A Robust and Accurate Potato Leaf Disease Detection System Using Modified AlexNet Model

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***Abstract*—This research addresses the economic and ecological losses caused by diseases that damage potato leaves, such as Late Blight, Early Blight, Septoria leaf spots, curly leaves, and bacterial wilt. The study utilizes machine learning and deep learning techniques to swiftly and accurately identify these diseases at an early stage, reducing damage and losses to farmers. The research focuses on four categorization groups, including three leaf illnesses and one healthy leaf, with the main goal of providing early detection of disease. The study employs three deep learning models, VGGNet16, RenNet101, and modified AlexNet, with modified AlexNet proving to be the most accurate, achieving a training accuracy of 99.97% and a testing accuracy of 61%.**

***Index Terms*—Potato leaf disease, Machine learning, Deep learning, VGGNet16, RenNet101, AlexNet, Deep learning,**

I. Introduction

Potatoes are an essential food crop that is rich in nutrients such as potassium, vitamin B6, and vitamin C and are consumed worldwide as a staple diet. With an annual production of about 51,300 million, India is the second-largest producer of potatoes in the world, behind China. Uttar Pradesh is the state that produces the most potatoes, accounting for 31.26% of the total, followed by West Bengal, Bihar, Gujarat, and Madhya Pradesh, which contribute 23.29%, 13.22%, 7.43%, and 6.20%, respectively. Despite being a nutrient-dense and inexpensive crop, the agriculture sector faces significant challenges in improving crop output rate due to plant diseases that affect both the quality and quantity of harvested crops. The identification and control of plant diseases pose significant challenges in agriculture, particularly in preventing their spread within fields. Traditional methods of visually inspecting leaves for colour and shape require extensive expertise and ongoing efforts, making them impractical for large-scale fields. However, recent advancements in deep learning have paved the way for more efficient and automated diagnosis techniques, leading to increased crop yields. By analyzing changes in symptoms, spots, colour, and other characteristics, different diseases affecting various parts of plants can be detected. In our research, we focused on potato leaf diseases and employed deep learning methods to successfully detect five specific diseases. Our study underscores the importance of automated disease detection systems in enhancing crop productivity [5] and safeguarding against widespread damage caused by various leaf diseases in potatoes, including Early Blight, Late Blight, Septoria leaf spot, Bacterial wilt, and Curly leaf as depicted in figure 1 and 2.

(a) Potato Leaf affected by Late Blight

(b) Potato Leaf affected by Early Blight

Fig. 1: Various diseases on Potato leaves

(a) Leaf rolling upward is one of the signs of potato leafroll virus.

(b) Plants that have been stunted by the potato leafroll virus.

Fig. 2: Leaf rolling upward and potato leafroll virus in plants.

