# Deep Leaf Detect Implementation: Utilizing CNN for Accurate Leaf Disease Detection in Agricultural Systems

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**Abstract–**Using artificial intelligence and state-of-the-art technology, the "Deep Leaf Detect Implementation: Utilizing CNN for Accurate Leaf Disease Detection in Agricultural Systems" is a cutting-edge agricultural initiative that focuses specifically on detecting the various leaf diseases. The cutting-edge method utilized in this presented research to provide automatic, real-time diagnosis of numerous leaf diseases is the Convolutional Neural Network (CNN). The system makes it possible for farmers to get timely with an efficient information about the condition of their crops by integrating CNN into the system. This ability is essential for making decisions quickly and enables farmers to carry out focused interventions, like applying the right amount of pesticides. Furthermore, the project's part on detecting the leaf diseases, aligns with the main objective of enhancing farming methods. The dataset used here contains 6000 images of tomato leaves and contains the five numbers of different diseases that occur. It acknowledges the importance of data-driven insights in well-informed decision-making, which is essential for farming that is both productive and sustainable.

**Keywords—agricultural sustainability, artificial intelligence, Convolutional Neural Network, data-driven insights, leaf disease detection.**

## 1. Introduction

To address the global challenge of feeding an expected nine billion people by the year 2050, innovative agricultural practices are required. In spite of challenges including labor scarcity, unpredictability in climate change, and volatile markets, utilizing Artificial Intelligence (AI) in smart farming methods shows promise. The beneficiaries of the National Food Security Act of 2013 have increased in India, reaching 99.51 percent in 2019–20. AI integration in agriculture offers a ground-breaking approach, especially for crop health monitoring.

This study presents a state-of-the-art agricultural system that uses AI and technology to enable farmers to monitor and control the health of their leaves. The research makes use of technologies to evaluate the specific leaf's accuracy and machine learning-driven suggestions for leaf disease identification. The principal aim is to furnish farmers with up-to-date details regarding the identification of leaf diseases.

The work uses Convolutional Neural Networks (CNN) matrices for performance analysis, with an emphasis on assessing leaf illnesses. The methodology consists of numerous essential processes, such as feature extraction, detection, classification, and pre-processing. RGB (Red,
Green, Blue) images are first preprocessed to transform them to grayscale, laying the groundwork for further investigations. The research also includes a system for diagnosing disorders of the leaves as well as suggesting

appropriate chemicals for treatment. The information appears in an easy-to-use interface with support for English. This all-encompassing strategy for using AI in agriculture is centered on improving diagnosis of disease and offering useful suggestions. Pre-processing, feature extraction, categorization, and detection are all involved in this work. The initial step in pre-processing is to convert RGB data to grayscale.

## 2. Objectives

1) Implement a system to detect diseases in leaves and recommend appropriate pesticides for treatment.
2) Perform performance analysis utilizing Convolutional Neural Networks (CNN).

## 3. Related Works

Smruti Kotian et al., [1] This study addresses the issue of cotton leaf disorders and suggests a technologically advanced solution based on KNN and Transfer Learning (ResNet50) algorithms. With an emphasis on detecting Curl Disease and Bacterial Blight specifically, the goals are to improve accuracy, develop a machine learning-based system, and offer solutions via a website. Using a "Kaggle" dataset of 2000 photos, ResNet50 obtains 95% accuracy, while KNN further classifies diseases with 86% accuracy. Benefits include shortened inspection times and expenses, accurate illness diagnosis, and possible increase in profitability. The outcomes demonstrate the methodology's effectiveness, and the new features are positioned within the context of earlier studies. With implications for enhancing output in India, this research concludes with a workable and effective method for detecting cotton leaf disease.

