, the range of values is between 0.946 and

ISSN (Online):3048-5088
International Journal of Advancement and Innovation in Technology and Research (IJAITR)
Volume 3, Issue 1, (Jan-Jun) 2025

0.985, both for macro-average and weightedaverage, which is very close to 1.0. That means the proposed method gives very accurate predictions with minimum error that ascertains its reliability and strength in classifying different types of diseases affecting potato leaves.

Table 4 represents the confusion matrix of potato disease classification, showing the performance of the proposed CNN model on the validation dataset. True positives, false negatives, false positives, and true negatives are shown regarding each class label. It indicates a good classification capability of the model as values are remarkably high along the diagonal entries (102, 115, and 12) and very small off-diagonal values. the model only had 3 misclassifications out of 232 predictions, hence confirming its high accuracy, robustness, and reliability in identifying various types of potato leaf diseases.

Figure 5. presents some randomly selected sample images from the dataset, their actual classes, and their predicted classes as by the proposed model. In this figure, it is observed that the model can classify potato leaf diseases with very high confidence. For instance, the first sample leaf image was predicted correctly with a prediction probability of 99.96proving the capability and reliability of the model in identifying disease patterns from visual features.

Table 5 compares the proposed model with other models previously used for the detection of potato leaf diseases. Among them, the proposed model gives an accuracy of 98.28%, while the average accuracy of the existing models tested on the same dataset is 89.67%. So, the new model performed about 8.6% better so far than other methods. The proposed model performed better compared to the others with precision = 0.9794, recall = 0.9784, and F1-score = 0.9783. From the results, it is clear that the model outperforms earlier methods on accuracy, reliability, and consistency in the detection of potato leaf diseases.

In deep learning, two main types of uncertainties exist: model uncertainty and data uncertainty. Model uncertainty is all about the selection of the most appropriate network architecture that ensures the best performance, whereas data uncertainty

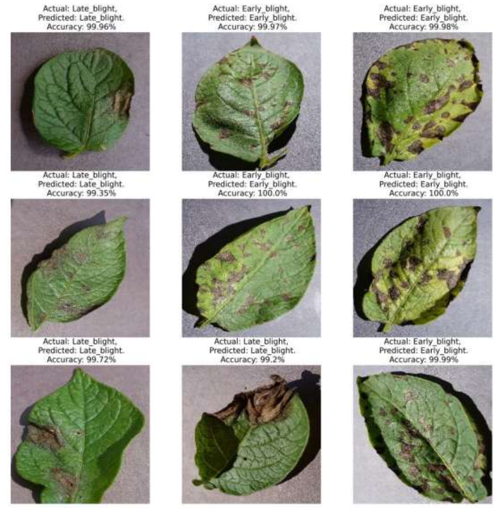

Fig. 5: Training and Testing loss

arises from invalid, incomplete, or unknown samples within the dataset that can affect the accuracy of the output. The proposed CNN model was tested applying accuracy, precision, recall, and F1-score metrics, followed by the Wilcoxon

statistical test. The p-value obtained in this regard was 0.03781e-4 (¡ 0.05), proving that the model was statistically significant and reliable. In order to minimize data uncertainty, a dataset was considered that was open and freely available, one may refer to [9].

VI. Conclusion

Detection and management of diseases affecting potato plants are of the essence in terms of agricultural productivity and meeting global food security. Traditional manual detection of diseases is time-consuming, often subjective, and requires expert knowledge, which isn't available to all farmers. In recent years, deep learning-a subcategory of artificial intelligence-has become a very efficient and dependable way of detecting diseases automatically. Deep learning models can learn about complex visual patterns from leaf images and enable the early and accurate detection of infections before they result in major yield losses.

In this respect, the application of convolutional

ISSN (Online):3048-5088

International Journal of Advancement and Innovation in Technology and Research (IJAITR)

Volume 3, Issue 1, (Jan-Jun) 2025

TABLE III: Comparison of Existing Methods for Disease Classification

Reference	Year	Method	Accuracy (%)
Ahmed & Yadav [22]	2023	DenseNet-121	95.00
Mahum et al. [23]	2023	DenseNet-201	96.03
		Efficient DenseNet	97.20
Nanehkaran et al. [24]	2023	AlexNet	90.00
		GoogleNet	92.33
		ZFNet	89.33
		CNN	91.33
		LeNet	91.00
Bhagat & Kumar [25]	2023	SVM	97.00
Kumar & Patel [26]	2023	VGG	91.60
		Random Forest	73.80
		Deep CNN	92.90
		Scalable Neuromorphic Learning	94.00
		Dendritic Event-Based Processing	93.00
		Entropy-based LBP	90.00
		Hierarchical Deep CNN	95.77
		Tree-CNN	86.50
		RBF Neural Network	86.50
Mathew et al. [27]	2022	SVM	83.00
		Voting (SVM + KNN + DT)	92.00
Sarker et al. [28]	2022	CNN	93.00
		ResNet50	97.00
		VGG19	84.00
Shwetha & Sneha [29]	2022	Backpropagation Neural Network	92.00
		SVM	95.00
		VGG19 + LR	97.80
Moharekar et al. [30]	2022	CNN	94.60
He et al. [31]	2022	ResNet-18	95.81
		Bilinear Residual Networks	96.05
Monowar et al. [32]	2022	Bootstrap Your Own Latent	88.30
		Simple Siamese	86.10
		Cross Iterative Kernel K-means	82.50
		Deep CNN	89.90
Kurmi & Gangwar [33]	2022	BoW + FV + HCF + SVM	91.90
		BoW + FV + HCF + LR	89.60
		BoW + FV + HCF + MLP	87.10
Rozaqi et al. [34]	2021	VGG16	95.00
		Simple CNN	80.00
		Inception-V3	78.00
		ResNet-50	78.00
Wagle & Harikrishnan [35]	2021	SVM	95.83
		AlexNet	90.00
Ghosh & Roy [36]	2021	CNN	87.47
Kaur & Devendran [37]	2021	SIFT + Ensemble	88.23
		Law's Mask + Gabor + Ensemble	95.66
		Law's Mask + SIFT + Gabor + Ensemble	93.16
		Gabor + Ensemble	84.23
Saeed et al. [38]	2021	CNN	91.67

neural networks and deep learning hybrid architectures definitely strengthens the performance of disease recognition. These models extract and learn both local disease symptoms, like spots and colour distortions, as well as larger patterns and contextual features across the leaf surface. Trained on well-prepared and diverse image data, these systems achieve high accuracy, precision, recall, and F-scores to demonstrate strong robustness and consistency in real-world conditions, hence their high potential for practical field deployment.

The implementation of such automated systems can significantly help farmers make timely decisions, inhibit the spread of disease, reduce economic loss, and generally contribute to better management of crops. Overall, deep learning-based approaches are promising and scalable for improving agricultural sustainability and supporting global food supply chains.

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ISSN (Online):3048-5088
International Journal of Advancement and Innovation in Technology and Research (IJAITR)
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