



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 4, April 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

 9940 572 462

 6381 907 438

 ijirset@gmail.com

 www.ijirset.com

Cotton Leaf Disease Analysis and Prediction Using Deep Learning Methods

Vadivelan N^{1,2*}, Dr. Krishna Prasad K²

Dept. of Computer Science and Engineering, Teegala Krishna Reddy Engineering College, Hyderabad, India¹

Institute of Computer and Information Sciences, Srinivas University, Mangalore, Karnataka, India-574146²

ABSTRACT: Cotton is an important crop that plays a significant role in the global economy. However, cotton plants are vulnerable to various diseases that can significantly affect crop yield and quality. Therefore, the early detection and diagnosis of cotton diseases are crucial for ensuring efficient crop management and reducing economic losses. Convolutional neural networks (CNN) will be used for predicting cotton disease. Based on the large dataset of cotton leaf images infected with different diseases, to train and evaluate our CNN model. The CNN model consists of multiple convolutional layers, followed by pooling layers and fully connected layers. The utilization of transfer learning involved fine-tuning a pre-trained CNN model for our specific classification task, based on its initial knowledge. Using transfer learning to fine-tune a pre-trained CNN model for our specific classification task.

KEYWORDS: Cotton Disease Dataset, Disease Detection, CNN.

I. INTRODUCTION

India is one of the oldest countries still practicing agriculture. Traditional farming methods are still in existence and thus end up with minimal crop yields and fewer benefits to farmers. Various factors have affected the health of agriculture in India. Selecting a crop for planting is one of the biggest challenges that farmers face while growing crops. The emergence of several crop-related diseases also affects the productivity of the agriculture sector. One of the common problems is the destruction of most of the production due to diseases. A large part of the production process is hampered by the presence of diseases in the plants grown. This leads to a focus on effective ways of detecting diseases in plants. The presence of various diseases in plants is a major concern for farmers. minimal. Recent advances have been made in the identification of plant diseases. This paper examines the effectiveness of using CNN models and Image processing for the identification and classification of plant diseases. Cotton cultivation is integral to global agriculture and economy, yet susceptible to debilitating diseases compromising yield and quality. Timely detection and diagnosis of these maladies are paramount for effective disease management and economic sustenance. Leveraging advancements in machine learning, particularly convolutional neural networks (CNN), offers a promising avenue for automated disease identification. Our study aims to harness the power of CNN to predict cotton diseases, utilizing a substantial dataset of diseased leaf images. By employing transfer learning, we seek to optimize a pre-trained CNN model for accurate classification of cotton diseases. This introduction sets the stage for exploring the potential of CNN-based approaches in revolutionizing cotton disease detection, addressing critical challenges in agricultural sustainability.

Need for a Prediction Model: The development of a predictive model for cotton disease detection is imperative due to the significant impact of diseases on the global cotton industry. Cotton serves as a crucial commodity in the agricultural sector, contributing substantially to economies worldwide. However, the susceptibility of cotton plants to various diseases poses a persistent threat to crop yield and quality. Traditional methods of disease detection are often time-consuming, labor-intensive, and prone to errors, leading to delayed responses and economic losses. By harnessing the power of convolutional neural networks (CNN), we aim to revolutionize disease detection in cotton crops. This model offers the potential for early and accurate identification of diseases, enabling timely interventions and efficient crop management practices. Moreover, the utilization of transfer learning further enhances the model's performance by leveraging existing knowledge and expertise from pre-trained CNN architectures. Ultimately, the deployment of this CNN-based predictive model holds the promise of mitigating the adverse effects of cotton diseases, ensuring sustainable agricultural practices and safeguarding the livelihoods of farmers worldwide.

Curl Virus: Cotton leaf curl virus is a viral disease transmitted by whiteflies. Infected plants exhibit symptoms such as upward curling of leaves, vein thickening, yellowing, and stunted growth. The leaves may also become brittle and have a leathery texture.

Fusarium Wilt: Fusarium wilt is caused by the fungus *Fusarium oxysporum* and results in yellowing, wilting, and eventual death of cotton plants. The disease often starts with lower leaves and progresses upward, causing vascular discoloration and blockage, leading to wilting and collapse of the plant.