Kiran R. Gavhale et al., [2] By using AIML and image processing to create an effective way to identify plant leaf disorders system, the research hopes to reduce agricultural losses. Pre-processing, feature extraction, picture acquisition, and neural network classification are all as part of the methodology. The advantages and disadvantages of several classifiers, comprising support vector machines and K-nearest neighbors, are contrasted. Feature extraction is accomplished by using texture analysis techniques such as Gabor filters. Digital camera photos of plant leaves in RGB format make up the dataset. Metric analysis assesses classification methods according to their robustness, speed, and simplicity. With an emphasis on leaf texture, encouraging results demonstrate the system's potential for accurately identifying plant leaf diseases. Challenges include the impact of background data and disease-specific optimization, which point to potential directions for upcoming studies and development.

B.V.Nikith et al., [3] For the purpose of recognizing and categorizing eight disorders of soybean leaves early on, this study integrates machine learning algorithms, like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Convolutional Neural Networks (CNN). The collection consists of images of soybean leaves. SVM scored 76%, KNN 64%, while CNN achieved higher accuracy of 96%. The analysis indicates that CNN is the most effective model. While acknowledging its shortcomings—such as the need for larger datasets to improve the accuracy of SVM and KNN—it also highlights the advantages of early sickness identification for higher agricultural yield. The results underscore the necessity of prompt disease identification in mitigating addressing concerns related to food scarcity and agricultural losses.

Vaishnavi Monigari et al., [4] The study article focuses on applying SVM, CNN, and K-NN for early tomato leaf disease detection. The process

includes contour tracing, feature extraction, K-means clustering, histogram equalization, and scaled photos with abnormalities. High accuracy is attained by the suggested model: SVM, K-NN and CNN. The algorithm, which combines machine learning as well image processing, utilized to automatically identify tomato leaf illnesses, according to the study's findings. Additionally, it presents chances for additional extension and fusion method study.

Sunil S. Harakannanavar et al.,[5] Within this research, convolutional neural networks (CNNs) are utilized to examine the identification of disease in plants using a dataset of 20,639 photographs. The methodology includes image processing techniques like capture, filtering, segmentation, feature extraction, and classification. The F1-score, precision, and recall measures demonstrate that the CNN architecture attains an exceptional 90% overall accuracy. The model's ability to accurately forecast diseases in a range of plant pictures is demonstrated in the study, which significantly advances the development of artificial intelligence and machine learning methods for identifying plant diseases.

Utkarsha N.Fulari et al., [6] This work offers a useful method for identifying healthy from diseased leaves using machine learning and image processing. The goals are to use CNN and SVM to identify damaged leaves, extract characteristics, and locate unhealthy parts. With SVM, the study's accuracy is 80%; with CNN (Alexnet), it greatly improves to 97.71%. The dataset includes 12,949 photos from Kaggle and open platforms for CNN and 52 images for SVM. Benefits include accurate disease identification (80% for SVM and 97.71% for CNN). Automated plant disease identification is being developed in this research to potentially increase agricultural productivity. Different CNN models may be investigated in future study to further boost accuracy, especially in the recognition of tomato leaf diseases.

Md Humaion Kabir Mehedi et al., [7] Utilizing models from EfficientNetV2L, MobileNetV2, and ResNet152V2, this research work applies a transfer learning technique to tackle the crucial issue of early plant disorder detection in agriculture. Among the objectives are assessing model performance, developing an outline for diagnosing 38 leaf diseases in 14 distinct plant species, and combining Explainable Artificial Intelligence (XAI) with LIME for interpretability. There are 38 diseases that impact various plants in the dataset, which was obtained via Kaggle. Included in the process are preprocessing the dataset, training the model with the Adam optimizer, and evaluating performance. The XAI framework reveals the model's focus on affected leaf regions. The results illustrate the effectiveness of EfficientNetV2L and show how the dataset has to be enlarged in the coming years to include geographic data for more sophisticated farming methods.

