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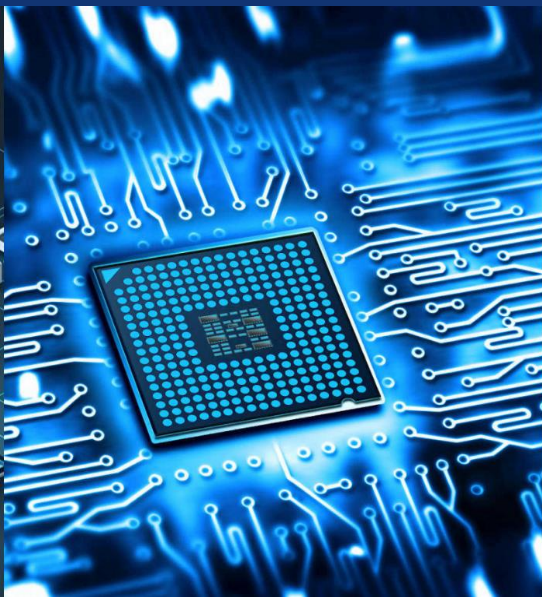


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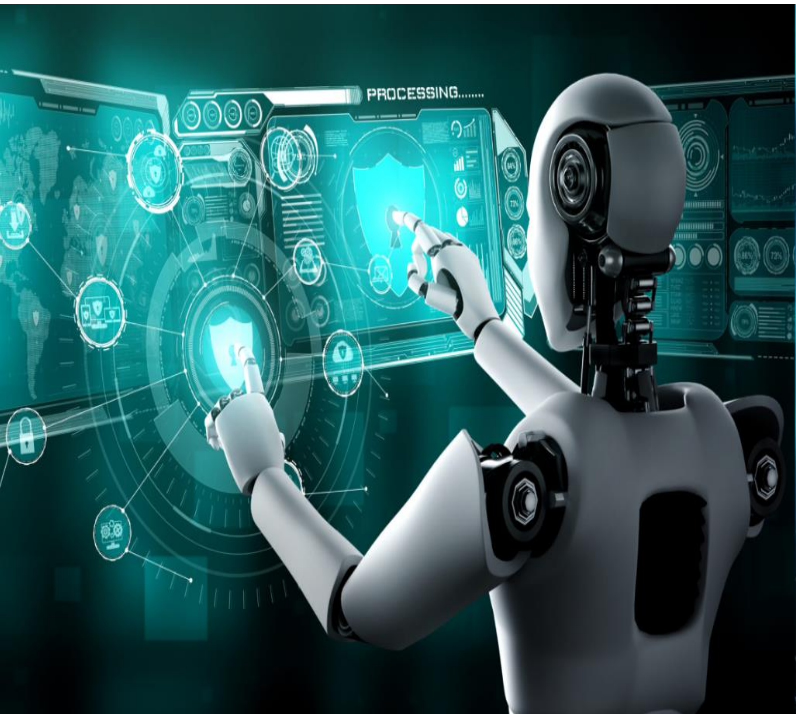

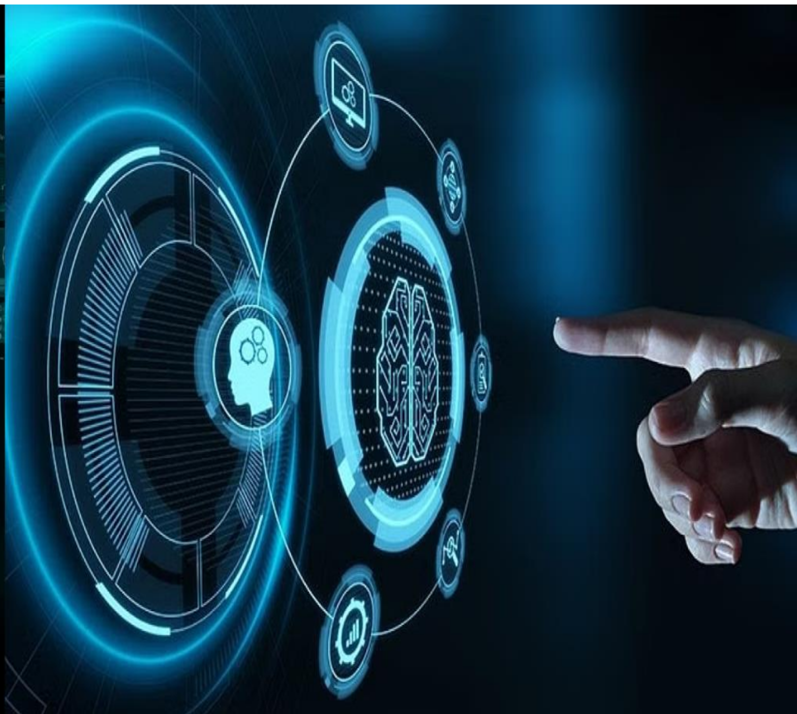

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Deep Learning Based Automated Detection and Classification of Plant Leaf Diseases Using Convolutional Neural Networks

