JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

STREAMLIT-ENABLED DEEP LEARNING FRAMEWORK FOR DETECTING COTTON AND APPLE LEAF DISEASES

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Abstract: Streamlit-enabled deep learning framework for identifying cotton and apple leaf illnesses, integrating Convolutional neural networks, or CNNs, are used to achieve accurate classification. The framework leverages Streamlit, a lightweight Python-based web application tool, to provide an interactive and user-friendly interface for illness detection in real time. The
Deep learning model is trained on an extensive dataset of diseased and healthy leaf images, enabling precise identification of conditions such as leaf blight, rust, mildew, and bacterial infections. By enabling farmers and agricultural specialists to upload leaf photos and get immediate diagnostic feedback, the suggested solution improves accessibility. By providing a scalable, economical, and effective method for detecting plant diseases, this research seeks to advance precision agriculture and ultimately support crop protection and yield optimization.

Index Terms - Streamlit, Deep Learning, CNN, Cotton Leaf Disease, Apple Leaf Disease, Plant Disease Detection, Precision Agriculture, Web-based Diagnosis, Image Classification, Smart Farming

I. INTRODUCTION

A Streamlit-enabled deep learning framework for detecting cotton and Leverages for apple leaf infections CNNs, or convolutional neural networks to classify and diagnose plant infections with high accuracy. By integrating Streamlit, a Python-based web application framework, the system provides an intuitive and platform that is interactive where users can Get real-time disease predictions by uploading leaf photos. A varied dataset of both healthy and sick people is used to train the model leaves, enabling it to identify conditions such as leaf blight, rust, mildew, and bacterial infections. This framework enhances precision agriculture by offering farmers and agricultural experts a cost-effective, scalable, and efficient solution for early disease detection, helping to minimize crop losses and optimize agricultural productivity. The system utilizes picture preprocessing methods, such as contrast improvement and noise reduction, to improve prediction accuracy. Additionally, the framework supports model retraining and updates, ensuring adaptability to new diseases and environmental conditions. The web-based deployment eliminates the need for complex installations, making it accessible even to users with minimal technical expertise. Cloud integration enables remote data processing, allowing for scalability and improved performance. The framework also incorporates visual analytics, such as heatmaps and confidence scores, to enhance user understanding of disease severity. Future improvements could involve IoT-based automation, integrating real-time leaf scanning through drones and smart farming devices. By combining deep learning with user-friendly web applications, this solution significantly advances agricultural disease management, empowering farmers with AI-driven insights for sustainable crop production.

II. OBJECTIVES

1. To develop an interactive web-based application using Streamlit that enables identifying and categorizing apple and cotton leaf diseases in real time.
2. To implement Convolutional Neural Network (CNN) model for precise illness detection, including leaf blight, rust, mildew, and bacterial infections from leaf images.
3. To enhance accessibility for farmers and agricultural experts by providing a user-friendly and cost-effective solution for early disease detection without requiring technical expertise.
4. To integrate image preprocessing techniques for improving model performance by reducing noise, enhancing contrast, and ensuring high-quality input data.
5. To explore future scalability by incorporating cloud-based processing, IoT automation, and real-time analytics for more efficient and widespread agricultural disease monitoring.

III. LITERATURE REVIEW

Year	Authors	Country	Objective	Contribution	Data	Methodology
2024	Yang Liu et.al.[31]	USA	To analyze the evolution of research in precision agriculture and identify key trends across different subfields	Introduced a comprehensive popularity index and identified 37 distinct topics categorized into eight subfields	BERTopic text mining approach, publications from journals	BERTopic (transformer architecture) for topic refinement and diversity, Information entropy for assessing topic diversity
2024	Prayma Bishshash et.al.[32]	Bangladesh	To create a comprehensive cotton leaf disease dataset for enhanced disease detection and classification in precision agriculture	Developed a dataset of 2137 original and 7000 augmented images, categorized into eight classes, for training deep learning models	2137 original images, 7000 augmented images of cotton leaves showing disease manifestations, pests, and stress	Inception V3 deep learning model