Aphids: Aphids are small, soft-bodied insects that feed on the sap of plants. They can cause curling, yellowing, or distortion of leaves. A characteristic sign of aphid infestation is the presence of sticky honeydew on leaves and stems, often accompanied by the growth of black mold.

Armyworm: Armyworms are caterpillars that feed on the foliage of cotton plants, resulting in skeletonized leaves and irregularly shaped holes. They can cause extensive damage to crops, and their feeding activity often occurs at night.

Bacterial Blight: Bacterial blight is caused by the bacterium *Xanthomonas citri* and manifests as water-soaked lesions on leaves that later turn brown or black. Infected leaves may also exhibit angular or irregularly shaped lesions with a yellow halo. In severe cases, the disease can lead to defoliation.

Healthy: This category represents healthy cotton leaves without any disease symptoms. Healthy leaves typically have a vibrant green color, smooth texture, and uniform shape without any signs of damage or discoloration.

Powdery Mildew: Powdery mildew is a fungal disease characterized by the presence of white or grayish powdery patches on the surfaces of leaves, stems, and other plant parts. Infected leaves may become distorted, curled, or stunted, and severe infections can lead to premature leaf drop.

Target Spot: Target spot, also known as *Corynespora* leaf spot, appears as circular to irregularly shaped lesions on cotton leaves with a dark brown to black center and a yellow halo. The lesions often resemble a target, hence the name. In severe cases, the spots may coalesce, leading to widespread defoliation.

II. LITERATURE SURVEY

N. Shah and S. Jain et al [1] conducted research on Detection of Disease in Cotton Leaf using Artificial Neural Network. The by, as presented in the 2019 Amity International Conference on Artificial Intelligence (AICAI) in Dubai, focuses on the "Detection of Disease in Cotton Leaf using Artificial Neural Network" [1]. The primary objective of the study is to address the challenge of visually assessing the health of cotton leaves, a crucial aspect of farming. To overcome this hurdle, the researchers propose a machine learning-based approach that evaluates leaf images to detect diseases and assess the overall quality of cotton plants. The core methodology involves the application of an artificial neural network (ANN) tool to identify various diseases affecting cotton. The approach incorporates image pre-processing techniques to analyze leaf images, highlighting the affected areas based on color changes. Subsequently, the type of disease is detected using data derived from the image analysis. This research stands at the intersection of machine learning, image processing, and agriculture, showcasing its potential significance in revolutionizing disease detection in cotton crops.

Rakesh Chaware, Rohit Karpe, Prithvi Pakhale, Prof. Smita Desai [2] This system identify three diseases- *aleternaria* *aterrnata*, anthracnose and bacterial blight. This system works parallel for healthy and defected leaf image. Two images has Been taken one for the healthy leaf other for the defected leaf. Disease detection starts from training process. In training process resizing of the healthy and defected image has been done. Then convert rgb to grey scale image then apply stem, stairs, canny edge detection, surf, entropy, warp images. This technique is applied on both the samples healthy as well as defected. Once the training process of first phase samples is finished, comparison has been done on the basis of values obtained for all the parameters used.

Hameed and Üstündağ el al [3] present research on Evolutionary Feature Optimization for Plant Leaf Disease Detection by Deep Neural Networks. as presented in the International Journal of Computational Intelligence Systems, focuses on "Evolutionary Feature Optimization for Plant Leaf Disease Detection by Deep Neural Networks" [8]. The study specifically addresses the issue of apple leaf diseases, a critical factor impacting both yield and quality. The existing diagnostic techniques often consume significant time, leading to delayed preventive measures by farmers. The proposed method in this article aims to detect apple leaf diseases using a deep neural

network (DNN). The researchers design the Plant Diseases Detection System (PDDS) architecture, incorporating Speeded Up Robust Feature (SURF) for feature extraction and Grasshopper Optimization Algorithm (GOA) for feature optimization. This dual approach contributes to achieving enhanced detection and classification accuracy.