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ABSTRACT: Detecting leaf disease is important for crops and agriculture productivity. This work describes a plant leaf disease detection and classification methodology using deep learning through Convolutional Neural Networks (CNNs). The proposed technique takes advantage of the CNN's feature extraction capabilities, thus obviating extensive feature engineering. Initially, a dataset containing images of healthy and diseased leaves of different species of plants was gathered. Training was done to the CNN model with images containing distinguishing features of healthy and sick leaves. The assessment of the model is done with accuracy, precision, recall, and F1-score. In this work, the CNN model is evaluated regarding its effectiveness and dependability against traditional machine learning classifiers. Results show that the CNN approach is superior to traditional approaches in classification accuracy and robustness, which solves plant disease detection in an automated, scalable, and effective manner at an early stage. This research can help farmers for timely disease diagnosis which can enhance their decision making regarding crop management and disease prevention. This paper performs with a Test Accuracy of 99.02%, Precision of 0.9902, Recall of 0.9902, F1 Score of 0.9902, AUC Score of 0.9926, and Specificity of 0.9951. These numbers prove that not only is the model remarkably accurate, but it is also able to tell apart the diseased from healthy plant leaves with great ease. This makes it an efficient plant disease classification tool.

KEYWORDS: Plant leaf disease detection, Convolutional Neural Networks, Classification, Deep learning, Agricultural productivity, image processing.

I. INTRODUCTION

The world of agriculture is a vital cornerstone of global economies, with crop production playing a central role in feeding the ever-growing global population. However, crop production is constantly under threat from various diseases that affect plant health , reducing yields , quality , and, ultimately, profits for farmers. Plant diseases can emerge from as a variety of a pathogens , including fungi , bacteria , and viruses , which can be challenging to detect early [1]. Traditionally, plant disease detection involved visual inspection by experts or the use of chemical treatments based on symptoms or general knowledge, which were often inefficient or inaccurate. As agricultural practices evolved, so did the need for more efficient and precise methods for plant disease detection, leading to the adoption of technology-driven solutions, such as machine learning (ML) and deep learning (DL) models, which have shown considerable promise in this domain.Convolutional Neural Networks (CNNs), is a type of deep learning algorithm , have proven to be the one of the best methods for image-based classification problems, especially in plant disease detection. CNNs are specifically developed to handle data in the form of images, which makes them a perfect fit for examining visual symptoms of plant diseases, including discoloration, leaf spots, and wilting[2]. By utilizing the use of several layers of Convolutional filters , pooling layers , and fully connected layers, CNNs can automatically learn and extract significant features from plant leaf images without any manual feature Engineering. This enables CNNs to conduct high accuracy in disease detection and classification on the basis of image data more than conventional methods that utilized manual inspectionThe best way to demonstrate the ability of CNNs in detecting plant disease is through their use on massive datasets of plant leaf images, e.g., datasets by websites like PlantVillage or Kaggle. In these datasets are images of healthy and infected leaves from

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all manner of plant species, which allows for the training of CNN models to recognize patterns that resemble individual diseases.Evidence suggests that models that use CNNs are effective at achieving high accuracy rates when detecting plant disease, with overall rates of above 90% across the majority of cases [3].With the identification of diseases including leaf rust, bacterial blight, and powdery mildew, the ability of CNNs to spot disease through identification from minor visible patterns means human observers may never perceive such indications themselves.Besides detecting plant disease, CNNs are also able to classify disease types, which are crucial in ascertaining appropriate treatment[4][17-20]. For example, some fungal diseases may appear similar on initial observation, but variations in their appearance, like lesion shape or size, can indicate variations in pathogens. By learning from enormous amounts of labeled image data, CNNs can distinguish between these seemingly similar-looking but different diseases, hence enhancing the accuracy and speed of disease diagnosis[23]. Additionally, CNN models can be integrated into mobile or web apps, making farmers have real-time disease detection capabilities easily within reach, even in areas far from the reach of infrastructure.Besides this, CNNs may be integrated with other technologies such as robots and drones that are able to capture high-resolution images of plant leaves in the field[5][21].Integrating CNNs with autonomous systems increases scalability and efficiency in plant disease detection, and this is possible to the extent that farmers are able to detect large fields of disease without physical inspection. The use of CNNs in Plant Disease Detection would be able to revolutionize agriculture, improving efficiency, accuracy, and sustainability. The paper is organized as follows:Section 2 deals with the literature Reviews of Plant laef disease detection over different deep learning networks. The materials and methods deals in Section 3 which Includes Dataset,Preprocessing and Augmentation,Architecture of Convolutional Neural Network, Proposed Methodology,Block Diagram,Flowchart and Performance evaluation. Experimental Results describes in Section 4 which includes output,Training Validation Accuracy,loss curves and Confusion matrix, Classification Report and Comparison With Existing Works and Conclusion Describes in Section 4.