2023	Mehwish Zafar et.al.[33]	Korea	To propose an optimized feature fusion-based model for accurate cotton leaf disease classification	Utilized EfficientNet-b0 and Inception-v3 for feature extraction, followed by feature selection using Emperor Penguin Optimizer (EPO)	Kaggle cotton disease dataset-I and Kaggle cotton-leaf-infection-II	Feature fusion, Emperor Penguin Optimizer (EPO), QDA and KNN classifiers
2024	R. Kumar et. al[34].	India	To develop a machine learning-based system for identifying cotton diseases through leaf images	Introduced several machine learning models (Random Forest, SVM, Multi-Class SVM, Ensemble model) for cotton disease classification	Cotton leaf images (dataset not specified)	Data pre-processing, model training, evaluation, and ensemble model development
2022	S. K. Noon et.al.[35]	Pakistan	To handle severity levels of multiple co-occurring cotton plant diseases using an improved YOLOX model	Introduced a modified Spatial Pyramid Pooling (SPP) layer and αIoU-based regression loss function to improve disease detection	1,112 cotton plant images with co-occurring diseases, including severity levels of cotton leaf curl and cotton sooty mold	YOLOX model with improved SPP layer, skip connections, and αIoU-based regression loss function

				and generalization		
2024	R. S et.al.[36]	South Korea	To detect whitefly infestations in cotton fields using vision transformers and acoustic sensors	Developed a novel method combining vision transformers and acoustic sensors for accurate detection of whitefly infestations	Large dataset of cotton fields with and without whitefly infestations	Vision transformer trained on a large dataset, combined with low-cost acoustic sensors

IV. METHODOLOGY

The proposed Streamlit-enabled deep learning framework for detecting cotton and apple leaf diseases follows a structured approach involving data collection, preprocessing, model training, and web deployment. Initially, a comprehensive dataset of healthy and diseased cotton and apple leaf images is gathered from public agricultural databases and field sources. The collected images undergo preprocessing methods, such as contrast improvement, noise reduction, and image resizing, to ensure uniformity and improve model accuracy. Following that, a Convolutional Neural Network (CNN) is created and trained on this dataset, employing layers for the extraction of features, pattern recognition, and categorization of diseases like leaf blight, rust, mildew, and bacterial infections. The CNN model is optimized using methods to improve resilience and avoid overfitting, including adaptive learning rate changes, dropout regularization, and data augmentation. To guarantee excellent classification performance, the trained model is assessed on a test dataset using measures like accuracy, precision, recall, and F1-score.

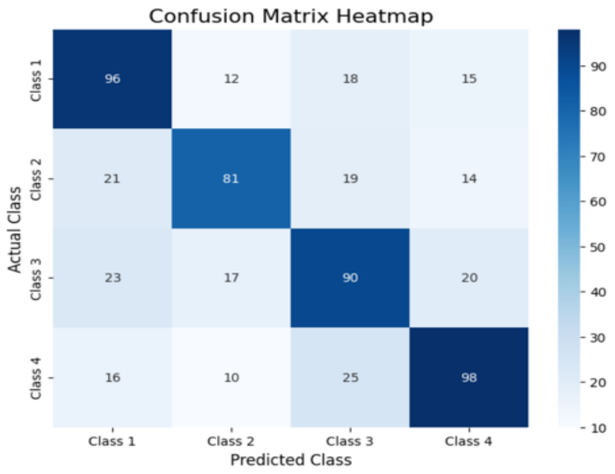
Once the model achieves satisfactory accuracyis incorporated into a Streamlit-based web-based application, providing users with an interactive platform can submit leaf photos and get disease forecasts in real time. The application utilizes cloud-based storage and processing to handle large-scale user inputs efficiently. A visual analytics module is incorporated to display confidence scores, disease severity levels, and heatmaps for better interpretability. The framework is designed for continuous improvement, allowing periodic model retraining with new datasets to maintain accuracy across different environmental conditions. Future enhancements include IoT integration with smart farming devices for automated disease detection and mobile-based deployment for improved accessibility among farmers. By combining deep learning, web technology, and agricultural data science, this methodology provides a scalable, cost-effective, and efficient solution for early plant disease detection and precision agriculture.

