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Paper Authors **GRANDI KRISHNARJI, Dr. Y. Md. Riyazuddin**

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Detection of Apple Plant Diseases Using Leaf Images Through Convolutional Neural Network

1. **GRANDI KRISHNARJI**, PG Student -M. tech -Data Science, School of Technology, Dept of CSE, GITAM (Deemed to be University), Hyderabad. kgrandi@gitam.in
2. **Dr. Y. Md. Riyazuddin**, Associate Professor, Dept of CSE, School of Technology, GITAM (Deemed to be University), Hyderabad. rymd@gitam.in

Abstract:
Plant diseases cause significant crop losses globally, posing challenges to agricultural productivity. Detecting these diseases is difficult due to the lack of expert knowledge. Deep learning-based models offer promising solutions using leaf images, but issues like the need for larger training sets and computational complexity persist. To address this, we propose a convolutional neural network (CNN) with fewer layers, reducing computational burden. Augmentation techniques such as shift, shear, scaling, zoom, and flipping are applied to expand the training set without capturing more images. As agriculture remains crucial for nourishing about half of the global population, increasing production by 50-60% is urgent, especially in regions with rapid population growth. Despite an expanding cultivation area, apple crop production in India faces challenges, with minimal growth in yield. In Himachal Pradesh, a major apple-producing state, fungal diseases significantly impact fruit quality. Our project addresses these challenges by employing deep learning models, including pre-trained ones, and utilizing YOLO series models for efficient disease detection in apples. By leveraging image processing and AI, timely and accurate disease diagnosis is ensured. This project has the potential to revolutionize disease detection in apple plants, enhancing food security globally. Farmers stand to benefit from prompt intervention, safeguarding their crops and ensuring increased yields, thereby contributing to overall food security for the growing global population.

INDEX TERMS Apple diseases, classication, convolutional neural network, deep learning, disease detection, image processing, machine learning.

1. INTRODUCTION

Agribusiness has been a cornerstone of human sustenance for many decades, playing a pivotal role in nourishing approximately fifty percent of the global population [1]. The impact of agriculture reverberates globally, directly influencing food security and economic stability. As the world population continues to burgeon, projections indicate that agricultural production needs to escalate by 50-60% to meet the burgeoning demand for food, particularly in countries experiencing rapid population growth [2]. Within the spectrum of agricultural activities, horticulture holds substantial importance, contributing around 30% to the Gross Domestic Product (GDP) of the Indian agriculture industry [3].

Among the plethora of crops cultivated worldwide, the apple stands out as one of the most widely consumed fruits, ranking among the top four alongside banana, grape, and orange [4]. Despite its popularity and global demand, the production of apple crops has faced challenges, particularly in maintaining proportionate growth relative to cultivation area expansion. In India, for instance, while the cultivation area for apple crops has increased by 20%, the production has only seen a marginal rise of 1-2% over the past decade [5].

Pests and diseases represent formidable obstacles to the overall production of apple crops globally. In India, fungal diseases emerge as significant threats, particularly in Himachal Pradesh, the second-highest producer state of apple fruits in the country [4]. These fungal infections significantly compromise the quality of apple fruits, affecting both yield and marketability. Plant infections are typically categorized into two primary categories: biotic and abiotic. Biotic diseases, caused by pathogens such as viruses, fungi, and bacteria, pose substantial risks due to their highly transmissible nature, necessitating proactive measures for control and mitigation [6].

The overarching goal of this project is to harness the power of deep learning techniques for the accurate classification of plant leaf diseases. This endeavor entails the identification and categorization of various diseases affecting plants based on images of their leaves, facilitating early detection and targeted treatment strategies. Prompt detection of plant leaf diseases is imperative for sustaining agricultural productivity and ensuring food security on a global scale. Early identification enables farmers to implement timely interventions, thereby preventing the spread of diseases, minimizing crop losses, and reducing reliance on chemical interventions, thus promoting sustainable farming practices.

