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Plant Disease Prediction

Recipes Recommendation system using home ingredients with Al Health chatbot

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Abstract: This research paper introduces a novel application for predicting plant diseases and curing the disease by using Convolutional Neural Networks (CNNs). Separate CNN models were trained on labeled datasets like cotton and potato leaves, each associated with their respective diseases. The primary goal is to employ of two standard CNN systems to detect various diseases in cotton and potato plants. Given India's heavy reliance on agriculture, this innovation is crucial to address challenges faced by the sector, including technological limitations, limited access to credit and markets, and the impact of climate change. this research paper are susceptible to various diseases that can impede their growth and result in substantial yield losses. The conventional disease detection methods involve manual inspection and disease prognosis, which are time consuming and less accurate. The research show- cases the effectiveness of the automated plant disease detection and curing system, with two best models achieving impressive accuracies of 97.10% and 96.94% . These results offer promising insights for potential applications in crop management, benefiting the agricultural sector and contributing to increased productivity and profitability.

Index Terms— CNN, Deep learning, ResNet50, VGG16 , Image classification, Transfer learning.

I. Introduction

system for the precise identification of various diseases affecting plants in India. Traditional methods like manual leaf examination and disease prediction lack accuracy in pinpointing specific ailments. The proposed system employs CNNs to extract intricate patterns from plant images and accurately predict diseases. The study utilizes 'The cotton leaf disease dataset,' featuring 2,000 images representing diverse cotton plant conditions, including Curl virus, bacterial blight, fusarium wilt, and healthy leaves, available on Kaggle. CNNs, being proficient in automatically learning image characteristics like texture, shape, and color, offer an ideal solution for plant disease identification. Transfer learning further enhances the system's efficiency and economizes computational resources. Effective disease detection is crucial for mitigating economic losses, ensuring food security, preserving biodiversity, promoting sustainable agriculture, and addressing the challenges posed by climate change, as new pathogens become more prevalent. This research contributes to improving crop yields and global food security.

1.1 Objectives And Aims

Objectives

1.Review of Literature: Conduct an extensive review of existing literature on plant disease detection and treatment methods. Identify gaps and opportunities for improvement.

2.Detection Methods Analysis:

Traditional Methods: Assess the efficacy of conventional techniques such as visual inspection, microscopy, and culture methods. Modern Technologies: Explore the use of remote sensing, machine learning, and IoT (Internet of Things) devices for disease detection. Evaluate the accuracy, speed, and practicality of these methods in different agricultural settings. Molecular and Genetic Techniques: Investigate the application of molecular markers, DNA sequencing, and CRISPR technology in identifying and diagnosing plant diseases.

3.Treatment Strategies:

Chemical Treatments: Examine the effectiveness of various fungicides, bactericides, and pesticides. Assess their environmental impact and potential for resistance development.

Biological Controls: Evaluate the use of beneficial microorganisms, natural predators, and biopesticides in managing plant diseases.

Genetic Engineering: Investigate the potential of genetically modified crops that are resistant to specific diseases.

4.Integrated Disease Management (IDM):

Develop a comprehensive IDM framework combining early detection, accurate diagnosis, and effective treatment methods.

Assess the economic viability and scalability of IDM practices for smallholder and large-scale farmers.

5.**Field Trials and Case Studies:**

Conduct field trials to test the proposed detection and treatment methods in real-world conditions.

Document case studies to illustrate the practical application and outcomes of the integrated approach.

6.Data Analysis and Interpretation:

Analyze the data collected from field trials and case studies to validate the effectiveness of the proposed methods.

Use statistical tools to interpret the results and draw meaningful conclusions.

7.Recommendations and Future Research:

Provide actionable recommendations for farmers, policymakers, and researchers based on the findings.

Identify areas for future research to address remaining challenges and improve plant disease management strategies.

Aims

1.To investigate and compare various methods for the early detection of plant diseases.

2.To evaluate the effectiveness of different treatment and cure strategies for plant diseases.

3.To develop an integrated approach combining detection and treatment to enhance agricultural productivity and sustainability.

II LITERATURE SURVEYS

This research present a fusion-based feature extraction technique that combines the VGG16 and ResNet50, two well- known convolutional neural network architectures, for precise and effective disease detection in plants. By utilizing the advantages of these two architectures and boosting the discriminative power of the retrieved features, the suggested strategy seeks to enhance the performance of plant disease detection systems. The primary goal of the proposed CNN- based application is the forecasting of plant diseases (cotton and potato). The suggested application makes use of different CNN models that have been trained on a dataset of labelled plant photos, where each image is labelled as either healthy or diseased depending on the plant. Transfer learning is used to optimise the CNN model’s performance.