II. Literature Review

Some authors have discussed how they discovered leaf diseases using different methodologies and advised using different implementations, as seen and described here. This study, Acharjee et al. [1], emphasizes the significance of the early diagnosis of plant diseases for preventing crop loss and maintaining agricultural output value. Monitoring and detecting plant diseases play a crucial role in achieving sustainable agriculture. However, accurately identifying these diseases can pose challenges. Crop production loss due to infections in India is estimated to range from 15% to 25%. In this study, Bachwenkizi et al. [3] used high-throughput sequencing and Sanger sequencing to detect and analyze the genetic diversity, recombination, and evolutionary selection pressure of sweet potato leaf curl viruses (SPLCVs) in Tanzania.SPLCVs appear to be adapting to many sweet potato genotypes and wild relatives in Tanzania, based on their great genetic diversity and expanding selection. In this paper study, A Bajpai et al. [4] focused on agricultural land. This study aimed to utilize image processing techniques to identify the diseases causing cotton leaf spots. The input photos underwent RGB pixel analysis, and the affected areas were detected using the Sobel and Canny Edge detection methods. The researchers employed an improved fast region with convolutional neural network features (fast RCNN) model, which utilized the ResNet50 architecture for feature extraction and the feature pyramid network (FPN) for feature fusion. This research by Chen et al. [6] contributed to the field of crop disease detection using object detection techniques. Artificial intelligence (AI) Chowdhury et al. [7] and computer vision can detect plant diseases early, reducing their negative impacts while addressing some of the drawbacks of constant human monitoring. In the paper, Goy et al. [8] proposed an image-processing-based approach that utilized the PlantVillage collection to classify plant types and diseases. The suggested techniques for background removal, including enhanced HSV and GrabCut segmentation, along with the implementation of deep learning models such as AlexNet and DenseNet121, achieved high accuracy rates. Jawad et al.[9] proposed the Random Forest machine learning technique to identify mango plant illnesses based on weather conditions. This recommended approach demonstrates high accuracy in identifying mango diseases.The research conducted by Joshi et al. [10] proposed a deep learning model for the identification of plant leaf diseases. This model outperforms existing approaches in terms of accuracy and efficiency, achieving a disease classification accuracy rate ranging from 93% to 95%. The implementation of this model has the potential to significantly enhance the speed and accuracy of disease diagnosis in crop production.In their research, Khalid et al. [11], used the CNN model to classify the image of the leaf as healthy or affected by early or late blight. They proposed legitimate sequential method algorithms.Our technique achieves an accuracy of 93.50%. Kianat et al. [12] provided a joint framework of feature reduction and robust feature selection for the recognition of cucumber leaf disease. This study by Kukreja et al.[13] is a valuable contribution to the field of potato disease recognition and detection using deep learning approaches. In this study, Liu et al.[14]. presented a machine learning (ML) strategy based on directly sensed crop field environmental factors through the Internet of Things (IoT) for early prediction of disease attack probability. The suggested model achieved a successful implementation, with 91% of the predictions made using the model proving to be accurate. This paper presents a method that utilizes an improved deep-learning algorithm.Muhum et al. [15] proposed a novel framework for detecting potato leaf diseases using an efficient deep-learning model.In this study, they proposed several image processing techniques that can discriminate accurately with an average accuracy of 83%. They presented a new approach to automatically detecting tea leaves in the disease of tea leaves studied in this article [16]. They proposed an algorithm to detect diseased regions in tea leaves using image clustering based on a non-dominant genetic classification algorithm (NSGA-II). They then used PCA and a multi-class SVM for tea leaf feature reduction and disease identification.Similarly, Pantazi et al. [17] provided an automated method to identify leaf diseases of crops.Researchers anticipate that this characteristic will be crucial in segmenting and categorizing plant diseases that have infected them because they are frequently cultivated and have significant economic advantages. We applied three critical measures to address the cucumber crop leaf disease, including initially improving image sample contracts using data augmentation. We lowered the feature extraction and fusion through the suggested probability distribution-based entropy (PDbE) approach. We then used the proposed Manhattan distance-controlled entropy (MDcE) to choose robust features following the serial-based fusion stage.This study by Rao et al. [19] aims to address the inefficiencies and imprecision in the current procedures for detecting and characterizing illnesses in various types of leaves. Using the LeNet model of convolutional neural networks, we are creating a web application to diagnose leaf diseases; our proposed system, utilizing deep learning, specifically the Inception v3 model, achieves an accuracy rate of 98.84% for identifying leaf diseases, making it suitable for use on smartphones. This approach is more practical for detecting illnesses in different kinds of leaves and can improve crop yields in India's agricultural industry.The authors P. Revathi et al. (2012) described a method for identifying the affected parts of leaf diseases in their study [20]. They applied an edge detection technique for picture segmentation. Additionally, they presented the Homogeneous Pixel Counting Technique for Cotton Disease Detection (HPCCDD) algorithm, which was used for disease categorization and image analysis.In this paper sholihati et.al 2020. [21] potato is a widely consumed staple food, and its demand has increased due to the pandemic. However, potato diseases can affect harvest quality and quantity. To address this, we propose a system using deep learning and VGG16/VGG19 models to classify four potato diseases based on leaf conditions. The experiment achieved 91% accuracy, demonstrating the effectiveness of the neural network approach.In this research, Prajwala et al.[23] employed the Convolutional Neural Network model architecture of LeNet to detect and classify Septoria Leaf Spot and Yellow Leaf Curl, two tomato leaf diseases frequently observed in tomato crops. The researchers obtained the dataset from the largest open-source image database, PlantVillage. The approach suggested in this study produces accuracy levels between 94% and 95%. In contrast to mutations in C5, ectopic expression of C5 causes severe symptoms and increased viral accumulation levels in plants, while suppressing its expression prevents viral reproduction and disease symptoms. The pathogenicity of TYLCV clones was enhanced by overexpressing C5 in transgenic organisms. These discoveries strengthen our knowledge of the TYLCV proteome. In their study, Yadav et al. [25] developed a convolutional neural network called ConRXG, which integrates knowledge from the PlantVillage dataset with ResNet50 and an XGBoost classifier to identify plant leaf diseases. In the paper N.Agrawal et al.[2] authors developed a highly accurate hybrid model for fraud message detection. It combines Naive Bayes, Random Forest, and Extra tree classifiers. The individual classifiers achieved impressive accuracy and precision, with the hybrid model outperforming other approaches in terms of accuracy (96.86%) and precision (99.366%).