Nishanth Shelar et al., [8] The project aims in order to produce an efficient Convolutional Neural Network (CNN) based plant leaf disorder detection system for real-time Android application, using the Plant Village Dataset as a heterogeneous training set. The method makes use of TensorFlow Lite for deployment, the VGG-19 CNN architecture, and the Image-data generating API from Keras. Among the advantages are early disorder detection and crop loss prevention; nevertheless, resource constraints and environmental sensitivity pose challenges. The study demonstrates an accuracy of 95.6% after 50 epochs. The findings demonstrate that it is feasible to identify healthy from unhealthy leaves on strawberry and potato plants. The creation of a practical deep learning-based plant leaf disorder detection system marks the study's conclusion. To guarantee that the requirements are satisfied, more research will focus on enhancing the model and expanding the dataset.

Shrutika Ingale et al., [9] This study looks on early plant disorder detection in Indian agriculture using image analysis and classification. Preprocessing of the images, disease categorization, feature extraction (gray-level co-occurrence matrix and shape features), and gradient boosting algorithm-based leaf segmentation are all included in the study. The RGB dataset addresses major challenges in agriculture by making disease diagnostics accurate, efficient, and reasonably priced. Many types of classification techniques are contrasted, comprising Support Vector Machine (SVM), Artificial Neural Network (ANN), Otsu Threshold Algorithm, K-means clustering, and Back Propagation. The results underscore the significance of morphological, color, and texture attributes in disease diagnostics, furnishing farmers with useful information and augmenting India's GDP.

Himansu Das et al., [10] This work focuses on early detection of maize leaf disease utilizing plant photos by supervised machine learning, namely Naive Bayes, Decision Tree, K-Nearest Neighbour, Support Vector Machine, and Random Forest. Using a dataset of 3,823 photos of maize plants, the study emphasizes how crucial early disease detection is in preventing losses to agriculture. With an accuracy percentage of 79.23%. Because Random Forest performs better than the others, farmers can detect infections early. The methodology includes preprocessing, segmentation, feature extraction, classification, and performance evaluation. The study's conclusion emphasizes how helpful machine learning can be in assisting farmers and provides recommendations for further study that should examine a several datasets and alternative classification methods.

Dimitrios Moshou et al., [11] To ensure that they identify vine leaf diseases, this work proposes the utilization of One Class Support Vector Machines (OCSVMs) in combined with Local Binary Patterns (LBPs). The collection consists of color smartphone photos with diseased leaves on natural backgrounds. After segmenting the image using the GrabCut technique, LBP features are taken outside the Hue plane. Using an eight-picture training set, OCSVMs are taught for each disease category (healthy, Powdery Mildew, Downy Mildew and Black Rot). Using 100 images of afflicted vine leaves for each disease, the recognition percentages for healthy plants are 100% accurate at 97%, 95%, and 93%, respectively. This study emphasizes effective early disease diagnosis while accounting for limitations in complex environments. The collection includes images of Powdery Mildew, Black Rot, Downy Mildew and healthy leaves, all of which are beneficial for precision farming.

Vijai Singh et al., [12] This study offers a genetic algorithm-based automatic picture segmentation method for identifying plant disorder. The system's objective is to increase agricultural productivity by streamlining disease surveillance through early symptom detection. The technique focuses on disease-affected areas and uses digital cameras for picture capture, preprocessing, and color segmentation using a genetic algorithm. The method achieves a high accuracy of 95.71% with the utilization of color co-occurrence data and Support Vector Machine (SVM) classification. By providing an automated, cost-effective alternative for large-scale crop monitoring, the suggested method meets the demand for prompt and effective plant disease identification.

## 4. METHODS

### 4.1. Pre-processing

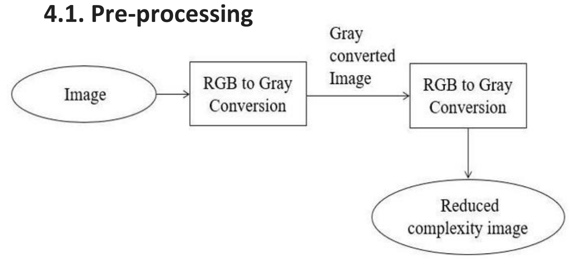


**Fig 1. Pre-processing Technique**

As shown in Fig 1, RGB photos are preprocessed to grayscale, which lowers the images' complexity.