This research explained the significance of small sample of plant leaf disease necessary for the discovery for early discovery of leaf infection that have been bandied. [1] In order to recognize disease, colorful ways of prognosticating the plant disease/infections were studied. This research efficiently paper also presented the yolo though CNN works very and with less complexity.

This research paper gave detailed information about bracket techniques like original image bracket, and multi-category bracket. The use of sliding window and heat chart can ameliorate the models performance. [2]

This research considered CNN to descry soyabean leaf disease prediction. Capability to achieve high bracket capability was the reason to use 3D CNN model. To test the accuracy of the model this research paper split the data into train, validate and test subsets(60 percent, 20 percent, 20 percent) and the delicacy was set up out to be 95.49 percent. [3]

A novel way to predict the plant's disease where CNN served as the foundation for a real-time finding method for apple splint situations. In order to accurately identify the distinguishing characteristics of photographs of infected apples and describe the five most common illnesses affecting apple leaves, this research paper employed a deep learning- based approach. This research paper also added images to improve the vaticination accuracy. [4]

This research paper proposed a system that uses KNN which gave better results and accuracy about is 98.56 percent While linear SVM was having problems in predicating correct results when it was given sample with more than 2 diseases. While direct SVM was having problems in resting correct results when it was given sample with further than 2 conditions. Their algorithm was tested on five different conditions i.e. Early scar, Down Mildew, White Fly, Leaf Miner, Mosaic Virus which impact the crops. [5]

III. RESEARCH METHODOLOGY

In this study, this research compared four different convolutional neural network (CNN) architectures for predicting cotton disease using a dataset of 1700 images. The four models were ResNet50, VGG16-ResNet50, a custom 15 layer CNN architecture, and another custom CNN architecture. This research work used the pre-trained ResNet50 network and added extra layers for fine-tuning for the ResNet50 model. This research specifically added a 256-filter convolutional layer, a 256- filter weight-free layer, a max pooling layer, a dropout layer, a flatten layer, three fully connected layers, and a final layer with a softmax activation function after this research had frozen the weights of the pre- trained layers. This research used the pre-trained VGG16 and ResNet50 networks to create the VGG16-ResNet50 model. Then integrated their feature sets using a global average pooling layer and concatenation. Then, for classification, this research work included a fully connected layer with a softmax activation function.