III. Proposed Methodology

This research focuses on utilizing deep learning principles to categorize diseases affecting the potato crop of Kannuaj City. Various studies have been conducted in the past using different approaches to categorize these diseases. The proposed study involves training the model using a deep learning approach before testing it. The workflow of the study is presented in figure 3, which outlines the different stages involved in the process of training and testing the model. By leveraging deep learning principles, this research aims to develop a more accurate and reliable method for categorizing diseases in potato crops.

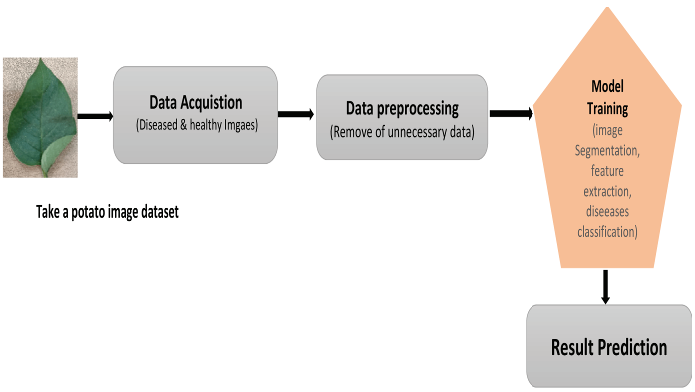

Fig. 3: Steps involved in disease detection & classification.

A. Data Acquisition

The first and most important step in training a model is data collecting. We have independently acquired and annotated data from the offline platform "Kannauj Village" picture collections. A total of 5456 photos, 1321 of which are for training and 329 of which are for testing, have been divided into healthy and diseased leaf images. There are 945 early blight training images, 1155 late blight training images, 2044 curly leaf training images, and 511 curly leaf training images. They have been split into training and testing in proportions of 80% to 20%, respectively. In addition to the healthy plant, three illnesses are detected in this article. The dataset's overall distribution is depicted in figure 4 & 5 respectively.

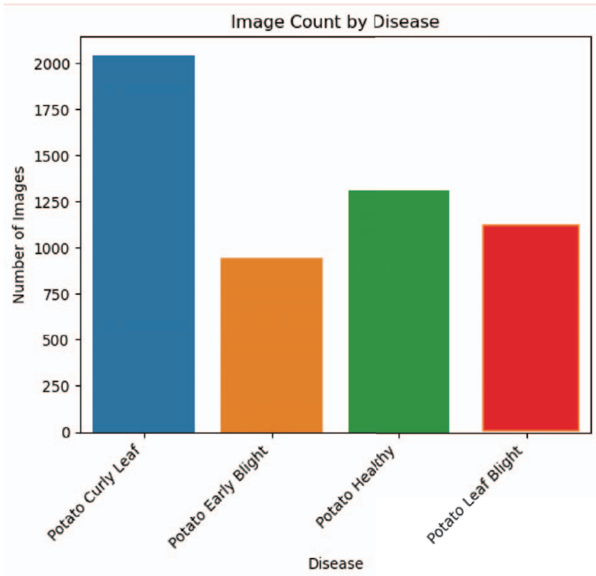

Fig. 4: Training Data Distribution

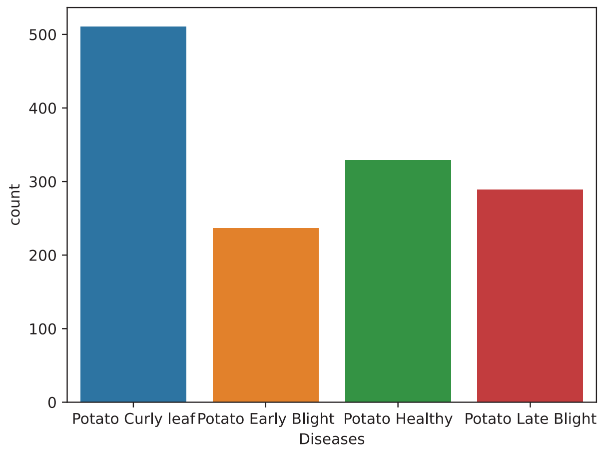

Fig. 5: Testing Data Distribution

B. Data Preprocessing

It is essential to do the preprocessing phase prior to training the model in order to remove unwanted or unneeded data and transform them into useful data. Where necessary, background noise is eliminated in this stage, and the image is enlarged to 257x257 pixels after being converted from BGR format to RGB.