Pranita P.Gulve, Sharayu S.Tambe, Madhu A.Pandey, Mrs S.S. Kanse[4] This paper uses GLCM, thresholding, segmentation, feature extraction for detecting the diseases. They create colour transformation structure for the rgb leaf image, apply colour space transformation structure then image is segmented. Unnecessary parts (green area) within leaf area is removed. Calculate the texture features for the segmented infected object. Extracted features are passed through a pre-trained neural network. Image is taken with the help of digital camera and all images are stored in a JPEG format. Image resize and image filtering is done. Here filtering is important to remove any noise content. For this they used gaussian low pass filter is applied and positive standard deviation sigma. In this the classifier used is euclidian distance classifier.

Jenifa, R. Ramalakshmi, V. Ramchandran[5] in this paper uses convolution neural networks, deep neural networks, leaf disease, classification, image processing. This training model contains 500 leaf images and testing model contains 100 leaf images. Cotton leaf diseases to be classified in this are - cercospora, bacterial blight, ascochyta blight, target spot. The tool which they used is MATLAB tool. Diseased cotton leaf taken as input image then input image converted into grey converted image then the noise co-efficient image, then it converted into filtered image, next morphological image then clustered image the segmentation image and finally the output image takes out the diseased part. This system shows the 96% accuracy for the classification of diseased cotton leaves

III. DATASET

The dataset comprises 2733 images belonging to 8 distinct classes, each representing a specific category of cotton plant disease. These classes include 'Aphids', 'Army worm', 'Bacterial Blight', 'Healthy', 'Powdery Mildew', 'Target spot', 'curl_virus', and 'fussarium_wilt'. The images are categorized based on the type of disease or the health status of the cotton plants they depict.

IV. METHODOLOGY AND IMPLEMENTATION

This study used a design science to build and evaluate an approach that creates innovations and defines ideas, practices, technical capabilities, Inserting preprocessed images into a network is the first and basic task in all image processing projects. Common image preprocessing tasks in any image processing project are vectorization, normalization, image resizing.

Input Image: The process begins with the input image, which serves as the raw data for disease detection.

Pre-processing: The input image undergoes pre-processing techniques such as normalization, resizing, or noise reduction to enhance its quality and suitability for further analysis.

Feature Extraction: Next, the pre-processed image is fed into the CNN model, where convolutional layers extract meaningful features from the image data. These features capture important patterns and characteristics relevant to the detection of diseases in cotton plants.

Classification: The extracted features are then passed through fully connected layers and classification algorithms, where the model learns to classify the input image into different disease categories based on the extracted features.

Results: The classification results indicate the predicted disease associated with the input image. These results are then presented to the user or further processed for additional actions such as generating reports or initiating treatments.

Dataset: The CNN model is trained on a dataset comprising labeled images of cotton leaves affected by various diseases. This dataset serves as the foundational source of knowledge for the model, enabling it to learn and generalize patterns from the input images.