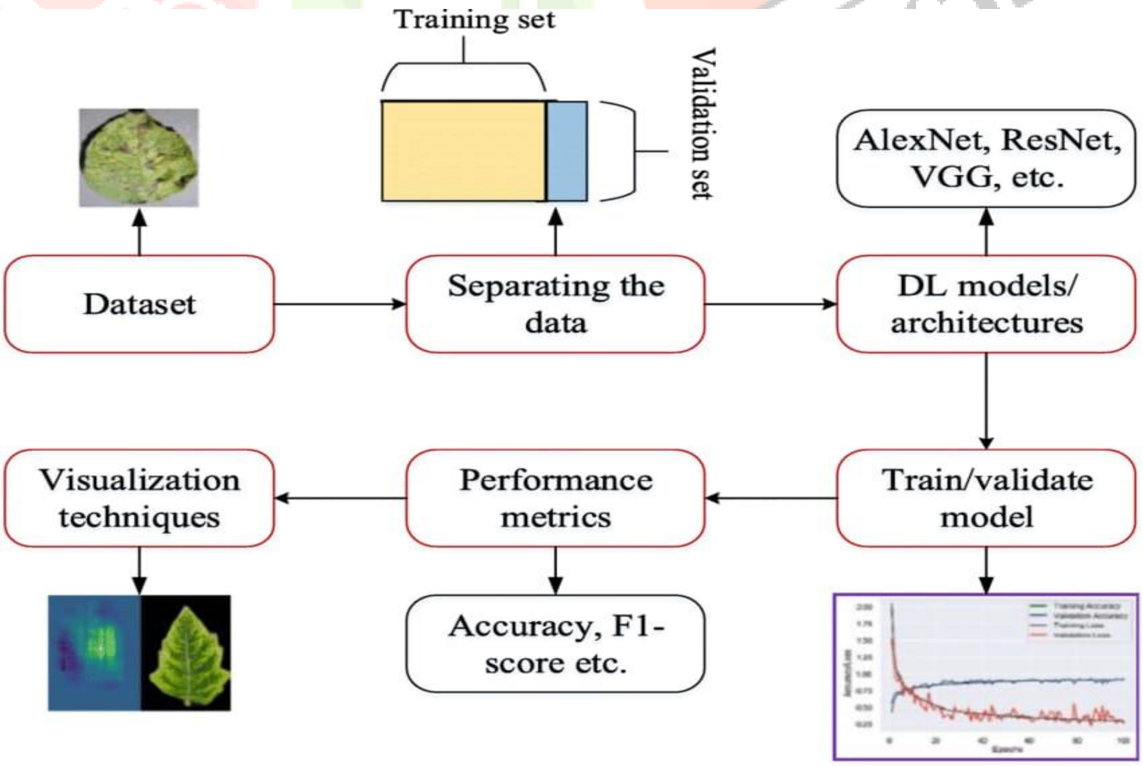

Fig. 1. Block diagram

The above fig1 states the block diagram of very working of our application. The plant disease prediction system operates through a sequence of steps. Initially, it analyzes an image of the plant to discern the plant's identity and any visible symptoms. Subsequently, it extracts pertinent features related to the plant and its symptoms from the image. These features are then input into a trained mathematical model. The model's primary function is to predict the probability of the plant having a specific disease. This prediction, represented as a probability value, is subsequently presented to the user. The utility of the plant disease prediction system extends to a wide range of users, including farmers, growers, and agricultural professionals. It empowers them to efficiently detect and manage plant diseases. Early identification of diseases allows farmers to implement preventive measures before the diseases inflict substantial harm on their crops. Growers can leveragethe system to assess the risk of potential disease outbreaks, enabling proactive measures. Additionally, agricultural profes- sionals can utilize the system to monitor disease spread and devise effective strategies for disease management. In essence, the plant disease prediction system constitutes a valuable asset for disease management

The General steps involved to successfully develop and develop the application were:

1]Data Collection: The first step in developing a CNN based application for plant disease prediction in cotton plants is to collect a large dataset of images of cotton plants. These images should include both healthy and diseased plants leaf, with a variety of different diseases represented. The dataset should also include images of different stages of leaf during plant growth, as well as images taken under differentlighting conditions.

2]Data Preprocessing: The next step is to preprocess the images to ensure that this research paper are in a format suitable for training a CNN. This includes resizing the images to a consistent size, normalizing the pixel values, and converting the images to grayscale if necessary.

3]CNN Model Design: A CNN model will be designed based on the dataset of images collected. This can be done by using a pre-trained model such as VGG or ResNet and fine-tuning it on the collected dataset. The model should be designed with multiple convolutional and pooling layers to extract features from the images, followed by fully connected layers to classify the images as healthy or diseased with their diseases.
4]Model Training: The model will be trained using the preprocessed dataset of images. This will involve dividing the dataset into training and validation sets, and using the training set to update the model's parameters. The model's performance will be evaluated using the validation set to ensure that it is generalizing well to new data.

5]Model Testing: The final step is to test the trained model on a separate test dataset of images. This will provide an estimate of the model's performance on unseen data and will be used to evaluate the overall accuracy of the model.

6]Deployment: After successfully testing the model, it will be deployed as a mobile application for farmers to easily and quickly identify the disease in their cotton plants. The application will have a user-friendly interface where the user can upload a picture of the plant and the model will predict the disease if any.

7]Evaluation: The deployed model's assessment involves farmer feedback and a comparison of predictions with ground truth. Three architectures were developed: Fusion of VGG16 and ResNet50, Six-Convolutional Layers CNN, and a CNN with dropout layers. Feedback guides further improvements.
7.1] Fusion of VGG16 and ResNet50 Architecture: Combining features from VGG16 and ResNet50 enhances transfer learning, providing diverse features. Global average pooling mitigates overfitting risks. However, fine-tuning may require substantial data due to reliance on two pre-trained models.
7.2] CNN with 6 Convolutional Layers Architecture: This simple model with six convolutional layers captures complex features from images. Suitable for smaller datasets, it may underperform on more complex datasets due to fewer layers.
7.3] CNN with Dropout Layers Architecture: Utilizing dropout layers to prevent overfitting, this model with four convolutional layers and dense layers is deep enough for complex features. However, its training demands may increase due to several dense layers, elevating the risk of overfitting.

