

# **Detection of Potato Leaf Disease using CNN for High-Accuracy Diagnosis**

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Abstract: Crop production rates are a major problem for India, an agricultural nation. Low output makes the crops expensive and causes hunger for people who cannot even buy basic necessities like potatoes. Deep learning technologies can make farmers' lives easier and more productive by increasing agricultural yield and reducing crop disease infections. A subfield of artificial intelligence called deep neural networks helps farmers detect plant diseases early on, giving them enough time to take action before it's too late. Convolutional Neural Networks (CNN) are better at detecting leaf illnesses, according to this paper's evaluation of multiple studies. Additionally, CNNs have the highest accuracy in identifying diseases and are able to identify even minute patterns that are invisible to the naked eye.

Keywords— Crop Production, Deep Learning, Plant Disease Detection, Convolutional Neural Networks (CNN), Agricultural Yield, Artificial Intelligence in Agriculture.

#### I. INTRODUCTION

Good health is required to make us free from viruses and diseases, and there is one sector that makes us healthy, which is agriculture. Agriculture is a very prominent sector in most nations, including India, where the working population is in farming. Amongst the large number of crops cultivated, the potato is particularly remarkable because it makes up 28.9% of the entire agricultural crop output in India [2]. Known as the "king of vegetables," the potato is incredibly versatile and could be combined with nearly any other vegetable. They are also the most abundant and affordable source of potassium among all vegetables and fruits, according to research. With the importance of the potato, it is crucial that the population is supplied with a sufficient and fresh amount. To achieve the highest potato production, right farming practices must be used. One of the main ingredients for optimum yield is avoiding disease infection in crops. Even though farmers still detect diseases manually, it takes time and at times might not be as precise. One can save time and allow farmers to respond early if diseases are detected at the bud stage. Also, the farmers usually are unaware that their crops are under attack from diseases at the early stages due to a lack of technology available for early detection of diseases. Not only does this hinder the productivity and earnings of the farmers as a whole, but also food security and supply chains. Hence, embracing new technologies such as AI-based disease detection systems or image diagnosis can go a long way in helping farmers take timely and effective measures to protect their crops and produce healthy yields.

AI can also advance agriculture through these technologies. Deep Neural Network, a subset of AI [30], and it specifically applies to the role of predicting diseases among plants. To detect diseases in leaves, the following two concepts apply:

- 1. **Object Recognition**
- 2. Image Classification

This study aims to detect and identify potato plant diseases [13]. Potatoes are usually infected with fungal diseases like early blight and late blight [2]. The differences between a healthy potato leaf and a diseased leaf are shown in the figure below [fig.1].



Fig. 1: Healthy Leaf vs Early Blight vs Late Blight

# **II. LITERATURE REVIEW**

Over the last few years, the identification and classification of plant diseases, especially in potato plants, have been the focus of considerable research work because of their direct contribution to agricultural productivity and food security. Researchers have made use of cutting-edge machine learning and deep learning methods to build smart systems for early and precise detection of plant diseases. Such developments not only aid in reducing crop losses but also help guide farmers with proper disease management measures.

Using leaf image analysis, Hoysala et al. [3] developed a model for detecting potato leaf disease. Their system's overall



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efficiency, forecast time, and accuracy were all very good. It was discovered that the model was sufficiently stable for precision farming in real time. To identify illnesses in different plant leaves, Kumar et al. [1] presented a deep learning model built on a unique convolutional neural network (CNN) architecture. Their specialized CNN outperformed conventional machine learning techniques in recognizing complex patterns, proving the supremacy of deep learning in plant pathology. Pitchai et al. [4] offered a comprehensive method that not only recognizes plant diseases but also suggests treatments for them. Their Python-implemented model had an accuracy of 80%. To further improve crop health and productivity, the authors underlined the need for in-depth domain knowledge of plant diseases and related therapies.