C. Model Training

In this step, the entire remaining processes like segmentation, feature extraction, and classification are carried out. 5 models have been used in this paper, out of which AlexNet has the highest accuracy. The modified AlexNet architecture includes an SVM layer for classification.

1) Alexnet Architecture: It is a pre-trained model and an enhanced version of the LeNet-5 neural network, as it incorporates more convolutional layers and a deeper network with a higher number of filters per layer. [5] The architecture consists of a total of eight layers, with five being convolutional layers and the remaining three being fully connected layers. The Dropout function is also included to prevent overfitting. ReLU has been used as the activation function in this architecture, as it reduces computational expenses compared to other activation functions like tanh and sigmoid, and speeds up model training by approximately six times.

2) VGGNet16: VGGNet, also known as Visual Geometry Group Network, VGGNet16 is a specific version of VGGNet that comprises 16 convolutional layers. It stands out for its straightforward and consistent architecture. In VGGNet16, all the convolutional layers use a 3x3 filter size with a stride of 1, while the pooling layers use a 2x2 filter size with a stride of 2.

The key components of the VGGNet16 architecture [22] are as follows:

1) Input image: Typically, the input image has a size of 224x224x3.
2) Convolutional layers: A sequence of convolutional layers with 3x3 filters is applied, followed by Rectified Linear Unit (ReLU) activations.
3) Max pooling layers: Max pooling [18] with 2x2 filters is performed to reduce the spatial dimensions.
4) Fully connected layers: The network includes fully connected layers with 4096 units, activated by ReLU.
5) Output layer: The final layer employs softmax activation for classification purposes.

VGGNet16 exhibited outstanding performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014. However, compared to more recent architectures, VGGNet16 has a relatively larger number of parameters. Nevertheless, its simplicity and regularity contribute to its ease of understanding and implementation.

3) ResNet101: ResNet101 [24] is a variant of ResNet that has 101 layers. The architecture consists of residual blocks with different numbers of layers. In ResNet101, you typically have blocks with 3, 4, 23, and 3 layers, respectively. The basic building block of ResNet is the residual block, which has two convolutional layers and a skip connection that adds the input to the output of the block. This way, the network can learn the residual between the input and output.

The architecture of ResNet101 can be summarized as follows:

1) Input image: Typically, the input image has a size of 224x224x3.
2) Convolutional layer: A convolutional layer with a 7x7 filter and stride 2 is applied, followed by batch normalization and ReLU activation.
3) Max pooling layer: Max pooling [18] with a 3x3 filter and stride 2 is performed.
4) Stacks of residual blocks: The network consists of stacks of residual blocks, with 4 blocks having 3 layers, 23 blocks having 4 layers, and 3 blocks having 23 layers.
5) Global average pooling layer: Global average pooling is performed to reduce the spatial dimensions.
6) Fully connected layer: The network includes a fully connected layer with softmax activation for classification purposes.

ResNet101 achieved state-of-the-art performance on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2015 and remains widely used due to its effectiveness in handling deep networks.

IV. Result Analysis

The construction of the model was carried out using the Anaconda-3 platform of Jupyter Notebook. The accuracy of the model during training was found to be 99.97%, while the accuracy during testing was 61%. The ROC curve in figure 6 displays the trade-off between the true positive rate and the false positive rate. In addition, figure 7 and 8 depicts the graphs for accuracy versus epochs and loss versus epochs, respectively. These results indicate that the model achieved high accuracy during training, but lower accuracy during testing, suggesting a need for further refinement and optimization.

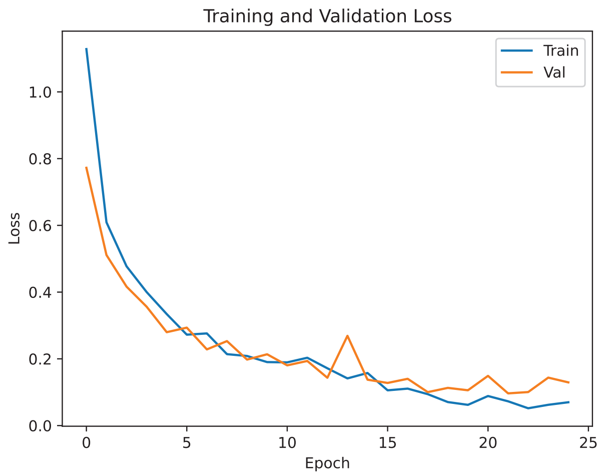

Fig. 6: ROC Curve

The confusion matrix used to analyze the overall classification performance is presented in the figure. 9. An image of Potato curly leaf disease is given to the model &, and the output generated by the model matches with the actual disease as shown in figure 10. It shows that the training and testing of our model went well. The evaluation metrics used in this study are Accuracy, Precision, Recall, and F1-Score.