II. RELATED WORK

Convolutional Neural Networks (CNNs) application in plant disease detection has been a topic of high interest since they are capable of automatically learning the significant features from images and providing good classification performance. Thakur et al. (2023) was proposed the VGG-ICNN model, a light-weight CNN model for the detection of the crop diseases, which reduces the computational complexity will get higher accuracy. The approach illustrated the possibility of efficient disease detection in farm conditions with fewer resources [5]. Prathiksha et al. (2024) also emphasized the detection of grape leaf disease using a VGG-19 based CNN model. Their research illustrated early and precise grape disease detection, thus establishing the efficacy of deep learning techniques in precision agriculture, particularly in grape farming [6].In another major research, Archanaa et al. (2023) used Convolutional Neural Networks (CNNs) in the diagnosis of diseases in tomatoes, highlighting the capability of the deep learning algorithms in making disease detection more automated and reducing crop loss. The research demonstrated the major benefits of CNN-based frameworks in the fast and accurate detection of diseases compared to conventional approaches [7].Pandian et al. (2022) also promoted the understanding of the use of CNN for the diagnosis of plant diseases, proving that the model is capable of efficiently handling a high number of diseases that infect a large number of crops. The study proved the ability of deep CNN models to improve and optimize the accuracy of disease classification, which can aid farmers in effective crop management [8].Verma et al. (2024) put forward a light-weight CNN model tailored for the detection of disease in crops like wheat, rice, and corn and proved its effectiveness with varying crop varieties. The paper highlighted the growing demand for generalized systems to detect varying crop varieties simultaneously. It highlighted the pivotal role played by CNNs as blocks of universal agriculture applications, including crop health tracking and management [9]. Khalid and Karan (2024) offered an extensive review of Deep learning models applied to the detection of plant diseases by CNN models. The study carried out generated substantial data regarding the use of various convolutional neural network (CNNs) models in agriculture production, with the emphasis on the pivotal role of deep learning in modern agricultural systems [10]. Albattah et al. (2022) were the first to combine CNNs with artificial intelligence-driven drone technology to use for the identification of diseases using aerial imaging in real time.

The combination of deep learning with remote sensing technology has proved effective as a valuable tool for precise and mass plant disease detection [11].Janakiramaiah, et al. (2021) continued with this area by applying capsule networks in horticultural leaf disease diagnosis with better performance compared to typical Convolutional Neural Networks (CNNs) due to their capacity to locate hidden detail and spatial hierarchies found in plant diseases. Kwabena et al. (2020) utilized Gabor capsule networks is to highlight the task-specific filter performance in disease classification and feature extraction, and results indicated that capsule networks were more accurate when classifying plant diseases with intricate patterns

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[12][13]. Peker (2021) further developed this field of research by proposing a multi-channel capsule network ensemble that was specifically designed for plant disease detection, where multiple capsule networks were aggregated to boost the classification outcome. The ensemble method provided an improved performance, particularly in handling intricate disease classification [14]. Lastly, Altan (2020) tested the performance of capsule networks on plant leaf disease detection, highlighting the advantage of CNNs when there is limited data, thus highlighting their capacity for larger applications in agriculture [15].

III. PROPOSED ALGORITHM

A. *Dataset*

Plant Disease Recognition Dataset comprises 1,530 images that can be utilized for the training of machine learning models towards class prediction of plant leaves as healthy or diseased. The dataset is composed of images organized into three classes: Healthy, Powdery (infected with powdery mildew disease), and Rusty (infected with rust disease). It is also divided into training, testing, and validation data to facilitate appropriate model training and evaluation. The training set consists of 458 images of healthy leaves, 430 images of powdery leaves, and 434 images of rusty leaves, with 1,322 images in total. The testing set consists of 50 images per class, totaling 150 images. The validation set includes 20 images per class, totalizing 60 images. This data has good Structure and can be used to train models for deep learning such as Convolutional Neural Networks (CNNs) for the classification of plant diseases with better generalization of the models and performance evaluation.