#### 4.1.1. Conversion from RGB into Grey Scale

The initial step in pre-processing is to convert the image from RGB to Grey scale. It is obtained by applying the shown formula to the RGB image. The Fig 2 depicts the Conversion from RGB image to grayscale.

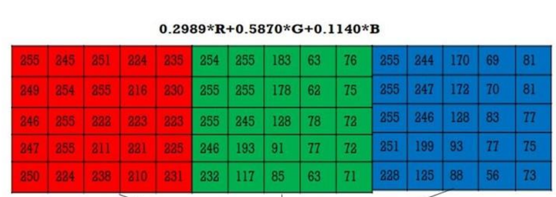

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**Fig 2. Conversion from RGB to Grayscale**

### 4.2. Feature Extraction

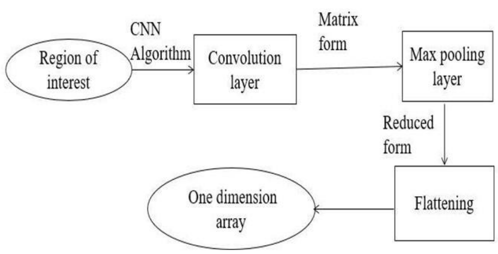



**Fig 3. Feature Extraction Technique**

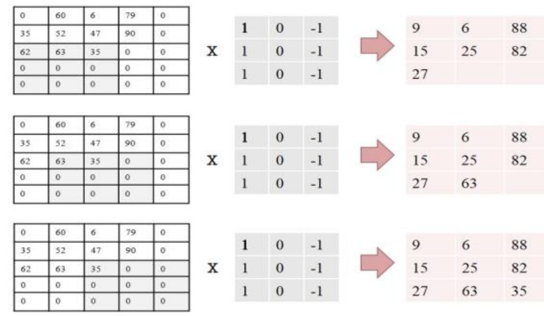
The CNN algorithm is used to reduce the image that is in RGB to grayscale. It does this by employing three different types of layers: convolutional, which reduces to a matrix form, max pooling, and flattening, whose outcome is a one-dimensional array, as illustrated in Fig 3.

#### 4.2.1. Convolutional Layer

In this layer once the computer reads the pixels of the image, it uses its convolution layers to extract a tiny portion of the images. The terms "features" and "filters" refer to these pictures or patches. The convolutional layer becomes far more adept at identifying similarities as compared to complete image matching scenes by sending rough feature matches to around the same position in the two images. When these filters and the newly input photos match, the image is correctly categorized. Here, the features and picture are aligned, and each image pixel is multiplied by its matching feature pixel. The pixels are then added together, and the total amount of pixels in the feature is divided. The filter values are placed in the appropriate places on the map. In a similar manner, we will shift the feature to each subsequent point in the image after which it is observed for how the feature corresponds with that region, as illustrated by Fig. 4.

**Fig 4. Output matrix of CNN Layer**

#### 4.2.2. ReLU Layer




ReLU, short for rectified linear unit, is the layer that eliminates any negative values present in the filtered images and substitutes them with zeros. This is done to avoid the values from summing up to zeroes. This transform function removes all negative values from the matrix and only activates a node if the input value is greater than a certain threshold. If the input value is less than zero, the output will also be zero.

##### 4.2.2.1. Noise removal

The method used to eliminate or lessen noise in an image is called a noise removal algorithm. By smoothing the complete image, the noise reduction algorithms leave areas near to contrast boundaries, reducing or eliminating the visibility of noise. Noise removal is the second step in image pre-processing. Here the grayscale image which was the outcome of the previous step is stated as input. In this process we are making use of Median Filter which is a Noise Removal Technique.