8]Cure suggestion: This Project work suggested the most general cure for the disease detected, and also provided the info of about the disease and what lack off, has caused the disease. This research render the cure front end pages on our web-application after the disease is detected.

IV OBJECTIVES OF PROPOSED SYSTEM

Objective 1: Develop a Robust Plant Disease Detection System Using CNN, ResNet-50, and VGG16

Sub-objective 1.1: Design and implement a Convolutional Neural Network (CNN) model tailored for plant disease detection.

Sub-objective 1.2: Fine-tune the ResNet-50 architecture to improve detection accuracy and efficiency for various plant diseases.

Sub-objective 1.3: Utilize VGG16 to compare performance metrics and establish a benchmark for detection accuracy, speed, and computational efficiency.

Objective 2: Create a Comprehensive Dataset for Training and Testing

Sub-objective 2.1: Collect and preprocess a diverse set of images representing various plant species and disease conditions.

Sub-objective 2.2: Augment the dataset to include a wide range of environmental conditions and stages of disease progression, ensuring robustness and generalizability of the models.

Sub-objective 2.3: Annotate the dataset with detailed labels to facilitate supervised learning and model evaluation.

Objective 3: Implement and Evaluate the Detection Algorithms

Sub-objective 3.1: Train the CNN, ResNet-50, and VGG16 models using the prepared dataset, optimizing hyperparameters for each model.

Sub-objective 3.2: Evaluate the models using standard performance metrics such as accuracy, precision, recall, F1-score, and computational efficiency.

Sub-objective 3.3: Conduct cross-validation and independent testing to assess the robustness and reliability of the detection algorithms.

Objective 4: Integrate the Detection System with Real-Time Monitoring Tools

Sub-objective 4.1: Develop a user-friendly interface for farmers and agricultural professionals to upload plant images and receive diagnostic results.

Sub-objective 4.2: Implement real-time monitoring capabilities using IoT devices and edge computing to facilitate timely disease detection and intervention.

Sub-objective 4.3: Ensure the system provides actionable insights and recommendations for disease management based on detection results.

Objective 5: Validate the System in Real-World Conditions

Sub-objective 5.1: Conduct field trials to test the performance of the detection system in diverse agricultural environments and conditions.

Sub-objective 5.2: Gather feedback from end-users to refine and enhance the system's usability and effectiveness.

Sub-objective 5.3: Analyze the impact of the detection system on crop health, yield, and economic outcomes.

Objective 6: Develop Guidelines and Best Practices for Plant Disease Management

Sub-objective 6.1: Based on the detection results, provide evidence-based guidelines for the treatment and management of identified plant diseases.Sub-objective

6.2: Collaborate with agricultural experts to create comprehensive disease management protocols integrating detection and treatment strategies.

Sub-objective 6.3: Disseminate knowledge through workshops, publications, and training sessions to ensure widespread adoption and effective use of the system.

V. RESULT AND DISCUSSION

[1]6 Layers CNN Model [Potato dataset]

A.Statistical Analysis

Trained on the potato dataset, the model initially had 42% training and 56% validation accuracy. Subsequent epochs led to significant improvement, reaching 97.86% training and 92% validation accuracy. The model demonstrates accurate photo classification and potential for further enhancement,serving as a valuable baseline for similar tasks.

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential (Sequential)     (32, 256, 256, 3)         0

 conv2d (Conv2D)             (32, 254, 254, 32)        896

 max_pooling2d (MaxPooling2D  (32, 127, 127, 32)       0
 )

 conv2d_1 (Conv2D)           (32, 125, 125, 64)        18496

 max_pooling2d_1 (MaxPooling  (32, 62, 62, 64)         0
 2D)

 conv2d_2 (Conv2D)           (32, 60, 60, 64)          36928

 max_pooling2d_2 (MaxPooling  (32, 30, 30, 64)         0
 2D)

 conv2d_3 (Conv2D)           (32, 28, 28, 64)          36928

 max_pooling2d_3 (MaxPooling  (32, 14, 14, 64)         0
 2D)

 conv2d_4 (Conv2D)           (32, 12, 12, 64)          36928

 max_pooling2d_4 (MaxPooling  (32, 6, 6, 64)           0
 2D)

 conv2d_5 (Conv2D)           (32, 4, 4, 64)            36928

 max_pooling2d_5 (MaxPooling  (32, 2, 2, 64)           0
 2D)