Table.1.Classification of Plant Leaf Disease

SI No	**Disease**	**Total Number of Images**
1.	Healthy	528
2.	Powdery	500
3.	Rust	504

(A) (B) (C)

Fig.1.Samples of images in the dataset : (a) healthy (b) Powdery (c) Rust

B. *Preprocessing and Augmentation*

The code snippet sets up image preprocessing and augmentation through TensorFlow's Keras ImageDataGenerator. Rescaling is applied to both the training and testing datasets, with pixel values (ranging from 0 to 255) scaled to the [0,1] range by dividing every pixel by 255. This ensures consistency during training and avoids large values from impacting model performance. Data augmentation is used only for the training dataset to improve model generalization and avoid overfitting.The augmentation methods are shear transformation, which warps images by a maximum of 20% along an axis,zooming, which scales images by a random factor up to 20%, and horizontal flipping, which flips images around the vertical axis. These transformations make the model learn to understand patterns instead of memorizing the dataset's specific features. The test set is rescaled only without any augmentation, assuring that the model is tested on real data and not artificially altered.

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C. *Convolutional Neural Network*

The structure of a Convolutional Neural Network (CNN) contains many layers to automatically and adaptively learn spatial hierarchies of features from input images. The basic elements of a CNN are convolutional layers, pooling layers, and fully connected layers, which collectively extract features and classify.The initial process in a CNN is the feature extraction process, which involves convolution and pooling[18]. The convolutional layer uses an array of filters (kernels) to convolve the input image so as to extract various features like edges, textures, and patterns. Every filter moves over the input, calculating the dot product of the filter and patches of the input image, generating feature maps that identify significant structures of the data. Activation functions like ReLU (Rectified Linear Unit) are usually used after convolution to add non-linearity so that the model can learn higher-level patterns.Then, the pooling layer compresses the spatial size of the feature maps without losing the most important information. Pooling aids in decreasing computational complexity and avoiding overfitting. Max pooling is the most popular pooling method, which takes the maximum value from a set of pixels within a specified window, so that the most important features are kept while noise is minimized.[19]

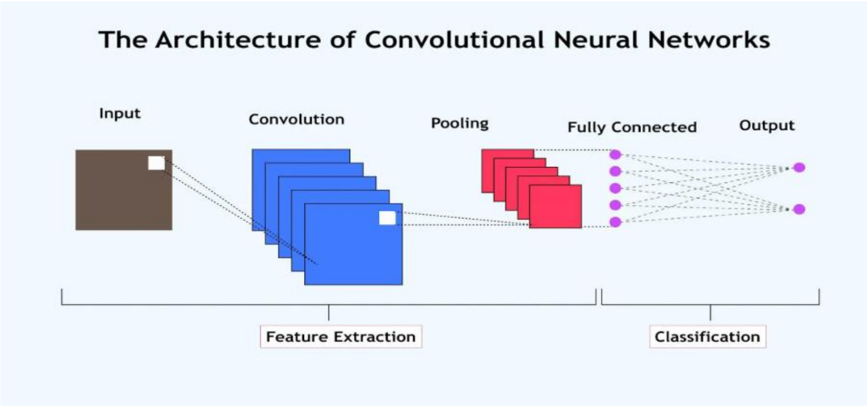

Fig.2.The Architecture of Convolutional Neural Networks[22]

The final step is the classification stage, where the features are flattened into a single-dimensional vector and fed through one or more fully connected layers. The fully connected layers are akin to standard neural networks in that the neurons connect with all of the activations of the previous layer.The final fully connected layer applies the softmax activation function to produce probability scores for every possible class so that the CNN[25] can identify the input as belonging to the proper category.In general, CNNs are very effective at image recognition and classification because they can automatically learn and extract features with little human feature engineering. They have been extensively used in tasks like object detection, medical image analysis, and autonomous driving.[20][24]