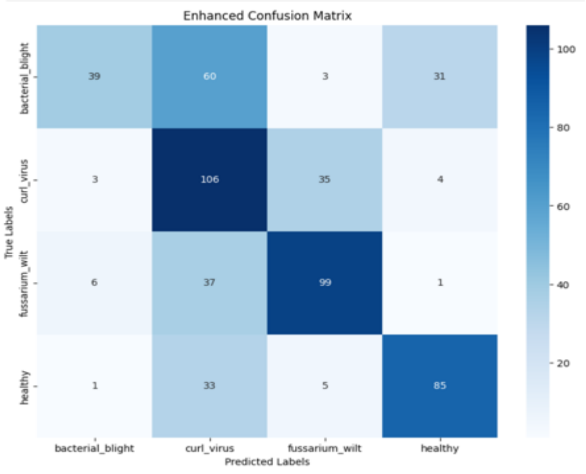
V. EXPERIMENTAL RESULTS & ANALYSIS

5.1 Confusion matrix:

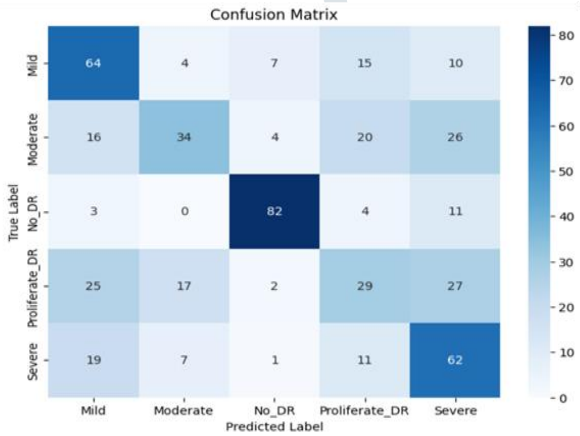
In classification models, a confusion matrix is a performance evaluation tool that compares expected and actual results. Its four components are False Negatives (FN), where the model incorrectly predicts a negative class (e.g., diseased leaf classified as healthy); False Positives (FP), where a healthy leaf is misclassified as diseased; True Negatives (TN), where a healthy leaf is correctly identified; and True Positives (TP), where the model correctly predicts a positive class (e.g., diseased leaf detected as diseased). Important metrics that evaluate the model's dependability, including accuracy, precision, recall, and F1-score, are derived with the use of the confusion matrix. For example, recall assesses how well the model detects real positives, whereas accuracy counts the number of projected positive situations that are actually true. Precision farming and early disease intervention depend on low misclassification, which is ensured by a well-balanced confusion matrix in deep learning-based disease detection.

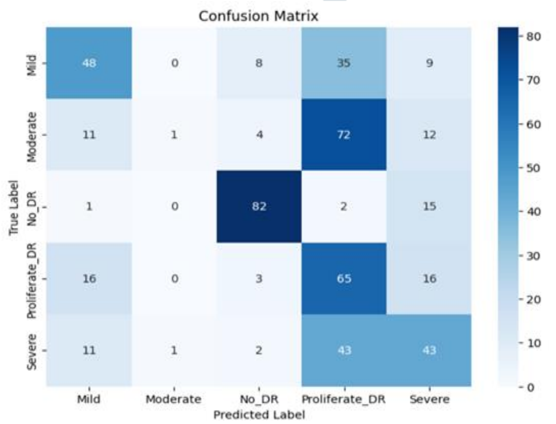
5.2 Apple Leaf Confusion Matrix:



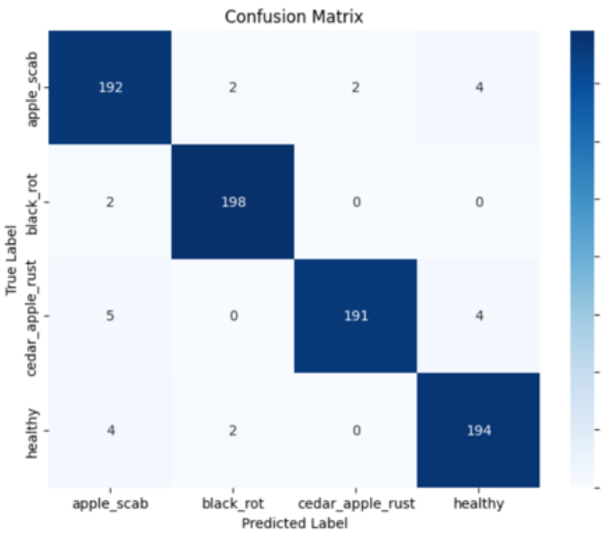


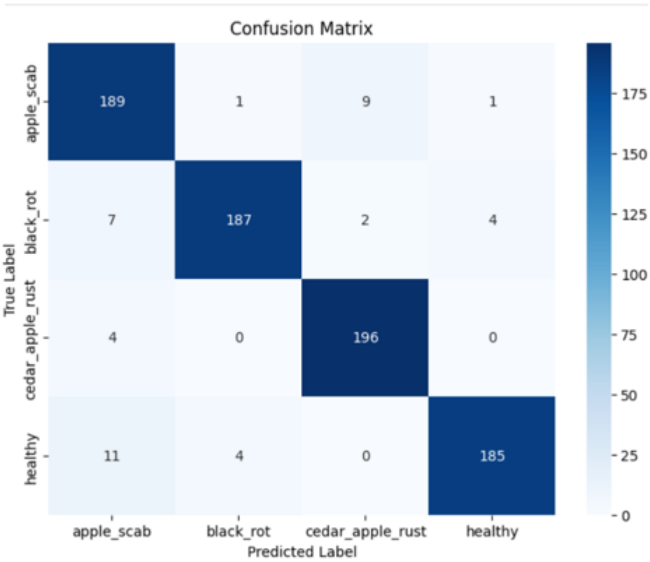
A) CNN **B) Resnet 50**



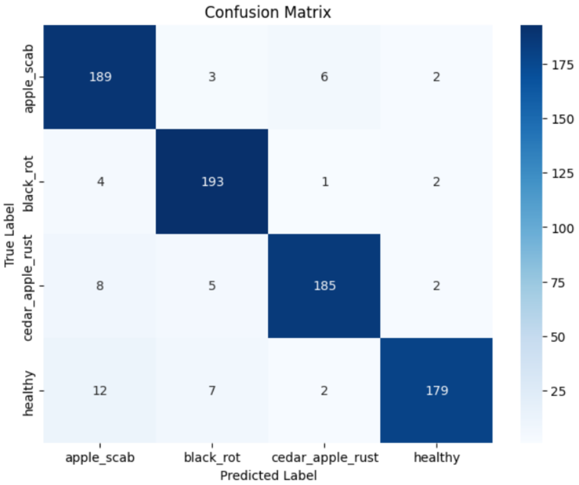


C) VGG 19 **D) VGG16**



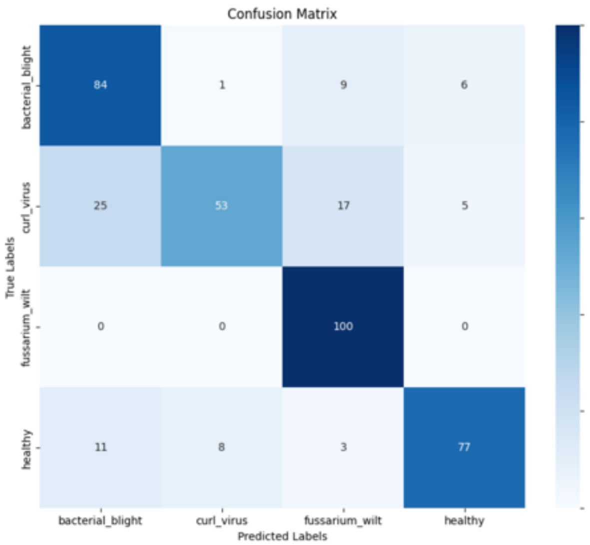


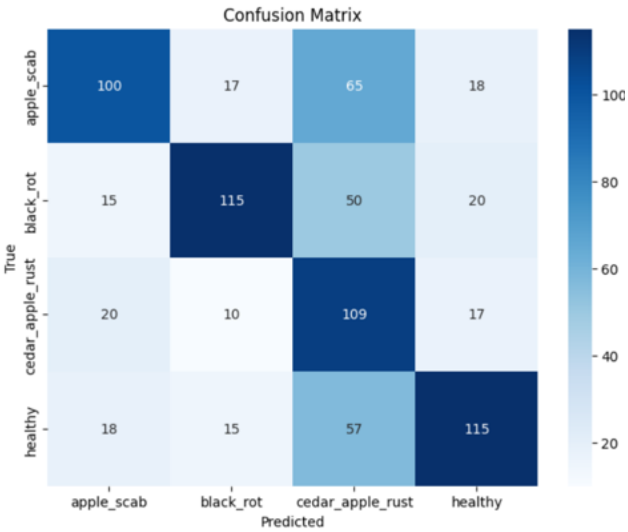
E) DENSENET 121 **F) XCEPTION**



G) Inception V3

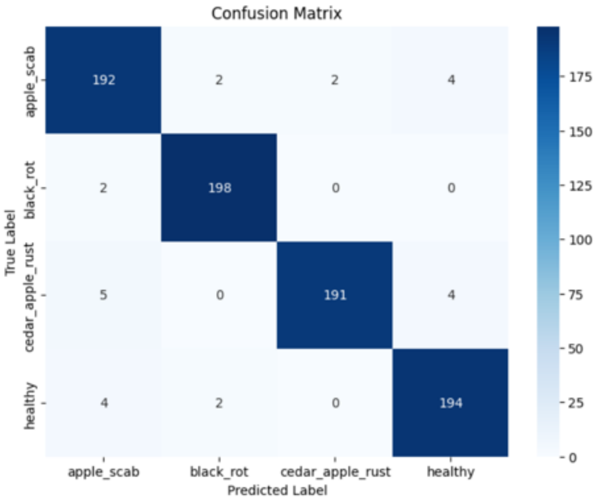
5.3 Cotton Leaf Confusion Matrix:

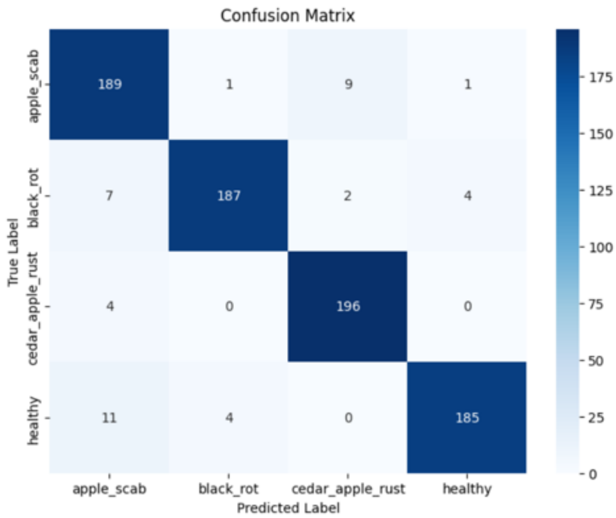




A) CNN

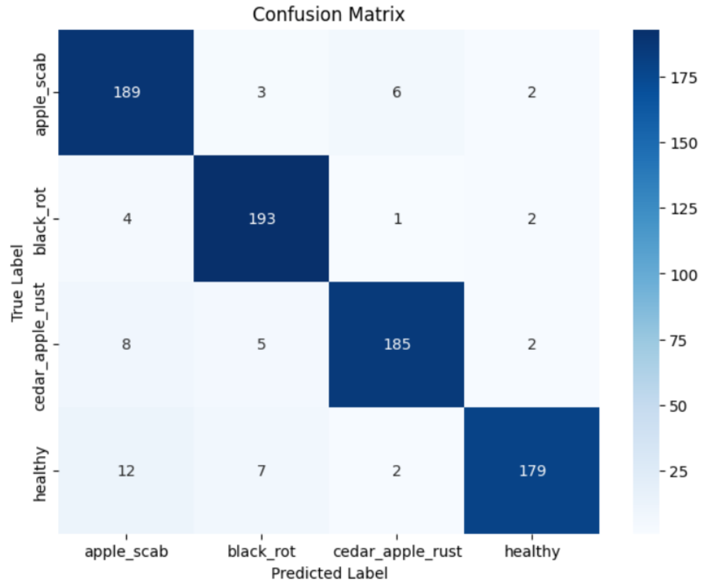
B) Resnet 50