 flatten (Flatten)           (32, 256)                 0

 dense (Dense)               (32, 64)                  16448

 dense_1 (Dense)             (32, 3)                   195

=================================================================
Total params: 183,747
Trainable params: 183,747
Non-trainable params: 0
_________________________________________________________________
```

Fig. 2. 6 Layers CNN architecture

B.Accuracy Graph

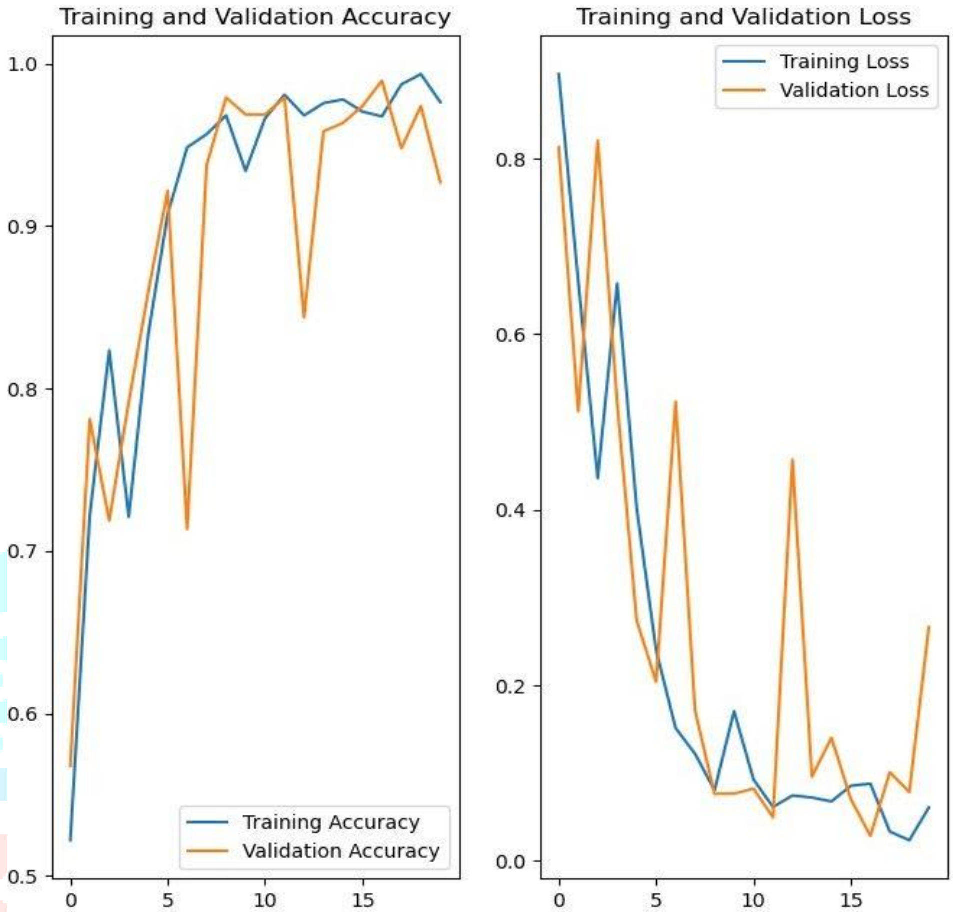

Fig.3. Model accuracy and Loss Graph

Fig 3 illustrates a machine learning model's trainingand validation metrics over epochs. Training accuracy andloss decrease as the model learns, but validation metrics lag slightly, suggesting potential overfitting. Strategies for improvement include expanding the training dataset, regularization, and early stopping. Retraining and validation evaluation are crucial post-enhancements.

C.Comparison of Models

Merging two powerful deep neural networks, VGG16 and ResNet50, can result in a highly effective model thatleverages the strengths of both architectures. VGG16 is known for its simplicity and uniformity in its convolutional layers, which enables it to extract features effectively from images. On the other hand, ResNet50 has a more complex architecture that includes residual connections, allowing it to