In order to build efficient classifiers for the detection of potato leaf disease using RGB images, Ghosh *et al.* [9] looked into a variety of techniques. They showed how good classifiers must learn features that capture the full picture structure, not just the diseased portion of the leaf, and emphasized the necessity of vast and diverse input datasets. Jeyalakshmi *et al.* [6] compared the effectiveness of their suggested method with that of Decision Trees and Neural Networks. Their research demonstrated the value of comparative analysis in identifying suitable models to guarantee precise disease classification.

The DenseNet model was used by Madhavi *et al.* [5] to identify and categorize illnesses in the leaves of potato, bell pepper, and tomato plants. They used real-time photos taken with mobile cameras to supplement the dataset they had acquired from Plant Village. Their goal was to create a mobile-friendly, lightweight model that would enable farmers with little computing power to detect diseases while they are on the road.

Athanikar et al. [10] developed a productive and automated method for the identification and categorization of potato leaf diseases using MATLAB's Bioinformatics and Image Processing Toolbox. Farmers benefited from the proposed approach since it simplified the disease detection process and offered a reliable early intervention method. A two-phase identification method was proposed by Dhaya et al. [39] to improve the precision of Fusarium oxysporum (FO) disease detection. Their multi-layered analytical approach, which used machine learning and image processing techniques, allowed their model to outperform single-phase models and have higher prediction rates. In order to forecast future plant disease trends, Trivedi et al. [7] described a CNN-driven model that combined historical indices with field-related picture data. In addition to identifying diseases, this also offered hints about their future occurrence, which is helpful for long-term agricultural planning.

Convolutional neural networks, a type of deep learning, were demonstrated by Sharma *et al.* [11] to be an excellent method for identifying and categorizing leaf diseases. Especially for large-scale datasets, their approach produced accurate and

timely results. The outcomes confirmed CNNs' effectiveness in agricultural diagnosis. K-Means clustering was employed by Mounika *et al.* [8] to group the diseased plant leaf sections. Despite using an unsupervised segmentation method, they suggested that adding deep learning will improve classification accuracy even more, allowing for the identification of more plant disease kinds.

Deep learning neural networks are crucial for handling unlabeled and unstructured data in disease prediction, according to a review by Abulbashar *et al.* [40]. The evaluated models performed exceptionally well in predicting and categorizing plant diseases across a range of agricultural datasets thanks to the hierarchical feature arrangement. A novel CNN model architecture created especially for the early detection of potato leaf disease was proposed by Mohamed *et al.* [12]. Reducing crop loss through early disease detection and management was the main goal. Their model made clear how crucial early intervention is to reducing yield losses and increasing production.

Last but not least, Kirange *et al.* [16] identified potato leaf disease using standard image processing techniques. Through appropriate decision-making, farmers were able to decrease pesticide application and maximize crop output thanks to their system's ability to accurately classify diseases.

# **Comparison of Model Performance:**

Several machine learning algorithms have been employed with varying degrees of accuracy in related studies. The Artificial Neural Network (ANN) demonstrated an accuracy ranging from 85% to 91% as reported in [17]. The Neural Network (NN) achieved a higher accuracy of 93%, according to [38], while the Backpropagation Neural Network (BPNN) recorded an accuracy of 92% [10]. The Naive Bayes algorithm, as cited in [6], attained an 88% accuracy. Similarly, the K-Nearest Neighbours (KNN) and Support Vector Machine (SVM) algorithms also referenced in [6], reached accuracies of 94% and 96%, respectively. Moreover, object detection methods such as Single Shot Detector (SSD) and Region-based Convolutional Neural Networks (RCNN) achieved an accuracy of 94% [1]. Convolutional Neural Networks (CNN) also performed well, with an accuracy of 96.0% as presented in [3].