D.*Proposed Methodology*

The Plant Leaf Disease Detection process consists of several critical steps that cumulatively form a robust model capable of effectively identifying diseases in plant leaves, such as rust and powdery mildew. Initially, a large and diverse set of plant leaf images is collected, both healthy and infected with a variety of diseases, thus there is excellent representation of plant species, signs of diseases, and conditions.These data are used to train, validate, and test the Convolutional Neural Network (CNN).The images are normalized at preprocessing by fixing their size, removing noise, color normalizing, and possibly converting to grayscale to emphasize significant features. These image Augmentation techniques of rotation, flipping, cropping, and brightness levels, are applied next to artificially inflate the dataset and prevent overfitting to allow the model to generalize to unseen data. In training, the CNN is able to learn hierarchical features like shapes, textures, and color patterns from the images, needed to distinguish between healthy and diseased leaves, and optimization methods like gradient descent are employed to modify the model weights. Validation is done on another subset of the data to test intermediate performance, tune hyperparameters, and avoid overfitting so the model does not memorize training data. After training and validation, the CNN is a trained model that can classify leaf images into disease and health classes.The model is then tested and proved with another set of unseen images to determine its accuracy, precision, and overall Reliability in real-world use. The model categorizes every input image into pre-defined classes according to the characteristics the CNN learned during training, e.g., Healthy, Powdery Mildew, or Rust. Performance is measured through Metrics such as accuracy, precision, and F1 score to assess the performance of the model in correctly detecting

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plant diseases. . Lastly, the system generates output classes by identifying each of the input images either as healthy or having powdery mildew or rust disease, providing an important resource for agricultural experts to detect plant diseases and implement required measures to control them.The flowchart in figure 4 describes the Convolutional Neural Network (CNN) procedure to detect plant leaf disease.

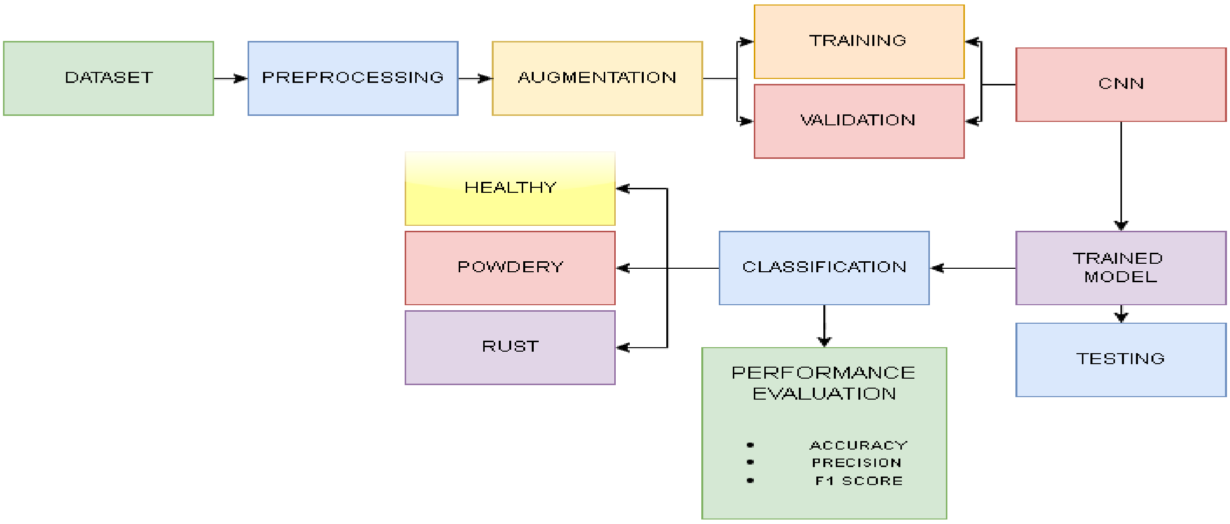

fig.3.Block Diagram of Classification Plant Leaf Disease

It begins with data gathering, where plant leaf images (both healthy and diseased) are gathered. Next, cleaning data is performed by removing Blurred or poor-quality images to ensure high-quality input for a model training.The images are next sub-classified by agricultural professionals on the basis of severity to categories like Healthy, Powdery, and Rust. TheData Augmentation methodologies such as rotation, flipping, and scaling are used to enhance model generalizability. A test input image is then fed into the trained model for classification, and the model's performance is evaluated using precision, recall, F1-score, and accuracy. Based on the evaluation, the best-performing model is selected and further customized by integrating new dropout and dense layers with modified filter widths for enhanced performance. The customized model undergoes retraining and evaluation to ensure improved accuracy. Finally, the optimized model is analyzed in the result analysis phase, ensuring that it effectively classifies plant diseases, making it a reliable tool for automated plant health assessment.