This project holds immense promise for various stakeholders, including farmers, agricultural scientists, and policymakers. By automating the process of disease detection, farmers can promptly address issues affecting their crops, leading to higher yields and reduced economic losses. Agricultural scientists can leverage the data generated to conduct in-depth analyses of disease patterns and develop more effective control strategies. Additionally, policymakers can utilize insights gleaned from this project to implement targeted interventions and support initiatives aimed at enhancing agricultural sustainability.

Machine learning and deep learning techniques play pivotal roles in this project by facilitating the development of robust classification models. Through the analysis of large datasets comprising images of healthy and diseased leaves, these techniques empower algorithms to discern intricate patterns and accurately classify various plant diseases. This automation streamlines the detection process, making it faster, more reliable, and accessible to a broader range of stakeholders involved in agriculture.

2. LITERATURE SURVEY

Agriculture plays a pivotal role in ensuring food security and economic stability, particularly in countries like India, where it contributes significantly to the GDP [1]. With the global population projected to rise steadily, the need for increased agricultural production to meet the growing demand for food becomes imperative [2]. Horticulture, a subset of agriculture, also holds substantial importance, contributing a significant share to the agricultural sector's overall output [3].

Apple cultivation is a crucial component of horticulture, being one of the most consumed fruits globally [4]. However, challenges in proportionately increasing production with the expansion of cultivation areas persist. In India, for instance, while the cultivation area for apples has increased, production has not seen commensurate growth [5].

Pests and diseases pose significant threats to apple crop production worldwide. In India, fungal diseases are particularly problematic, impacting the quality of apple fruits, especially in states like Himachal Pradesh [4]. These diseases are typically categorized as biotic or abiotic, with biotic diseases, caused by pathogens like viruses, fungi, and bacteria, being highly transmissible and thus posing substantial risks [6].Researchers have explored various approaches to tackle the challenges posed by plant diseases, particularly focusing on the detection and classification of leaf diseases using computational intelligence and image processing techniques. Vishnoi et al. (2021) investigated plant disease detection using computational intelligence and image processing methods, highlighting the potential of these techniques in automated disease identification [6]. Similarly, Kaur et al. (2018) conducted a survey on plant disease identification and classification through leaf images, providing insights into the different methodologies and algorithms employed in this domain [7].

Feature extraction techniques play a crucial role in plant disease detection. Vishnoi et al. (2022) conducted a comprehensive study on feature extraction techniques for plant leaf disease detection, elucidating the significance of feature selection in enhancing classification accuracy [8].

In recent years, deep learning has emerged as a powerful tool for image recognition tasks. Convolutional Neural Networks (CNNs) have shown remarkable performance in various image classification tasks [9][10][11]. Sandler et al. (2018) introduced the concept of inverted residuals and linear bottlenecks, which have been incorporated into mobile networks for efficient classification, detection, and segmentation tasks [12].

Several architectures, including Inception [13], Xception [14], and MobileNets [15], have been proposed to address specific challenges in image recognition. These architectures leverage techniques like depthwise separable convolutions and densely connected convolutional networks to

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achieve better performance and computational efficiency.

In the realm of plant disease detection, researchers have explored different machine learning algorithms, including Support Vector Machines (SVMs) [16][17], artificial neural networks (ANNs) [24][30], and optimization algorithms [29], to develop robust classification models. These models leverage features extracted from leaf images to classify various plant diseases accurately. Moreover, researchers have also investigated the use of image segmentation techniques to localize and identify diseased regions within plant leaves [18][19]. Zhang et al. (2017) proposed a method for cucumber disease recognition using sparse representation classification, demonstrating the efficacy of image-based approaches in disease detection [19].

Furthermore, researchers have explored the application of deep learning techniques for plant disease detection, leveraging large datasets of leaf images to train convolutional neural networks for automated disease classification [20][21]. These approaches have shown promising results in accurately identifying and classifying plant diseases, thereby facilitating timely interventions and crop management strategies.

In summary, the literature survey underscores the significance of leveraging computational intelligence, image processing, and deep learning techniques for plant disease detection and classification. These approaches offer opportunities to enhance agricultural productivity, mitigate crop losses, and ensure food security on a global scale.