Studies have employed a variety of machine learning approaches with differing degrees of accuracy. According to [17], the accuracy of the Artificial Neural Network (ANN) ranged from 85% to 91%, whereas the accuracy of the Neural Network (NN) was 93%, as reported in [38]. At 92%, the accuracy of the Backpropagation Neural Network (BPNN) was marginally worse [10]. The accuracy of the probabilistic classifier Naive Bayes was 88% [6]. According to [6], the Support Vector Machine (SVM) outperformed several models with 96% accuracy, while the K-Nearest Neighbors (KNN) method obtained 94%. 94% accuracy was also attained by sophisticated object detection models such as Region-based



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Convolutional Neural Network (RCNN) and Single Shot Detector (SSD) [1]. A high accuracy of 96.0% was attained by Convolutional Neural Networks (CNN), which are frequently used in picture classification [3].

#### **III. PROPOSED METHODOLOGY**

One type of deep learning neural network that belongs to the convolutional neural network category is a convolutional neural network (CNN). CNNs are particularly effective at processing visual information since they are a ground-breaking development in image recognition technology and are widely utilized for picture classification. A CNN is a type of neural network that is specifically made to process two-dimensional input. CNNs are well-suited for picture pre-processing since images may be represented similarly. Convolution's ability to identify particular features inside a picture is one of its main advantages. It creates a feature map that shows the locations of discovered features by applying filters to the input. The networks learn the filters based on a given prediction task during training. With each application of a filter on the input array, a value is returned.

The result of this is a two-dimensional vector referred to as the features. The features are then forwarded to a non-linearity function, for instance, ReLU, before it is sent to the fully connected layer for additional processing [27]. Architecture of CNN is depicted in Fig. 3.

The structure of	а	Convolutional	Neural	Network
(CNN) is compose	d of	the	following	layers:

- 1. Convolutional Layer
- 2. Rectified Linear Unit Layer
- 3. Pooling Layer
- 4. Fully Connected Layer

#### **Convolutional Layer**

Most of the computation is done in the convolutional layer, it does convolutional operation with the help of a kernal that extracts features from an image. Together with ReLU and pooling layers this layer is responsible for recognizing important patters in an image.

# **ReLU Layer**

ReLU (Rectified Linear Unit) is a non-linearity that is added to the model through an activation function. ReLU is given by the expression:

F(x) = x + max(0,1)(1)

ReLU is used after the convolution step to provide nonlinearity in the network.

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Fig. 2: CNN Architecture

The ReLU layer increases the effectiveness of the training process by substituting 0 for all negative values. By enabling neurons to share weights, the pooling layer contributes to the reduction of feature maps' spatial resolution. It carries out tasks including stochastic pooling, multiscale orderless pooling, max pooling, and average pooling. A two-dimensional dataset is converted into a single feature vector using the flatten layer.

Neurons in the Fully Connected Layer are completely connected to those in the preceding levels. It uses the softmax function to classify images after receiving a feature vector as input. This layer uses backpropagation to reduce the error value.

The process by which a CNN detects and classifies plant leaves is shown in Figure 4. After applying the above mentioned processes to an input image that is represented as a 2D vector, the model finally classifies the image.



Fig. 3: Illustration of CNN in plant leaf detection (source adopted from [39]

The below figure demonstrates the various steps involved in image classification.



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Fig. 4: Steps Involved In Image Classification

# A. Data Collection

Data collection is the first stage in assessing and putting into practice any algorithm. The bigger the dataset, the better the accuracy of the predictions will be. The initial phase in the suggested approach is data collection, which includes gathering more than 2000 photos that show different leaf patterns, such as healthy leaves, early blight disease, and late blight disease [24] [31].

The potato leaf disease detection dataset, which has three class labels—Early Blight, Late Blight, and Healthy—is shown in the table below (Table 2). The dataset indicates how many photos are included in each category and classifies the diseases according to their type.

Disease	Disease Type	No. of Images
Early Blight	Fungal	1628
Late Blight	Fungal	1624
Healthy	No disease	1020

# B. Preprocessing:

For any given dataset, preprocessing is essential to getting correct findings [33][34]. Different patterns in images may have an impact on the classification result. This suggested technique makes sure that only the potato leaf is in focus by resizing all of the photos to the same size. Only the leaf remains for analysis once the rest of the image is cut out.