C) VGG 19

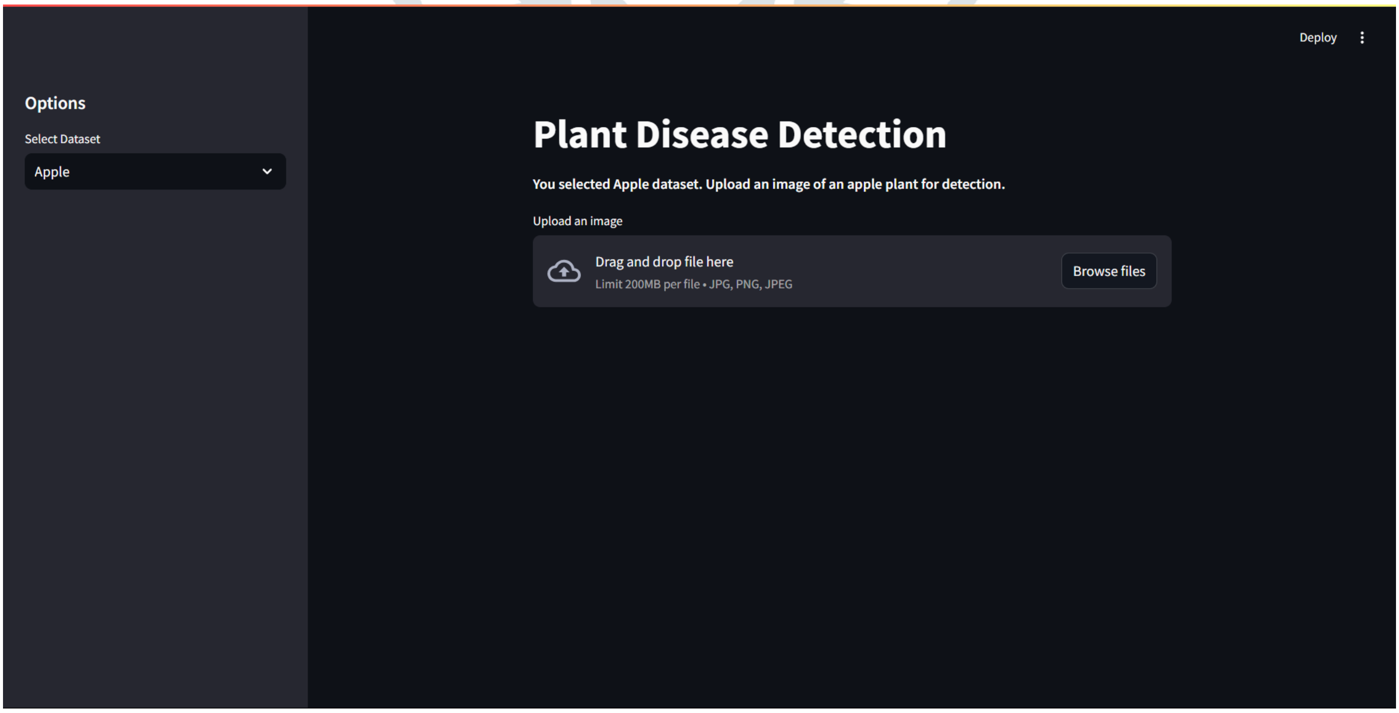
D) XCEPTION

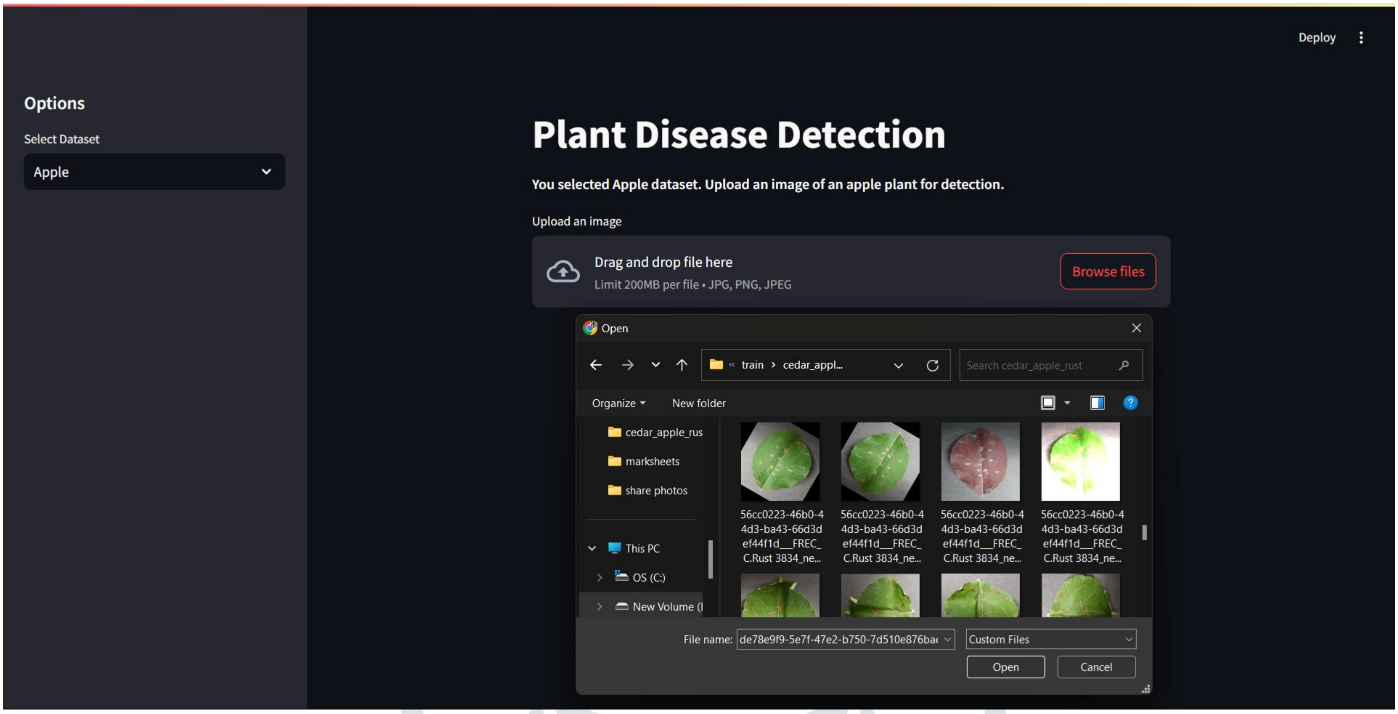