V. Conclusion and Future Scope

In conclusion, this study compared various deep learning models namely Resnet 101, and VGGNet, and proposed a modified AlexNet model, to classify potato leaf diseases. The dataset used was obtained from Kannauj Village and comprised four classes: early blight, late blight, curly leaf, and healthy leaves. Among the models tested, AlexNet achieved

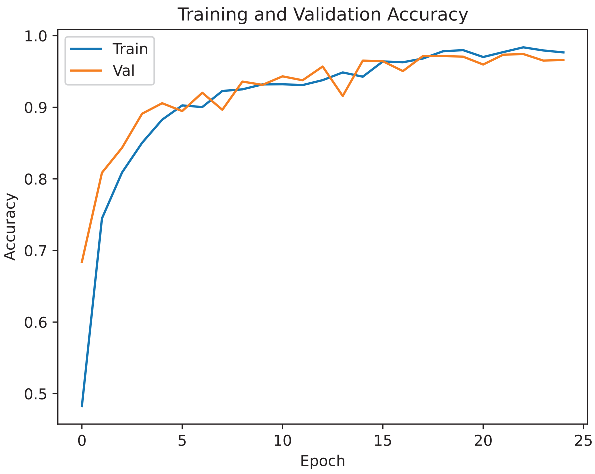

Fig. 7: Graph between Accuracy and Epochs.

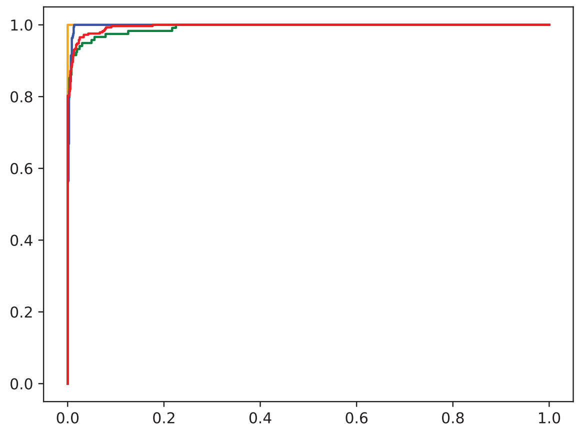

Fig. 8: Graph between loss and Epochs.

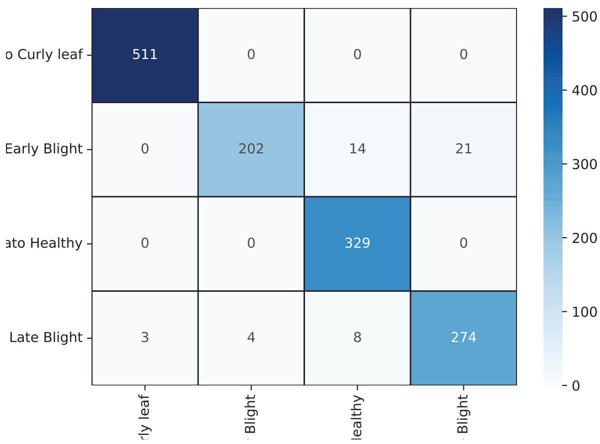

Fig. 9: Confusion Matrix.

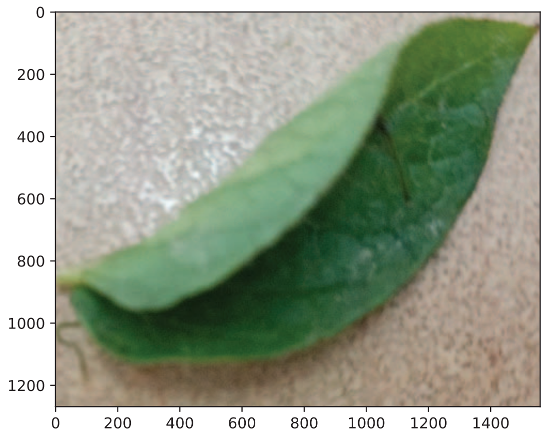

Fig. 10: Disease Checking (Curly Leaf).

the highest accuracy, as validated by the confusion matrix analysis. Remarkably, the AlexNet model achieved an accuracy of 99.97% in identifying the curly leaf disease, with a computation time of less than one second. This research highlights the potential of deep learning approaches in accurately and efficiently detecting potato leaf diseases, offering valuable insights for disease management and crop yield optimization.

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