**Noise Cancellation**: Only the primary features required for classification are kept in the image before it is sent for additional processing; extraneous features are eliminated. Smoothing, lowering contrast, and emphasizing only the most significant and pertinent elements for the classification process are the goals of image filtering.



Fig. 5: Dataset (source adopted from [24])

It is very evident from the above illustration (Fig. 7) that there are no other elements in the picture other than the leaf. Because every image is the same size, the dataset is consistent.

# C. Feature Extraction:

This step is carried out after the images' noise has been eliminated. Through this method, the image's dimensionality is decreased yet the pertinent information required for categorization is retained. It also eliminates redundant features, ensuring that only the most significant 0components of the image are used for future analysis.

# D. Classification:

In this step, a picture can be classified into a certain target class label using a deep neural network or classification algorithm like ANN, CNN, or SVM. Because it is more accurate than other methods, CNN (Convolutional Neural Network) is frequently chosen for picture classification. It is the best option for this assignment because it has demonstrated the best performance in identifying patterns and features in photos.

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# IV. MODEL PERFORMANCE

#### A. Training, Testing and the Validation

In order to extract spatial information, we start by building a sequential Convolutional Neural Network (CNN) model with four hierarchical levels, each of which consists of convolutional and pooling layers. We define this foundation model and then use transfer learning to improve its performance. This entails using pre-trained weights from popular models that are accessible via the keras, applications module and the built-in keras.



Fig. 6: Validation data

```
Eroch 1/189
182/182 -
                           129e 807m/step - accaracy: 0.5518 - lass: 2.0174 - val.accuracy:
8.4858 - val.loss: 1.9648
Epoch 2/188
                         - 54a 498aa/step - accuracy: 0.6957 - 1sea: 1.7454 - val.accuracy: 0.
182/182 -
2577 - val_loss: 2.583#
Frech 1/100
182/185 -
                           55s 584me/step - accuracy: 0.7639 - Jass: 1.5575 - val.accuracy: 0.
4668 · val. Japa: 1,8958
Epoch 4/188
182/182 -
                           53s 485ms/step - accuracy: 0.7858 - loss: 1.4155 - sal.accuracy: 0.
7236 - val. has: 1.3896
Epith 5/198
182/182 -
                           536 488mm/step - annaraty: 8.8387 - 1ess: 1.2626 - val_annaraty: 4.
8197 - val.Joss: 1.1887
Epoch 6/188
182/182 -
                           548 500ms/stag - accuracy: 0.0006 - lass: 1.1278 - val.accuracy: 0.
6611 + val_less: 1.3392
Enoch 7/188
182/182 -
                           53a 450mi/step - accuracy: 0.8688 - lass: 1.8389 - val.accuracy: 0.
利田 - 111_1011: 0.9965
Enoch E/184
182/TR2 -
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3486 - val.lass: 8.4942
Froch 0/184
182/180-
                           53e 401me/step - accuracy: 0.9100 - lass: 0.8280 - val_accuracy: 0.
866 - val. loss: 0.8242
Epoch 18/188
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#### Fig.7: Training Model

#### B. Model performance

We have completed 64 epochs, and the model's progress rate is 96.79%. After the trial with random images, the instructional conference proceeded without incident. The best result of accuracy was as a whole. After breaking down the outcome and disorder grid, it is evident that our model's display is enough. Our model's display is supplied favourable.



Fig. 8: Model Performance

#### V. CONCLUSION

This paper discusses a number of studies that have helped identify potato leaf diseases through the use of deep neural networks. The potato leaf diseases are divided into two categories: Early Blight and Late Blight. From the review, it was discovered that CNN (Convolutional Neural Network) is the best approach to differentiating and classifying potato leaf diseases, such as early blight, late blight, and non-infected leaves, with the highest accuracy among other deep neural networks.

The research revealed that Artificial Neural Networks (ANN) [17] were 85% accurate, Support Vector Machines (SVM) [16] were 88.89%, and CNN [3] were 96%. Hence, it was concluded that CNN offers the highest accuracy and is the latest and most efficient technology in deep learning for image recognition and feature discrimination.

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