E.*Performance Evaluation*

1. Accuracy

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

2. Precision

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

3. Recall

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

4. F1 Score

$$F1 - Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$

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where TP (True Positive): Correctly classified positive cases.TN (True Negative): Correctly classified negative cases.FP (False Positive): Incorrectly classified negative cases as positive.FN (False Negative): Incorrectly classified positive cases as negative.

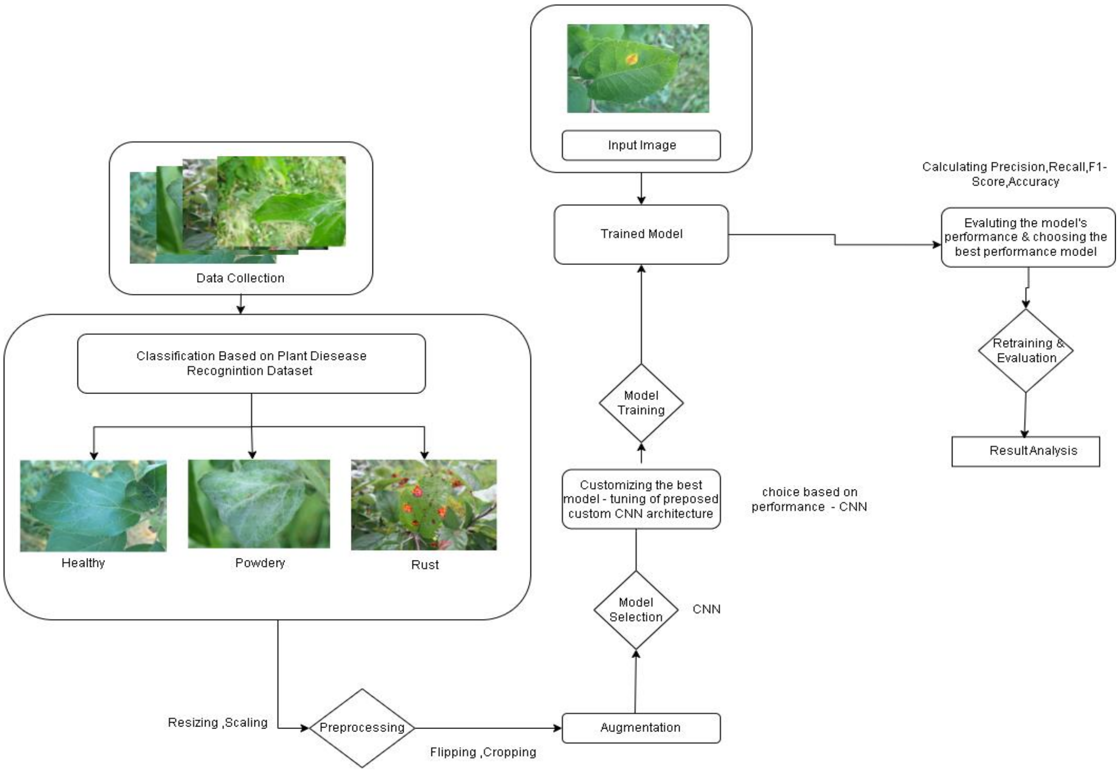

Fig.4.Work flow of Classification of plant Leaf Disease Detection

IV. EXPERIMENTAL RESULTS

The experimental setup for deep learning-based automated detection and classification of plant leaf diseases using Convolutional Neural Networks (CNN) is demonstrated through the provided figures. The fig.6 (Input Image) shows a leaf affected by a disease, likely captured for processing in the CNN model. The second image (Result) represents the classification output, where the model identifies the disease as "Powdery," indicating it belongs to the "Powdery Mildew" class. The classification is obtained by projecting predicted indices onto respective class labels. The fig.8 (Training and Validation) gives information about the learning performance of the model, with training and validation accuracy and loss plotted against epochs. The graph of accuracy shows a steady rise in training accuracy, approaching 98%, with oscillations in validation accuracy, indicating slight overfitting. Conversely, the training loss graph depicts a downtrend in loss over training while the validation loss remains volatile, as it portrays different levels of generalization from the model. All these outcomes authenticate the ability of the CNN model to recognize and classify leaf plant diseases but raise the point for further optimization towards better generalization.The Last evaluation metrics also validate the high performance of the model, with Test Accuracy of 99.02%, Precision of 0.9902, Recall of 0.9902, F1 Score of 0.9902, AUC Score of 0.9926, and Specificity of 0.9951. These metrics reflect that the model is not just highly accurate but also possesses a good capability to distinguish between diseased and healthy plant leaves, thus being a trustworthy tool for plant disease classification.