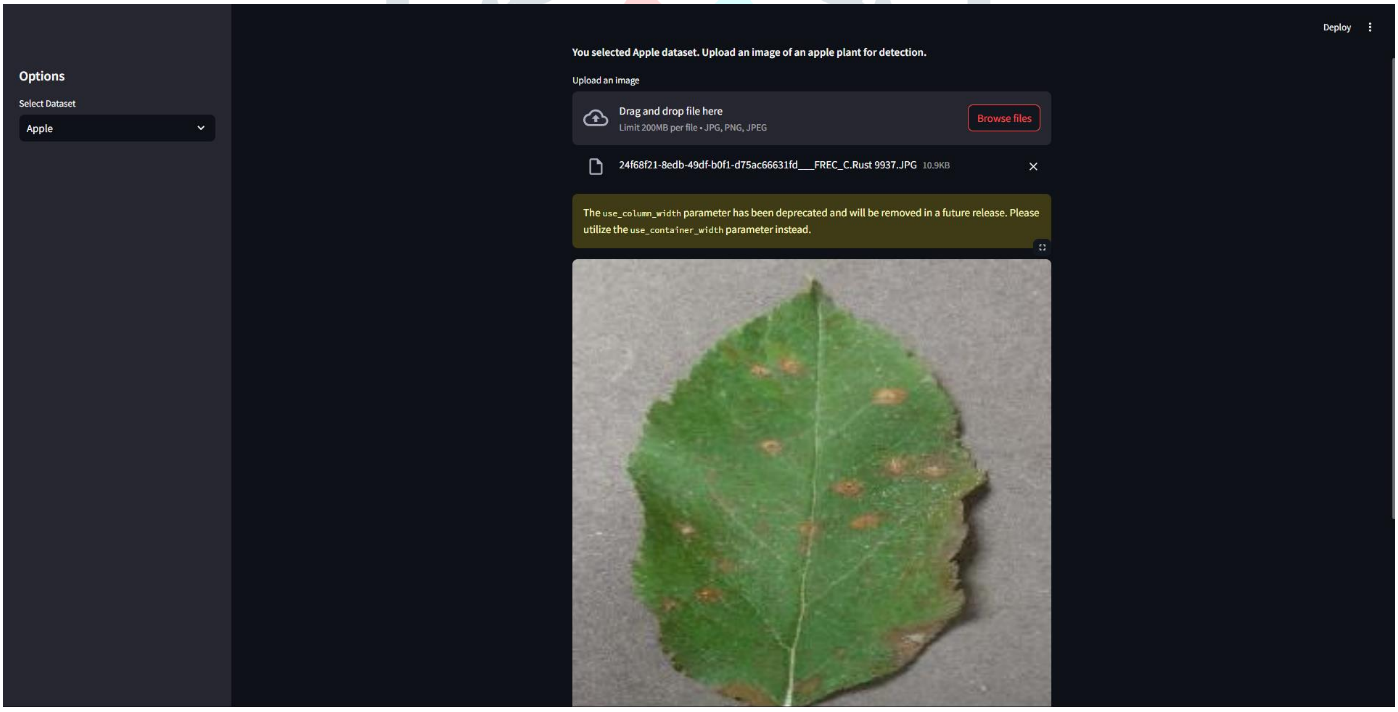
G) Inception V3

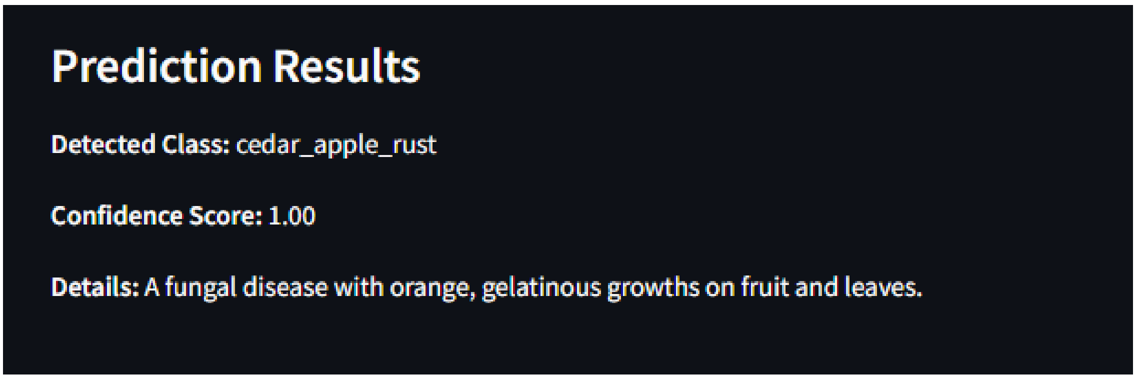
5.3 UI Interface :