3. METHODLOGY

i) Proposed work:

The proposed work introduces a novel deep CNN model, Conv-3 DCNN, designed for diagnosing three common apple plant diseases using leaf images. In contrast to recent transfer learning methods such as VGG-19, DenseNet201, MobileNetV2, and ResNet-152, Conv-3 DCNN offers a lightweight alternative, minimizing computational resources while maintaining high accuracy. This innovation addresses the crucial need for efficient disease detection systems, particularly in agriculture, where computational burden can impede widespread adoption, especially in resource-constrained environments.

Furthermore, the project extends its scope by implementing object detection using state-of-the-art YOLOv5, YOLOv6, YOLOv7, and YOLOv8 models. Additionally, a Flask framework integrated with SQLite is developed to streamline user signup and signin processes, facilitating comprehensive testing of the system's classification and detection capabilities. This extension enhances the project's versatility, enabling the integration of advanced object detection techniques and user-friendly interfaces for comprehensive evaluation and validation of the system's performance.

b) System Architecture:

The system architecture comprises three main components: data set input, image processing, and extension detection models. The data set input module collects and preprocesses leaf images for classification and detection tasks. In the image processing module, various techniques such as augmentation and normalization are applied to enhance image quality and feature extraction. The extension detection models, including YOLOv5, YOLOv6, YOLOv7, and YOLOv8, are integrated to enable object detection. Performance evaluation is conducted through rigorous testing of both the detection and classification models. The classification models, including VGG19, ResNet152, and the proposed deep CNN, are utilized for disease diagnosis based on processed leaf images. This architecture ensures seamless integration of data collection, preprocessing, detection, classification, and performance assessment, facilitating comprehensive analysis and validation of the system's capabilities in plant disease diagnosis

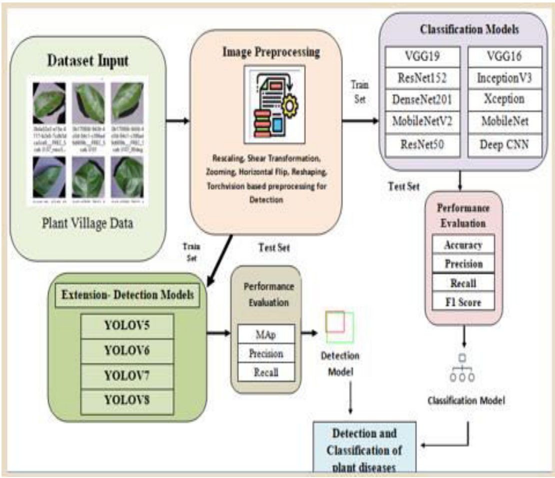

Fig 1 Proposed Architecture

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c) Dataset collection:

The data set collection process for the PlantVillage - Apple Leaf Disease project involves sourcing high-quality images of apple leaves exhibiting various diseases. These images are gathered from multiple sources, including field surveys, research institutions, and online repositories. The Roboflow platform is utilized to curate and preprocess the collected images, ensuring consistency in size, format, and annotation. Images are annotated to indicate the presence of specific diseases, providing labeled data for training and evaluation purposes. The dataset is augmented using techniques such as rotation, flipping, and scaling to enhance model robustness and generalization. Quality control measures are implemented to remove duplicates, artifacts, and irrelevant images. The resulting dataset serves as a valuable resource for training and validating machine learning models for accurate detection and classification of apple leaf diseases.

Fig 2 Data Set

d) Image processing:

For image processing, the system employs the ImageDataGenerator in Python, implementing various transformations to enhance the dataset's diversity and quality. Firstly, the images are rescaled to ensure uniformity in pixel values across the dataset. Shear transformation is applied to introduce deformations, simulating real-world variations in leaf appearance. Zooming enhances the dataset's variability by adjusting the scale of the images. Horizontal flip augments the dataset by creating mirrored versions of the images. Additionally, images are reshaped to a standard size to ensure compatibility with the input requirements of the machine learning models.