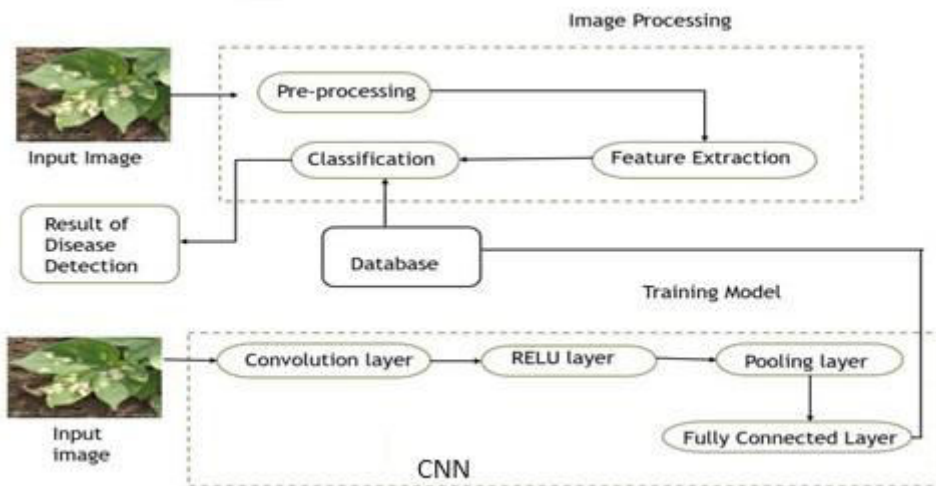


Fig no 1: System Architecture

In deep learning, Convolutional Neural Networks (CNNs) are a class of neural networks specifically designed for processing grid-like data, such as images. CNNs consist of several layers, each serving a specific purpose in extracting features from the input data and making predictions. Here's an explanation of some key layers commonly used in CNNs: CNN working in this paper/model In the cotton leaf disease detection paper, CNN (Convolutional Neural Network) plays a pivotal role in automating the process of identifying various types of cotton leaf diseases from images. Here's an overview of its role and functionality. Feature Extraction: CNNs are adept at automatically learning and extracting meaningful features from images. In this paper, the CNN analyzes the visual characteristics of cotton leaf images to discern patterns associated with different diseases. These patterns could include color variations, textures, shapes, and other visual cues specific to each disease type. Pattern Recognition: CNNs excel at recognizing complex patterns within images. By training on a dataset comprising labeled images of healthy and diseased cotton leaves, the CNN learns to differentiate between various disease symptoms and categorize them accordingly. It discerns subtle differences between healthy and infected leaves, enabling accurate disease classification. Classification: Once the CNN has extracted relevant features and learned to recognize disease patterns, it classifies new, unseen cotton leaf images into predefined disease categories. By employing techniques like softmax activation, the CNN assigns probabilities to each disease class, indicating the likelihood of the leaf exhibiting specific symptoms. This classification enables farmers or agricultural experts to identify and diagnose cotton leaf diseases efficiently. Automation and Efficiency: The CNN automates the disease detection process, eliminating the need for manual inspection of each leaf by human experts. By leveraging deep learning techniques, the CNN can analyze large volumes of images rapidly, providing swift and accurate assessments of disease presence. This efficiency facilitates timely interventions, such as targeted treatments or preventive measures, to mitigate the spread of diseases and minimize crop damage.

CNNs serve as powerful tools for image-based disease detection in agriculture, offering speed, accuracy, and scalability. In this paper, CNN's ability to learn from labeled data and generalize its findings to new images proves instrumental in enhancing crop management practices and ensuring agricultural sustainability.

The implementation of cotton leaf disease detection using DL/CNN involves several essential steps to develop an effective model for accurate diagnosis. Initially, the dataset containing images of cotton leaves affected by various diseases is loaded and preprocessed. This preprocessing step often includes resizing, normalization, and augmentation to ensure consistency and enhance model generalization. The dataset is then divided into training, testing, and validation sets to train and evaluate the model's performance. A Convolutional Neural Network (CNN) architecture is designed and implemented to learn meaningful features from the input images. The CNN model typically consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The model is compiled with appropriate loss functions and optimizers, and training is performed using the training set.

During training, the model's performance is monitored using metrics such as accuracy, loss, and validation accuracy to assess its effectiveness in learning patterns from the training data and generalizing to unseen data. The training process involves iterative optimization of the model's parameters to minimize the loss function and improve performance.

After training, the model is evaluated using the testing set to assess its ability to accurately classify cotton leaf diseases. The evaluation metrics provide insights into the model's precision, recall, and overall performance, guiding further optimizations and adjustments if necessary. Early detection of diseases can aid in timely interventions and preventive measures, ultimately improving crop yield and quality. Regular monitoring and updates to the model may be required to ensure its efficacy in detecting emerging diseases and adapting to changing environmental conditions. Overall, DL/CNN-based approaches offer promising solutions for automated and accurate cotton leaf disease detection, benefiting agriculture and crop management practices.