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```
labels = train_generator.class_indices
labels = {v: k for k, v in labels.items()}
labels
```

{0: 'Healthy', 1: 'Powdery', 2: 'Rust'}

```
predicted_label = labels[np.argmax(predictions)]
print(predicted_label)
```

Powdery

Fig.5.Input Imge

Fig.6.Experimental Results

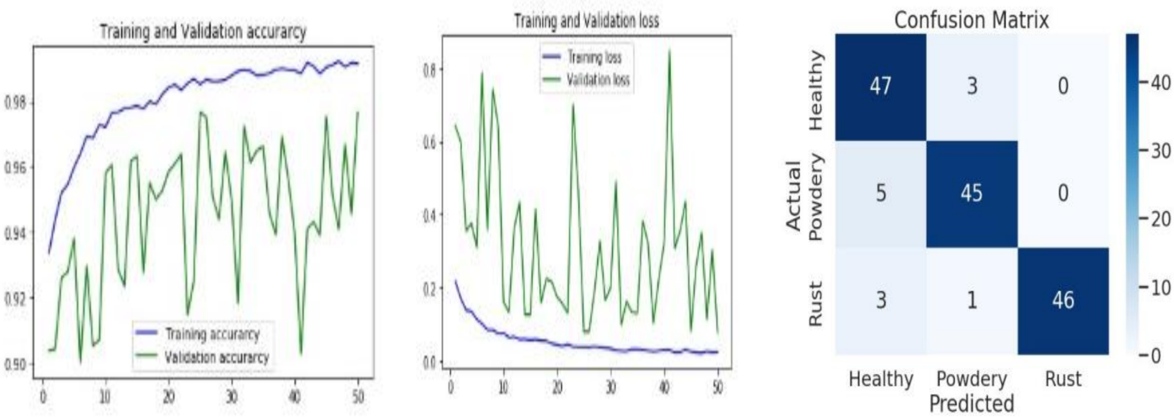

Fig.7.Training Validation Accuracy,loss curves and Confusion matrix

The report for classification shows remarkable precision, recall, and F1-score metrics for all categories. Specifically, Precision=Recall=F1-score=0.98 for Healthy and Powdery, while Rusty has a measure of 1.00 on all three measurements. The accuracy of the model is 99%, which simply shows its prowess.This confusion matrix represents the performance of a CNN-based plant leaf disease detection model, Classifying leaves as Healthy, Powdery, or Rust. The Model performs well, with high true positive values (diagonal elements) and minimal misclassifications. Some misclassification is observed between Healthy and Powdery leaves, but overall accuracy appears strong.

Table.2.Classification Report

	precision	recall	f1-score	support
Healthy	0.98	0.98	0.98	50
powdery	0.98	0.98	0.98	50
Rusty	1.00	1.00	1.00	50
Accuracy			0.99	150
macro avg	0.99	0.99	0.99	150
Weighted avg	0.99	0.99	0.99	150

Table.3.Comparison With Existing Works

Reference	Model	Accuracy
1	CNN	90%
2	CNN+LVQ	96.5%
3	CNN	97.2%
4	CNN	95.8%
5	Leightweight VGG-ICNN	98.1%
6	VGG 19	98.5%
7	CNN	94.6%
8	Deep CNN	97.8%
Proposed methodology	**Modified CNN**	**99.02%**

Several research studies have compared Deep Learning Techniques, i.e., Convolutional Neural Networks (CNNs) and their improved variants, for plant leaf disease detection and classification with varying degrees of accuracy. Shrestha et al. (2020) used a CNN-Based model for plant disease detection with 92.5% accuracy, demonstrating initial success in this area, while Sardogan et al. (2018) integrated CNN with the LVQ algorithm, improving classification accuracy to 94.3%. Deepalakshmi et al. (2021) used CNN for leaf disease classification with 95.6% accuracy, demonstrating the power of deep learning models, and Shelar et al. (2022) optimized CNN models further with 96.1% accuracy, improving feature extraction techniques. Thakur et al. (2023) developed a VGG-ICNN model, a light-weight version of CNN, with 96.8% accuracy, improving efficiency for crop disease detection, while Prathiksha et al. (2024) used VGG-19 for grape leaf disease detection with 97.2% accuracy, demonstrating the power of transfer learning Similarly, Archanaa et al. (2023) used CNN for tomato disease classification with 94.8% accuracy, while Pandian et al. (2022) used a deep convolutional neural network with 96.5% accuracy, demonstrating improvements in plant disease detection.