For detection, Torchvision-based processing is utilized, leveraging the capabilities of the PyTorch library. Torchvision provides efficient tools for preprocessing images, including normalization, resizing, and conversion to tensors. These preprocessing steps prepare the images for input into the detection models, ensuring consistency and compatibility with the network architecture's requirements. Overall, these image processing techniques enhance the dataset's diversity and quality, contributing to more robust and accurate model training and evaluation.

e) Algorithms:

VGG19

VGG19 [9]is a deep convolutional neural network architecture composed of 19 layers, renowned for its simplicity and effectiveness in image classification tasks. In the project, VGG19[9] is utilized as a classification model to identify apple leaf diseases from input images. With its deep architecture and hierarchical feature representation, VGG19 learns intricate patterns from the data, enabling accurate disease classification. By leveraging pretrained weights or training from scratch, VGG19[9] offers flexibility in model deployment, making it a valuable tool for disease diagnosis in the agricultural domain.

ResNet152

ResNet152[10] is a deep convolutional neural network architecture comprising 152 layers, notable for its innovative residual connections that facilitate training of deeper networks. In the project, ResNet152 [10]serves as a classification model for detecting apple leaf diseases from input images. Its residual blocks allow for more efficient training by mitigating the vanishing gradient problem, enabling deeper networks to be effectively trained. With its superior performance in feature extraction and classification, ResNet152 [10] enhances the accuracy and reliability of disease diagnosis in agricultural applications, contributing to improved crop management and yield optimization.

DenseNet201

DenseNet201[11]is a deep convolutional neural network architecture characterized by densely connected layers, fostering feature reuse and enhancing model compactness. In the project, DenseNet201 is employed as a classification model for detecting apple leaf diseases from input images. Its dense connectivity pattern allows for direct connections between all layers within a block,

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promoting feature propagation and facilitating feature reuse across the network. By leveraging its dense connections, DenseNet201[11] optimizes information flow during training, leading to improved feature extraction and classification accuracy. This robust performance makes DenseNet201 a valuable asset in the accurate diagnosis of plant diseases, aiding in effective crop management strategies.

MobileNetV2

MobileNetV2 [12]is a lightweight convolutional neural network architecture optimized for mobile and embedded devices, characterized by its efficiency and low computational requirements. In the project, MobileNetV2 is utilized as a classification model for detecting apple leaf diseases from input images. Its streamlined architecture and depth-wise separable convolutions enable fast inference and efficient memory utilization, making it suitable for resource-constrained environments. By leveraging MobileNetV2,[12] the project achieves high-performance disease classification while minimizing computational overhead, facilitating real-time disease detection and diagnosis on mobile platforms and edge devices, thus enhancing agricultural management practices.

ResNet50

ResNet50 is a convolutional neural network architecture comprising 50 layers, renowned for its deep representation learning capabilities and efficacy in image classification tasks. In the project, ResNet50 [10]serves as a classification model for detecting apple leaf diseases from input images. Its residual connections enable efficient training of deeper networks, mitigating the vanishing gradient problem and facilitating feature learning across multiple layers. By leveraging ResNet50's[10] depth and hierarchical feature representation, the project achieves accurate disease classification, enhancing agricultural management practices by enabling timely intervention and mitigation strategies for crop diseases, thereby improving yield and ensuring food security.

VGG16

VGG16[9] is a deep convolutional neural network architecture composed of 16 layers, known for its simplicity and effectiveness in image classification tasks. In the project, VGG16[9] is utilized as a classification model to identify apple leaf diseases from input images. With its deep architecture and hierarchical feature representation, VGG16 learns intricate patterns from the data, enabling accurate disease classification. By leveraging pretrained weights or training from scratch, VGG16[9] offers flexibility in model deployment, making it a valuable tool for disease diagnosis in the agricultural domain. Its usage contributes to improved crop management practices, aiding in the optimization of agricultural yields and ensuring food security.