train deeper models with improved accuracy and better generalization. By combining the two architectures, a potent synergy is achieved. VGG16's role in feature extraction is crucial, as its convolutional layers act as effective filters, progressively revealing hierarchical features within images. ResNet50 complements this by addressing the vanishing gradient problem through residual connections, enablingthe training of deeper, more accurate models. The resulting hybrid model capitalizes on both simplicity and depth, making it a versatile solution for various computer visiontasks, from image classification to complex medical image analysis. Researchers and practitioners in the deep learningand computer vision domains can benefit from this fusionapproach for improved model performance and flexibility. The above fig10 states that the VGG16-ResNet fused model, which had the maximum accuracy of 97.1% according to the comparison study's findings, was the most effective and accurate model for classifying images. With an accuracy of 96.94%, the suggested scratch CNN model came in second place, demonstrating its potential to be a formidable opponent in the area of CNN models. The ResNet50 model's accuracy of 96.59% demonstrated its prowess in properly classifying pictures. While Srikanth Tammina CNN [11] and

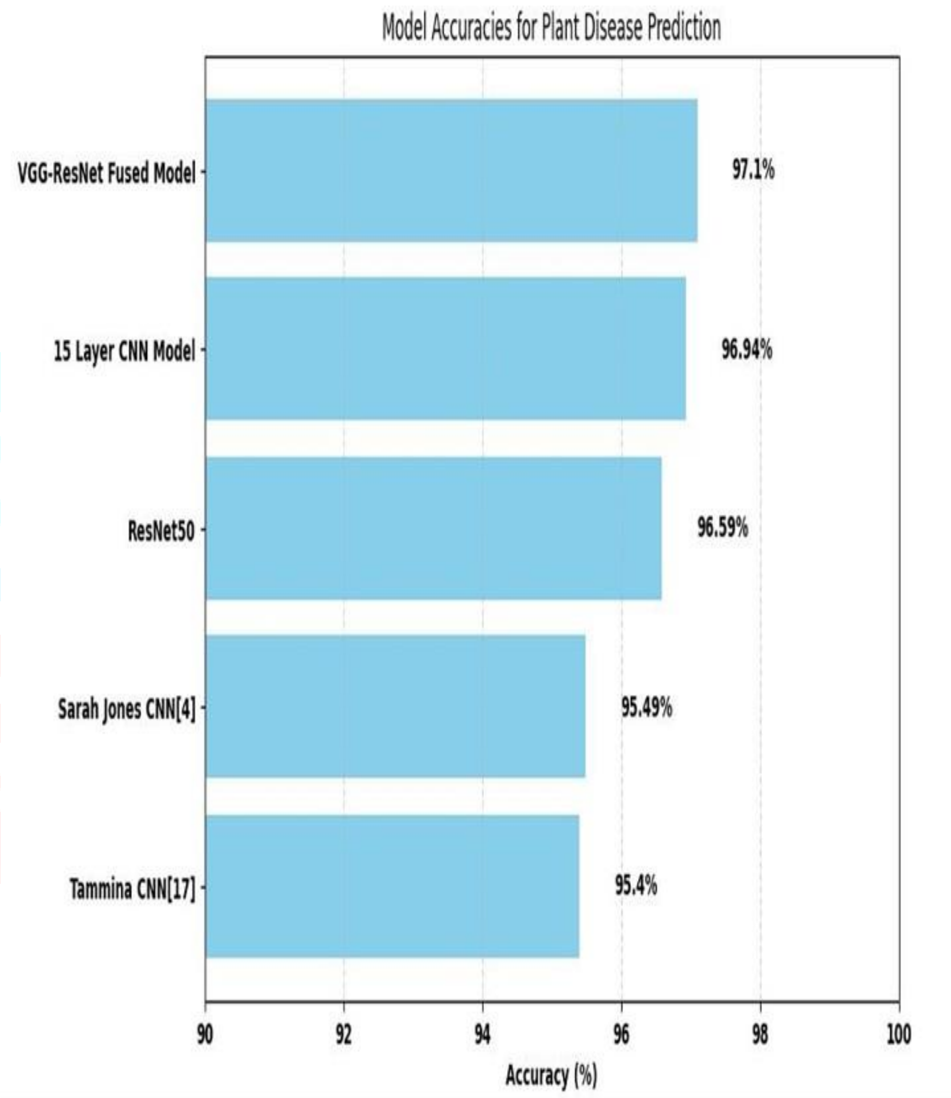

Fig. 4. Comparison Of models

Sarah Jones CNN [3] both had accuracy rates of 95.49 and 95.40, respectively, demonstrating that this research paper also have the potential to be trustworthy models for image categorization. Overall, the comparison research emphasizes how crucial it is to investigate many CNN models in orderto decide which is most appropriate for a given task. Whilethe suggested scratch CNN model and the VGG+ResNet fused model had the best accuracy rates, other models also showed great promise, indicating that further testing and study are need to completely decide which model is the most efficient for a given application.This research may employ ResNet50's residual connections in the deeper layers to enhance the model's accuracy and generalizability and take advantage of VGG16's simplicity in the early levels to extract low-level features. Overall, the combined modelcan successfully complete a variety of computer vision tasks, such as segmentation, object identification, and image classification. It's crucial to remember that careful tuning and experimentation are necessary when combining various models in order to get the best outcomes.

D .Project result :-

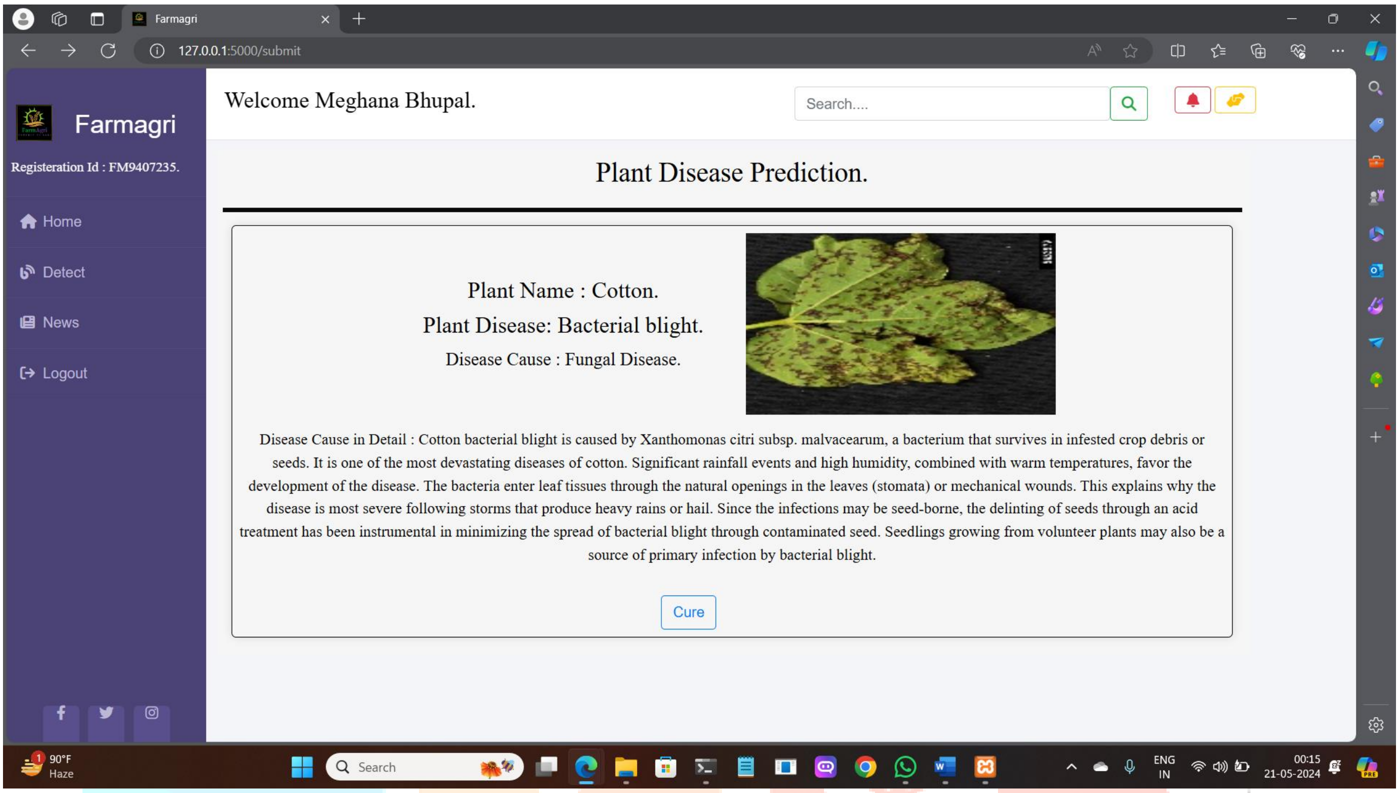

Fig .5 plant diseases prediction

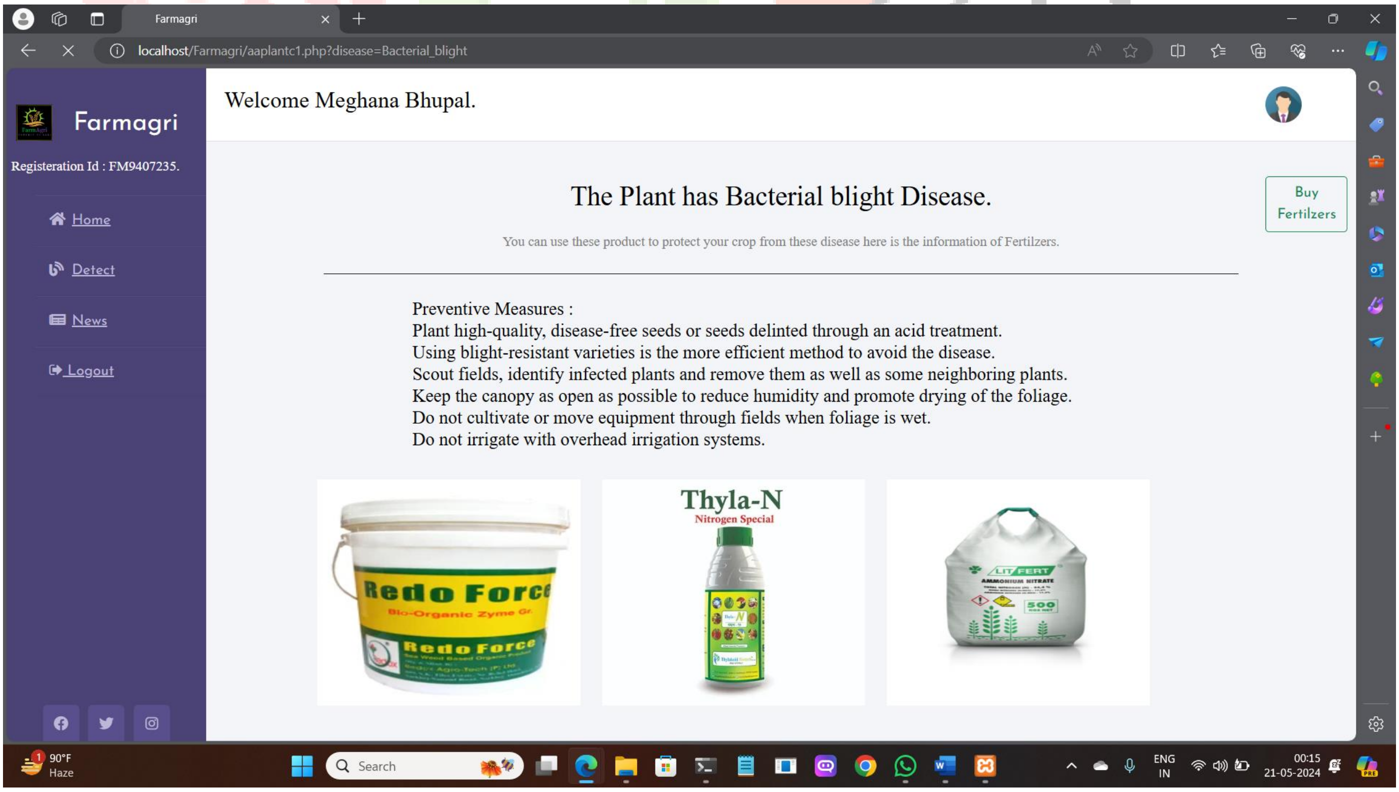

Fig .6 disease curing solution

VI. Conclusion

This study demonstrates the potential of CNNs for plant disease prediction. The proposed CNN-based application is able to accurately predict the presence of diseases with high precision and recall and gives the solution of the curing the diseases, showing its potential as a powerful tool for plant disease detection. The importance of early detection in sustainable agriculture is highlighted by this study. Future work could include expanding the dataset to include a greater variety of plant species and diseases and incorporating other data such as weather and soil conditions to improve the performance of the CNN model. The use of CNNs in plant disease prediction can also be applied to the field of botanical research. By using this technology to analyze images of plants,researchers can quickly and accurately identify and study the effects of different diseases on different plant species. Overall, the creation of a CNN-based plant disease prediction program has the potential to completely alter how this research think about plant health and conservation. This technology enables us to provide more precise and effective outcomes, enabling us to better safeguard and maintain our plant resources for future generations.

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