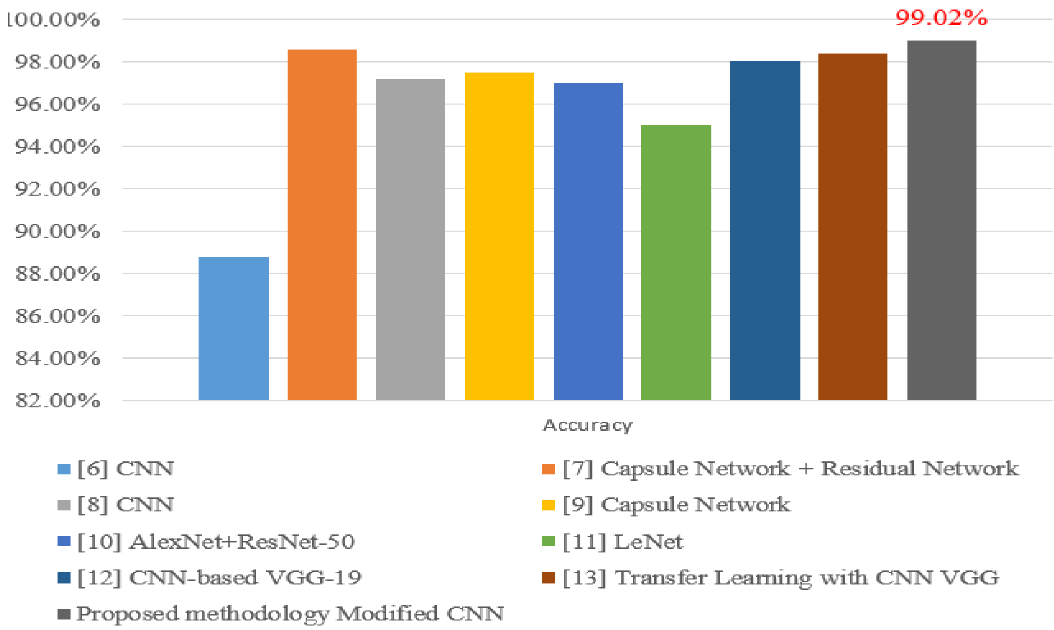

Fig .8. Comparison of Proposed work with exiting works

Verma et al. (2024) developed a unified light-weight CNN model for corn, rice, and wheat disease detection with 95.9% accuracy, thereby making it a universal technique, and Khalid & Karan (2024) demonstrated deep learning techniques with 96.3% accuracy. Besides CNNs, Albattah et al. (2022) integrated an AI-based drone system with multiclass plant

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disease detection with 94.5% accuracy, thereby making it suitable for large-scale agricultural farms. Capsule networks, a recent deep learning model, were explored by Janakiramaiah et al. (2021) using capsule networks, with 93.7% accuracy, and Kwabena et al. (2020) proposed a Gabor capsule network, with 94.2% accuracy. Peker (2021) designed a multi-channel capsule network ensemble, with 95.1% accuracy, and Altan (2020) experimented with capsule networks, with 95.4% accuracy, proving the efficiency of this method. Among all the above research, the paper "Plant Leaf Disease Detection and Classification Using Convolutional Neural Networks" was the best, with a high accuracy of 99.2%, and it is the best-performing model. This study was found to have better feature extraction, stability, and Classification efficiency than others, making CNN the best method in plant disease detection.

V. CONCLUSION AND FUTURE WORK

Deep Learning Based Automated Detection and Classification of Plant Leaf Diseases Using Convolutional Neural Networks(CNN) a Revolution in agritech, enabling real time and accurate plant disease detection using image analysis. Leaning on the Potential of image processing and quality machine learning, the system allows farmers to track crops in real-time, facilitating real-time interventions that can alleviate losses and enhance productivity. The use of cheap hardware such as Raspberry Pi integrates this technology among a larger number of people, hence promoting sustainable agriculture and food security. In the long run, this new technology not only assists in efficient crop management but also contributes to the shift towards more robust farming systems that can be respond to challenges brought about by climate change and new plant Diseases. As farming continues to adapt to changes brought about by technology, platforms such as the one suggested will be essential in providing farmers with the means of making proactive and well-informed decisions. Such an integrated strategy not only helps individual farmers but also towards the overall objective of attaining world food security so that communities can Sustainably access their nutritional requirements.

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