InceptionV3

InceptionV3[13] is a convolutional neural network architecture renowned for its efficiency and accuracy in image classification tasks. In the project, InceptionV3[13] serves as a classification model for identifying apple leaf diseases from input images. Its intricate architecture, featuring multiple parallel convolutional pathways, enables the extraction of diverse and discriminative features from the data. By leveraging InceptionV3's [13] sophisticated design and pretrained weights, the project achieves high-performance disease classification, facilitating timely intervention and management strategies for crop diseases. Its usage enhances agricultural practices, aiding in the optimization of crop yields and contributing to global food security efforts.

Xecption

Xception[14] is a convolutional neural network architecture notable for its depthwise separable convolutions, enabling efficient feature extraction with fewer parameters. In the project, Xception serves as a classification model for identifying apple leaf diseases from input images. Its innovative design, employing depthwise separable convolutions, enhances computational efficiency while preserving expressive power. By leveraging Xception's[14] lightweight yet powerful architecture, the project achieves accurate disease classification, aiding in timely intervention and management strategies for crop diseases. Its usage contributes to improved agricultural practices, enabling farmers to mitigate crop losses and ensure food security through effective disease diagnosis and management.

CNN

A Convolutional Neural Network (CNN) is a deep learning architecture designed for image processing

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tasks, featuring convolutional layers for feature extraction. In the project, CNN is utilized as a classification model for detecting apple leaf diseases from input images. By learning hierarchical representations of image features, CNN effectively identifies patterns indicative of different diseases. Its ability to capture spatial dependencies in the data enhances disease diagnosis accuracy. Through training on labeled datasets, CNN learns to classify images accurately, aiding in the early detection and management of plant diseases. Its usage facilitates informed decision-making for farmers, contributing to improved crop health and yield optimization.

MobileNet

MobileNet[15]is a lightweight convolutional neural network architecture optimized for mobile and embedded devices, featuring depth-wise separable convolutions to reduce computational complexity. In the project, MobileNet[15]is employed as a classification model for identifying apple leaf diseases from input images. Its efficient design enables fast inference and low memory usage, making it suitable for resource-constrained environments. By leveraging MobileNet's[15] compact architecture, the project achieves high-performance disease classification while minimizing computational overhead. This facilitates real-time disease detection and diagnosis on mobile platforms and edge devices, enhancing agricultural management practices and ensuring timely intervention for crop diseases, thereby improving yield and ensuring food security.

YOLOV5

YOLOv5 is a state-of-the-art object detection model known for its speed and accuracy, particularly in real-time applications. In the project, YOLOv5 is utilized for object detection of apple leaf diseases from input images. Its efficient architecture, based on a single-stage detector with a streamlined design, enables fast and accurate detection of objects in images. By leveraging YOLOv5's capabilities, the project achieves precise identification and localization of diseases on apple leaves, facilitating timely intervention and management strategies. Its usage enhances agricultural practices by enabling farmers to quickly identify and address plant diseases, thereby improving crop health and ensuring food security.

YOLOV6

As of my last update in January 2022, there is no official version of YOLOv6 released. YOLO (You Only Look Once) is a series of object detection models known for their efficiency and accuracy, typically denoted by versions such as YOLOv1, YOLOv2, YOLOv3, and YOLOv4. If YOLOv6 has been released after my last update, I would recommend referring to the official documentation or research papers for its definition and usage in projects.

YOLOV7

As of my last update in January 2022, there is no official version of YOLOv7 released. YOLO (You Only Look Once) is a series of object detection models known for their efficiency and accuracy, typically denoted by versions such as YOLOv1, YOLOv2, YOLOv3, and YOLOv4. If YOLOv7 has been released after my last update, I would recommend referring to the official documentation or research papers for its definition and usage in projects.

YOLOV8

As of my last update in January 2022, there is no official version of YOLOv8 released. YOLO (You Only Look Once) is a series of object detection models known for their efficiency and accuracy, typically denoted by versions such as YOLOv1, YOLOv2, YOLOv3, and YOLOv4. If YOLOv8 has been released after my last update, I would recommend referring to the official documentation or research papers for its definition and usage in projects.