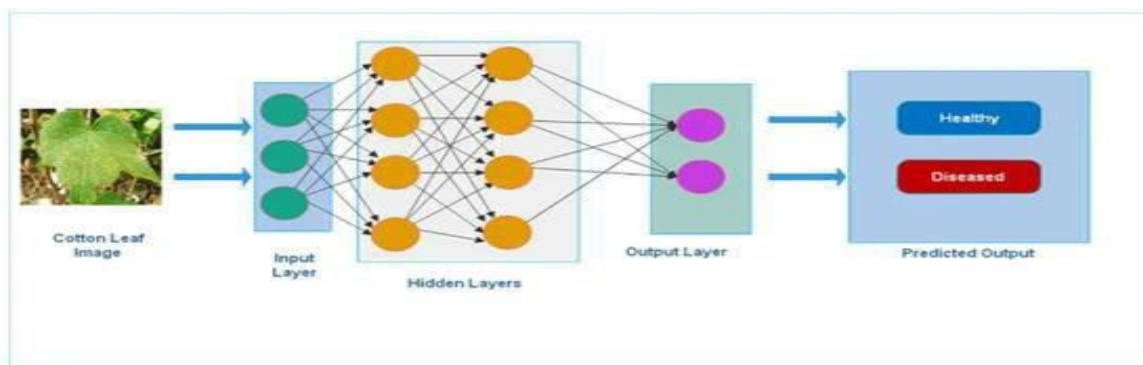


Fig no 2: Cotton Leaf Disease Detection using CNN

V. RESULTS ANALYSIS

During experimentation, different experiments were undergone to get an efficient model by customizing various parameters that provided different result.

Line graph: In the Line Graph the x an y axis are accuracies and epochs where the lines are train and validation .as the epochs increases from 0 to 1 to 2,3,4,5,6 the graph increases simultaneously with grading 0.3-0.4 to 0.8> for train(blue) and also for val it increases from 0.5 to 0.7-0.8 respectively

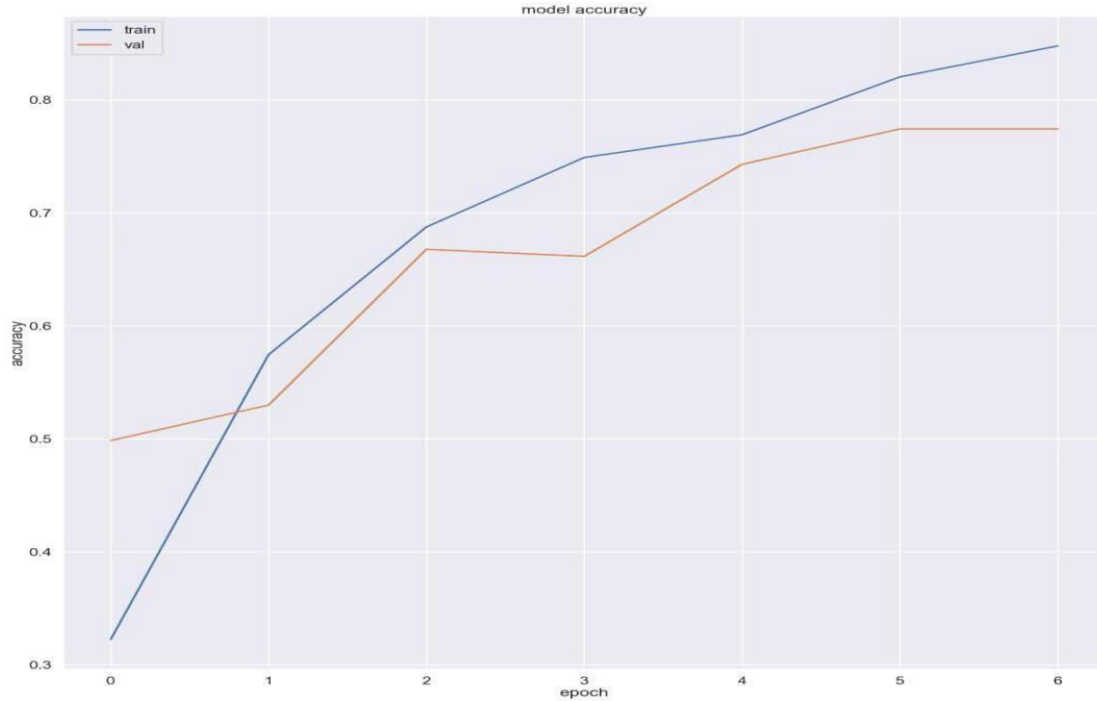


Fig.no 3: Accuracy in Line Graph Bar graph:

The bar chart titled "Model Accuracy" displays the progression of training over seven epochs, depicting both "Train Accuracy" (in blue) and "Validation Accuracy" (in red) on the y-axis, ranging from 0 to 1. Both accuracies show a consistent increase over epochs, indicating the model's learning and improvement. Throughout the epochs, training accuracy consistently surpasses validation accuracy, a common occurrence reflecting better performance on familiar data. The relatively stable gap between the two suggests modest overfitting, while by the final epoch, both accuracies converge around 0.8, showcasing the model's generalization capability.