Streamlit is an open-source Python framework that enables the evolution of interactive and easy to use web applications for deep learning models. In relation to cotton and apple Identification of leaf diseases, Streamlit provides a seamless interface where users can upload leaf images and receive instant disease classification results powered by a CNN-based deep learning model. Its lightweight architecture simplifies deployment without requiring extensive web development expertise, making it accessible to farmers and agricultural experts. The framework supports interactive visualizations, displaying confidence scores, disease severity levels, and heatmaps to enhance user understanding. Additionally, cloud storage integration allows for remote access, ensuring scalability for large-scale agricultural monitoring. Real-time processing enables quick decision-making, while automatic model updates ensure adaptability to new diseases. Streamlit also facilitates the integration of IoT-based smart farming devices, enhancing precision agriculture. By offering a cost-effective, scalable, and efficient solution, Streamlit significantly contributes to modern AI-driven plant disease detection systems.









VI. CONCLUSION

The Streamlit-enabled deep learning framework provides an efficient, user-friendly, and scalable solution for detecting cotton and apple leaf diseases. By integrating CNNs, or convolutional neural network with a The system's web-based interface allows real-time disease detection, empowering farmers and agricultural experts with accurate diagnostic insights. The framework's ability to process images instantly, display confidence scores, and offer visual analytics enhances decision-making in precision agriculture. Additionally, cloud integration and IoT-based automation improve scalability and remote accessibility, making disease detection more efficient. The continuous model updates ensure adaptability to new plant diseases, maintaining high accuracy and reliability. Its lightweight and accessible nature eliminates the need for technical expertise, allowing broader adoption in the agricultural sector. Furthermore, the system's cost-effectiveness makes advanced AI-driven disease detection more feasible for small-scale farmers. Future enhancements could include mobile integration and real-time IoT monitoring for automated disease prediction. Overall, this framework significantly contributes to sustainable farming practices by reducing crop losses and optimizing agricultural productivity.

References

1.] Rajan Bhatt, Akbar Hossain, Debjyoti Majumder, Mandapelli Sharath Chandra, Rajiv Ghimire, Muhammad Faisal Shahzad, Krishan K. Verma, Amarinder Singh Riar, Vishnu D. Rajput, Mauro Wagner Oliveira, Adel Nisi, Riyadh S. Almalki, Viliam BÃ¡rek, Marian Brestic, Sagar Maitra, Prospects of artificial intelligence for the sustainability of sugarcane production in the modern era of climate change: An overview of related global findings, Journal of Agriculture and Food Research, Volume 18,2024,101519, ISSN 2666-1543, https://doi.org/10.1016/j.jafr.2024.101519.

2. Sofia Bahmutsky, Florian Grassauer, Vivek Arulnathan, Nathan Pelletier, A review of life cycle impacts and costs of precision agriculture for cultivation of field crops, Sustainable Production and Consumption, Volume 52,2024,Pages 347-362, ISSN 2352-5509, https://doi.org/10.1016/j.spc.2024.11.010.

3. Abderahman Rejeb, Karim Rejeb, Alireza Abdollahi, Abdo Hassoun,Precision agriculture: A bibliometric analysis and research agenda,Smart Agricultural Technology, Volume 9, 2024, 100684, ISSN 2772-3755, https://doi.org/10.1016/j.atech.2024.100684.

4. Xiaomo Zhang, Gary Feng, Xin Sun, Advanced technologies of soil moisture monitoring in precision agriculture: A Review, Journal of Agriculture and Food Research, Volume 18, 2024,101473, ISSN 2666-1543, https://doi.org/10.1016/j.jafr.2024.101473.

5. Sergio VÃ©lez, JoÃ£o Valente, Tamara Bretzel, Max Trommsdorff, Assessing the impact of overhead agrivoltaic systems on GNSS signal performance for precision agriculture, Smart Agricultural Technology, Volume 9, 2024,100664, ISSN 2772-3755, https://doi.org/10.1016/j.atech.2024.100664.

6. T.A. Alka, Aswathy Sreenivasan, M. Suresh,Seeds of Change: Mapping the Landscape of precision farming technology adoption among agricultural entrepreneurs, Journal of the Saudi Society of Agricultural Sciences, 2024, ISSN 1658-077X, https://doi.org/10.1016/j.jssas.2024.09.001.

7. Iftekhar Anam, Naiem Arafat, Md Sadman Hafiz, Jamin Rahman Jim, Md Mohsin Kabir, M.F. Mridha,A systematic review of UAV and AI integration for targeted disease detection, weed management, and pest control in precision agriculture,Smart Agricultural Technology, Volume 9,2024,100647, ISSN 2772-3755, https://doi.org/10.1016/j.atech.2024.100647