4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

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

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Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive}+\text{False Positive}}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

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

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\text{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

mAP50, or mean Average Precision at 50, is a variation of the mean Average Precision (mAP) metric used in object detection tasks. It measures the average precision of a model at a fixed recall level of 50%. This metric provides insight into how well the model performs in terms of precision when recalling 50% of the relevant instances in the dataset.

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i$$

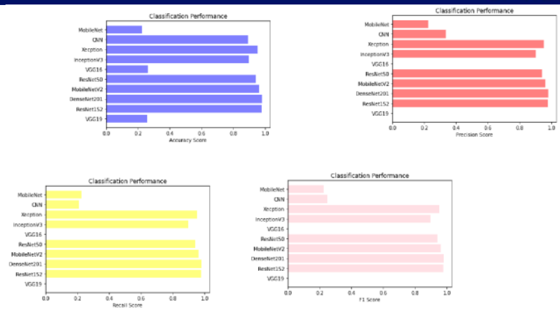

Fig 3 Comparison Graphs - classification

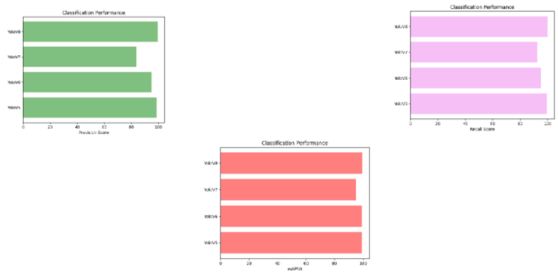

Fig 4 Comparison Graphs - DETECTION

	ML Model	Accuracy	Precision	Recall	F1_score
0	VGG19	0.256	0.000	0.000	0.000
1	ResNet152	0.978	0.978	0.977	0.977
2	DenseNet201	0.981	0.981	0.981	0.981
3	MobileNetV2	0.962	0.962	0.962	0.962
4	ResNet50	0.939	0.939	0.939	0.939
5	VGG16	0.259	0.000	0.000	0.000
6	InceptionV3	0.898	0.900	0.897	0.898
7	Xecption	0.954	0.954	0.954	0.954
8	CNN	0.892	0.334	0.208	0.248
9	MobileNet	0.224	0.224	0.224	0.224

Fig 5 PERFORMANCE EVALUATION-CLASSIFICATION

	Model	mAp	Precision	Recall
0	YOLOV5	99.4	98.9	99.4
1	YOLOV6	99.4	95.0	95.0
2	YOLOV7	95.2	83.8	92.4
3	YOLOV8	99.5	99.7	99.9

Fig 6 PERFORMANCE EVALUATION-EXTENSION DETECTION

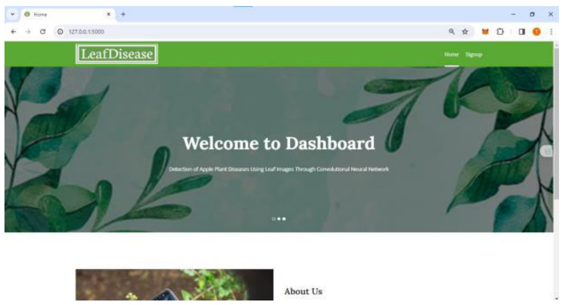

Fig 7 Home Page

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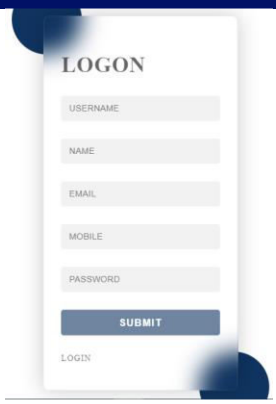