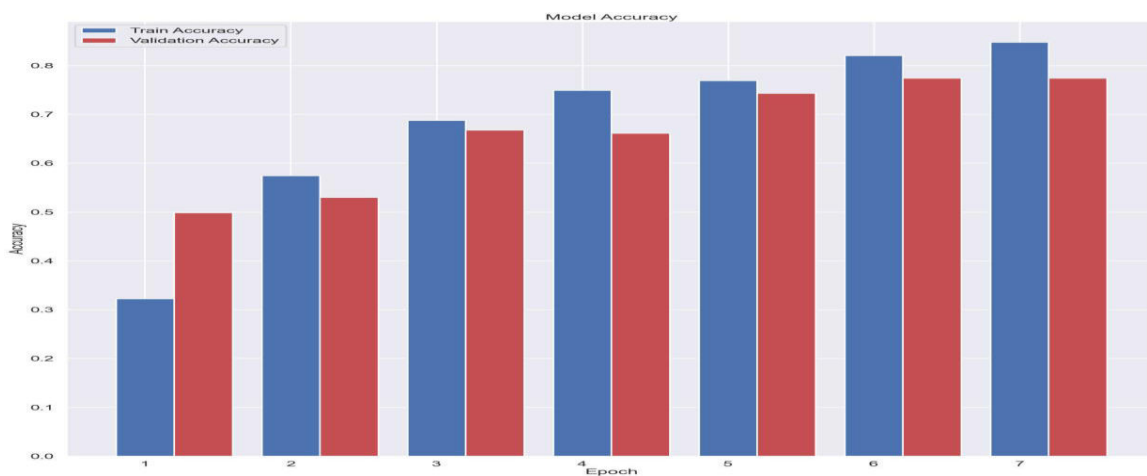


Fig no 4: Accuracy in Bar Graph



Confusion matrix:

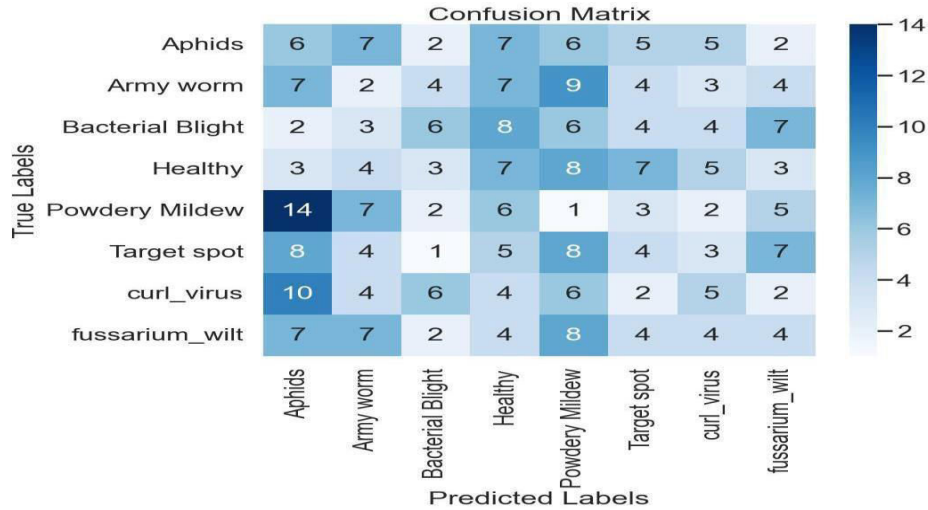


Fig no 5: Confusion matrix

The confusion matrix provided reveals the performance of a classification model across different classes. Each row represents the true class labels, while each column represents the predicted class labels. The values within the matrix indicate the frequency of instances where the true class matches the predicted class. For instance, in the top-left cell, there are 6 instances where the true class and predicted class both belong to the first category. Conversely, in the bottom-right cell, there are 4 instances where both the true and predicted classes belong to the eighth category. Analyzing the matrix provides insights into the model's strengths and weaknesses. It's evident that some classes are better distinguished than others, as indicated by higher values along the diagonal, suggesting accurate predictions. In contrast, off-diagonal elements highlight misclassifications, with varying degrees of confusion among different class pairs. Understanding this matrix aids in evaluating the model's overall performance, identifying areas for improvement, and tailoring strategies for refining its classification accuracy.