##### 4.2.2.2. Median Filtering

The median filter used in non-linear digital filtering techniques, often removes noise from an image or signal. Here 0's are appended at the edges and corners to the matrix which is the representation of the grey scale image. Then for every3*3 matrix, arrange elements in ascending order, then find the median/middle element of those 9 elements, and write that median value to that particular pixel position. The Fig 5 depicts Noise filtering using Median Filter.

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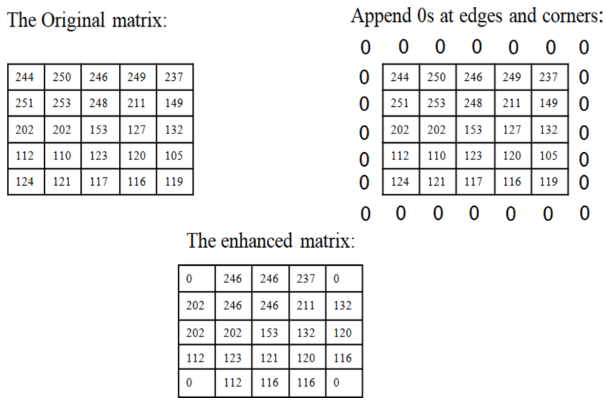



**Fig 5. Noise filtering using Median Filter**

### 4.2.3 Basic Global Thresholding

Thresholding is a type of image segmentation, where we change the pixels of an image to analyze it easily. When A(i,j) is larger than or comparable to the threshold T, it is retained. Else, it is replaced by 0. Here, the value of T can be manipulated in the frontend, to suit the varying needs of different images. We use trial and error methods here to obtain threshold values which may be best suited for us. Thresholding using basic global thresholding is displayed in Fig 6.

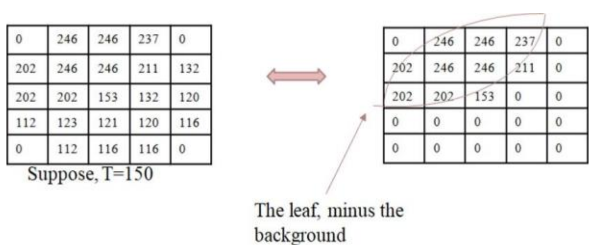



**Fig 6. Thresholding using Basic global Thresholding**

### 4.2.4. Pooling Layer

Shrink or reduce the image's size in this layer. Choose window size first, then add the necessary stride and walk your window over filtered photos. Then, extract the maximum values from each window. As an outcome,

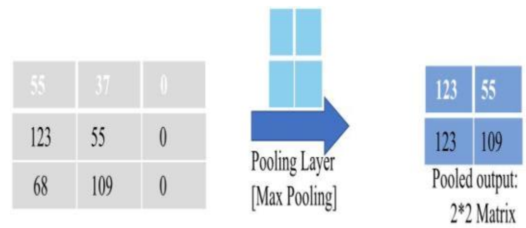



**Fig 7. Output matrix of pooling layer**

the layers will be pooled, the image and matrix sizes will decrease. As illustrated in Fig. 7, the reduced size matrix is provided as the input to the fully connected layer.

### 4.3 Classification and Detection using CNN

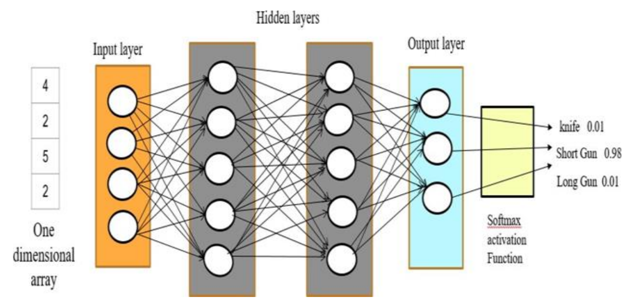
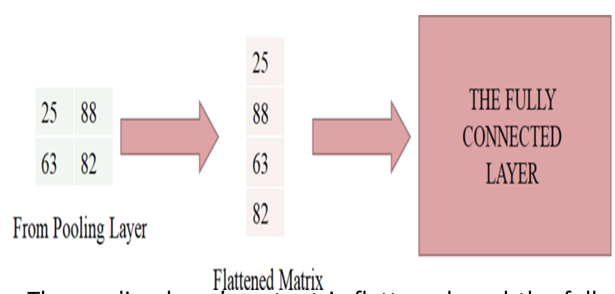