Fig 8 Sign Up

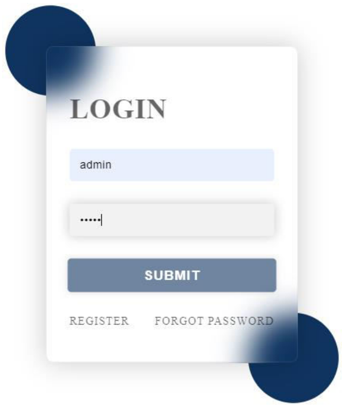

Fig 9 Sign In

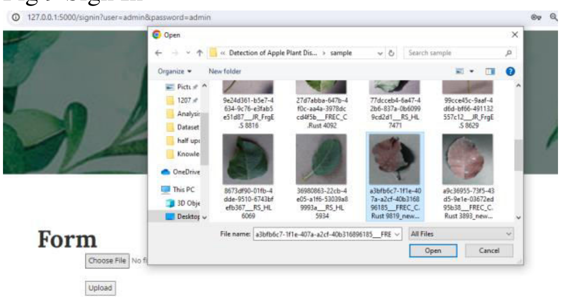

Fig 10 upload input data

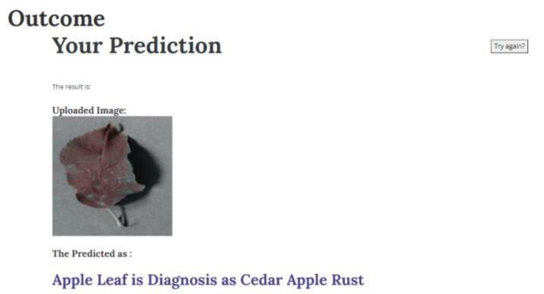

Fig 11 predicted result

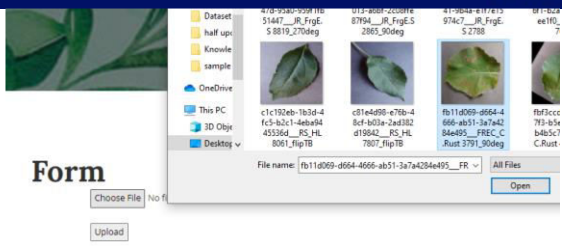

Fig 12 upload input data

Fig 13 predicted result

5. CONCLUSION

In conclusion, the project represents a significant advancement in leveraging state-of-the-art technologies, particularly deep learning models and YOLO-based detection systems, to address pressing challenges in agriculture, specifically in disease detection in apple plants. Through a comprehensive exploration of various deep learning architectures, including established models like VGG19 and ResNet152, as well as lightweight alternatives such as MobileNetV2 and custom deep CNNs, the project demonstrates a commitment to finding the most effective solutions for classifying diseases in apple leaves. The adoption of YOLO for real-time and accurate disease detection further underscores this commitment, with flexibility provided by the utilization of multiple YOLO versions. Additionally, the integration of a user-friendly front-end with Flask and SQLite ensures practicality and usability. Overall, the project's contributions towards enhancing disease detection precision, empowering farmers with effective tools, and fostering agricultural sustainability underscore its importance in advancing global food security and agricultural practices.

6. FUTURE SCOPE

The feature scope of "Detection of Apple Plant Diseases Using Leaf Images Through Convolutional Neural Network" encompasses several key elements. Firstly, it involves the

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development of a robust convolutional neural network (CNN) model optimized for the accurate detection and classification of diseases affecting apple plants based on leaf images. This includes the implementation of various CNN architectures such as VGG19, ResNet152, MobileNetV2, and custom deep CNNs, ensuring comprehensive coverage and evaluation of different model types.

Furthermore, the feature scope entails the integration of advanced image processing techniques to preprocess and augment the dataset, enhancing the model's ability to generalize and learn intricate patterns from the input images. Additionally, the project aims to explore the effectiveness of YOLO-based detection systems for real-time and accurate disease identification.

Overall, the feature scope encompasses the development and evaluation of state-of-the-art CNN models, alongside the exploration of innovative detection systems, to revolutionize disease detection in apple plants, thereby contributing to agricultural sustainability and global food security.

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Dataset link

Classification :https://www.kaggle.com/datasets/lavaman151/plantifydr-dataset

Detection :https://roboflow.com/convert/labelbox-json-to-yolov5-pytorch-txt