Classification report on precision, recall, F1, support: The classification report provides a comprehensive overview of the model's performance across multiple evaluation metrics for each class, as well as overall metrics. For each class, precision, recall, and F1-score are reported. Precision measures the proportion of true positive predictions out of all positive predictions, indicating the accuracy of positive predictions. Recall, also known as sensitivity, measures the proportion of true positives that were correctly identified out of all actual positives, indicating the model's ability to capture positive instances. The F1-score is the harmonic mean of precision and recall, providing a balanced measure that considers both false positives and false negatives. Additionally, the support column indicates the number of instances belonging to each class. Overall accuracy is also reported, representing the proportion of correctly classified instances out of the total. The macro and weighted average metrics provide aggregated scores across all classes, with the macro average giving equal weight to each class, while the weighted average considers the class imbalance by weighting each class's score by its support. This report enables a detailed assessment of the model's performance for individual classes and overall, aiding in identifying areas of improvement and optimizing the model's predictive capabilities.



```

Classification Report:

```

	precision	recall	f1-score	support
Aphids	0.11	0.15	0.12	40
Army worm	0.05	0.05	0.05	40
Bacterial Blight	0.23	0.15	0.18	40
Healthy	0.15	0.17	0.16	40
Powdery Mildew	0.02	0.03	0.02	40
Target spot	0.12	0.10	0.11	40
curl_virus	0.16	0.13	0.14	39
fussarium_wilt	0.12	0.10	0.11	40
accuracy			0.11	319
macro avg	0.12	0.11	0.11	319
weighted avg	0.12	0.11	0.11	319

Fig no: 6 Classification report

VI. CONCLUSION

The cotton leaf disease detection paper demonstrates the application of deep learning and web development techniques to address agricultural challenges. Through the integration of deep learning models, web frameworks, and data visualization tools, the paper offers a comprehensive solution for identifying and diagnosing diseases affecting cotton plants. The paper begins with the collection of a diverse dataset containing images of healthy cotton leaves and leaves affected by various diseases such as fungal infections, viral infections, and pest infestations. These images serve as the foundation for training a convolutional neural network (CNN) model, leveraging TensorFlow and Keras libraries. The CNN model is designed to learn distinctive features from the images and classify them into different disease categories.

To facilitate user interaction and accessibility, a web application is developed using Flask, a lightweight web framework. The application provides a user-friendly interface where users can upload images of cotton leaves for disease detection. Upon uploading an image, the application processes it through the trained CNN model and returns the predicted disease diagnosis.

Future Works: The main challenge while developing an object detection model on deep learning was to collect many trainings high-quality images with different shapes, sizes, different backgrounds, light intensity, and orientations in different classes. Therefore, future researchers should try to include a solution for such challenges in their work and not only identify but also suggest remedies for diseases and pests.

REFERENCES

- [1] N. Shah and S. Jain, "Detection of Disease in Cotton Leaf using Artificial Neural Network," 2019 Amity International Conference on Artificial Intelligence (AICAI), Dubai, United Arab Emirates, 2019, pp. 473-476, doi: 10.1109/AICAI.2019.8701311.
- [2] RakeshChaware, RohitKarpe, PrithviPakhale, Prof.SmitaDesai, "Detection and Recognition of Leaf Disease Using Image Processing", (2017).
- [3] Hameed, Jalal & Üstündağ, Burak. (2020). Evolutionary Feature Optimization for Plant Leaf Disease Detection by Deep Neural Networks. International Journal of Computational Intelligence Systems. 13. 12. 10.2991/ijcis.d.200108.001.
- [4] Pranitha P. Gulve, Sharayu S. Tambe, Madhu A. Pandey, Mrs S.S.Kanse, "Leaf Disease Detection of Cotton Plant Using Image Processing Technique", 2015
- [5] A.jenifa, R. Ramalakshmi, V. Ramachandran," Classification of cotton leaf Disease using Multi-Support Vector Machine", 2019.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details