**Fig 8. Classification and detection using CNN layers**

One dimensional array is formed after passing it through convolutional layer. ReLU layer and pooling layer. In convolutional layer there are many layers. input layer, output layer and hidden layers and then the output is fed into the classifier, SoftMax Activation Function as displayed in Fig 8.

### 4.3.1. Fully Connected Layer

After the data has passed through the pooling, ReLU, and convolutional layers, all the layers must be stacked. The fully linked layer is applied to the input picture classification process. These layers must be repeated if needed unless you get a 2x2 matrix. Then, the real classification takes place in the fully connected layer.




The pooling layer's output is flattened, and the fully connected layer receives this flattened matrix. There are numerous layers in the fully linked layer, some of which are the input, hidden, and output layers. The output is then input into the classifier—SoftMax in this case—using the Activation Function to detect if railway track cracks are present in the image, as seen in Fig. 9.

## 5. ARCHITECTURE

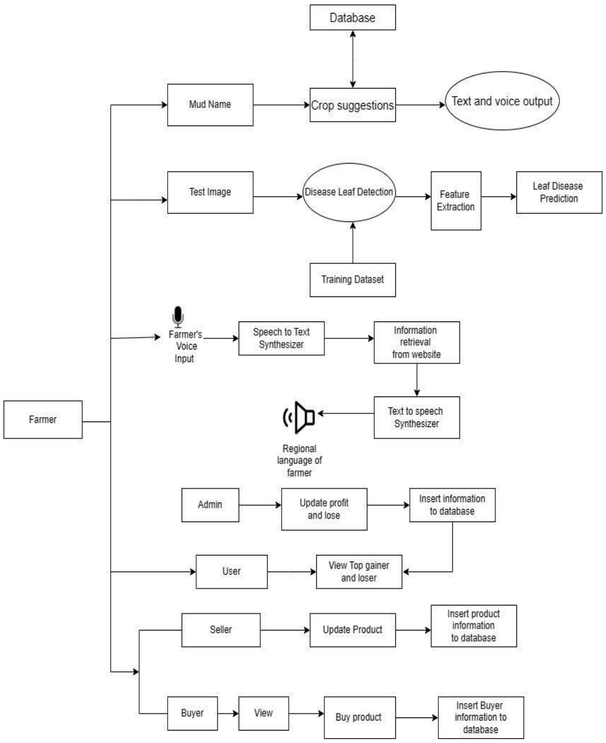
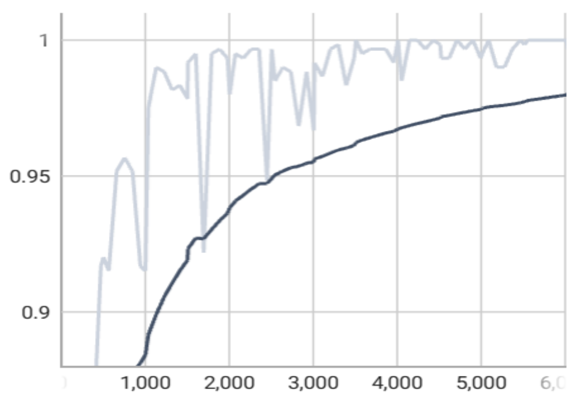



**Fig 10. Complete System Architecture**

As seen in Fig 10 the procedure for speech recognition

**Fig 11. Accuracy vs Training steps**




involves capturing and processing audio signals, extracting relevant features, and utilizing acoustic and language models to translate spoken language to written language. In parallel, the GTTS (Google Text-to-Speech) module transforms text into synthesized speech through pre-processing, text normalization, linguistic analysis, prosodic prediction, and waveform generation. Convolutional neural networks (CNNs) play a vital function in image data processing, using convolution and pooling layers to realize patterns effectively and classify images. Transitioning to an agricultural context, an e-commerce application streamlines the farmer-consumer interaction, enabling farmers to submit product information, which are then accessible to users for viewing and purchasing. The system incorporates features of an e-commerce website, providing a user-friendly interface for farmers to upload, manage, and sell their products, contributing to a seamless and efficient marketplace experience. Additionally, the system analyzes profit and loss data, displaying information on top gainers and losers, offering valuable insights to both buyers and sellers. A data flow diagram visualizes the information flow in the system, providing an outline of data processing.

## 6. PERFORMANCE ANALYSIS

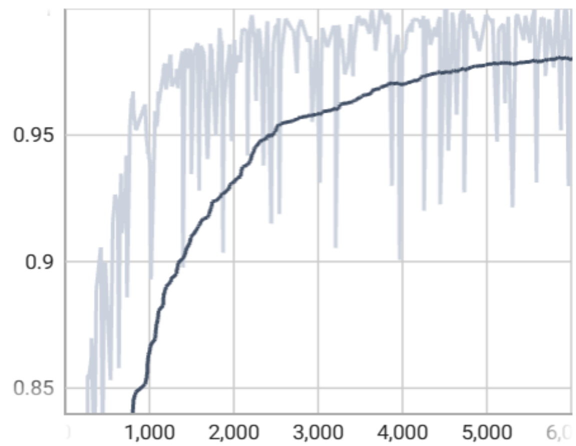



**Fig 12. Analysis of Accuracy/Validation**

The graph as displayed in Fig 11. shows the evolution of our leaf illness detection model in the accuracy vs training steps graph. First, there are rapid advances, which are followed by a plateau or convergence, showing significant feature learning. Fluctuations draw attention to the influence of regularization or model sensitivity. The record is noted for instances of overfitting or underfitting and record the final accuracy as a performance indicator. The graph helps us make changes, which improves our technique for automatically identifying leaf illness.

Considering the above fig 12. The generalization capacity of leaf disorder detection algorithm is assessed by the accuracy versus validation graph. It gives possible overfitting by comparing the accuracies of data used for training and validation. This serves as a nice addition to the accuracy versus training stages graph, which emphasizes the procedure for training. A balanced model is aided by optimization strategies like regularization and learning rate adjustment. Changes are guided for efficient automatic leaf disease diagnosis by insights from both graphs.

| Model | %Accuracy |
|---|---|
| Sunil S Harakannanavar[5] (CNN) | 90 |
| Utkarsha N.Fulari [6] (SVM and CNN) | 80 and 97.71 |
| Nishanth Shelar [8] (VGG-19 CNN) | 95.6 |
| Vijai Singh [12] (SVM) | 95.71 |
| Proposed System (CNN) | 98 |

**Table 1: Comparative Analysis of different models**

Table 1 displays the accuracy percentage for various methods. The suggested architecture provides a higher accuracy rate than the other models and architectures listed above, as the table illustrates. Thus, reducing error rates can be accomplished with the help of the suggested model.

## 7. CONCLUSION

An innovative agricultural system that uses automated leaf disease detection using convolutional neural networks. The suggested methodology outperforms current approaches with an amazing accuracy of 98%, focusing on timely and accurate insights. Pre-processing, feature extraction, and classification are important steps in the methodology that provide a reliable and accurate leaf disease detection system. A comparative study shows that our suggested system is better than other models. Optimization is guided by the accuracy versus training steps and validation graphs, which guarantee a well-balanced and high-performing model. All things considered, our research offers farmers cutting-edge instruments for effective crop management in precision agriculture, providing a state-of-the-art response to the critical problem of leaf disease identification. To further improve accuracy, future study may involve growing the dataset and investigating different CNN models.

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