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Deep Learning based Plant Leaf Disease Detection with Real-Time Alerting

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ABSTRACT: A comprehensive system for the detection and classification of plant diseases is presented, leveraging advanced deep learning techniques, specifically Convolutional Neural Networks (CNNs). Employing a sequential model architecture, the learning process is optimised for enhanced accuracy and efficiency. Transitioning towards real-time monitoring, live web cameras are integrated into the system and deep learning models are seamlessly embedded into a user-friendly Flask-based web application. This integration marks a significant advancement, allowing farmers to conveniently access the system for swift on-the-spot diagnosis of plant diseases. In the event of disease detection, the system triggers immediate alerts to farmers via SMS, facilitating rapid response and mitigation strategies. This proactive notification mechanism empowers farmers with timely information, enabling them to take swift actions to prevent further spread and minimise crop loss. By bridging the gap between cutting-edge technology and agricultural practices, this solution addresses critical challenges in global food security efforts. Timely interventions facilitated by the system not only enhance crop productivity but also contribute significantly to the sustainable management of agricultural resources. In conclusion, the integrated approach towards plant disease detection and classification not only offers practical solutions for farmers but also underscores the potential of deep learning and real-time monitoring technologies in revolutionising agricultural practices. This initiative represents a crucial step towards building resilience in the agricultural sector and ensuring food security for future generations.

KEYWORDS: CNN, Sequential model, Flask, Keras, Alert message.

I. INTRODUCTION

Plant disease detection software systems are essential tools for modern agriculture, aiming to revolutionise disease management by providing timely and accurate diagnosis. Traditional methods of disease detection often fall short in terms of speed and reliability, leaving farmers vulnerable to crop losses. These software systems leverage advanced algorithms and data analytics, such as Convolutional Neural Networks (CNN), to analyse images captured by web cameras installed in agricultural fields. By utilising CNN algorithms, these systems can identify signs of diseases or pest infestations in real-time, enabling early detection and intervention.

The prevalence of plant diseases poses a significant threat to global food security, with crop losses ranging from 10% to 40% in severity, depending on factors such as the outbreak's severity and crop susceptibility. To address these challenges, the developed software solution utilises web camera technology to capture images of crops, which are then analysed using CNN algorithms. Upon detection of diseases or pests, the system automatically sends alert messages to farmers, providing timely notification of potential threats to their crops. Additionally, the system delivers solutions via SMS, empowering farmers with actionable steps to mitigate the impact of these threats promptly.

By implementing this solution, farmers can proactively manage plant health and minimise crop losses, contributing to global food security and sustainable agriculture. These software systems represent a proactive approach to disease management, enabling farmers to make informed decisions and effectively address disease outbreaks and pest infestations.

II. LITERATURE SURVEY

Literature research is the most important step in the software development process. Before creating a tool, it is important to determine the time factor, profitability, and company strengths. With these in place, the next 10 steps are to decide which operating systems and languages you can use to develop your tools. Once programmers start building tools, they need a lot of external support. This support can come from experienced programmers, books, or websites. The above evaluations will be considered in the development of the proposed system before building the system.

P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks, 2019.

Alternaria leaf spot, Brown spot, Mosaic, Grey spot, and Rust are five common types of apple leaf diseases that severely affect apple yield. However, the existing research lacks an accurate and fast detector of apple diseases for ensuring the healthy development of the apple industry. This project proposes a deep learning approach that is based on improved convolutional neural networks (CNNs) for the real-time detection of apple leaf diseases. In this project, the apple leaf disease dataset (ALDD), which is composed of laboratory images and complex images under real field conditions, is first constructed via data augmentation and image annotation technologies. Based on this, a new apple leaf disease detection model that uses deep-CNNs is proposed by introducing the GoogLeNet Inception structure and Rainbow concatenation. Finally, under the hold-out testing dataset, using a dataset of 26,377 images of diseased apple leaves, the proposed INAR-SSD (SSD with Inception module and Rainbow concatenation) model is trained to detect these five common apple leaf diseases. The experimental results show that the INAR-SSD model realises a detection performance of 78.80% mAP on ALDD, with a high-detection speed of 23.13 FPS. The results demonstrate that the novel INAR-SSD model provides a high-performance solution for the early diagnosis of apple leaf diseases that can perform real-time detection of these diseases with higher accuracy and faster detection speed than previous methods.

Lili Li; Shujuan Zhang; Bin Wang, Plant Disease Detection and Classification by Deep Learning, 2021.

Deep learning is a branch of artificial intelligence. In recent years, with the advantages of automatic learning and feature extraction, it has been widely concerned by academic and industrial circles. It has been widely used in image and video processing, voice processing, and natural language processing. At the same time, it has also become a research hotspot in the field of agricultural plant protection, such as plant disease recognition and pest range assessment, etc. The application of deep learning in plant disease recognition can avoid the disadvantages caused by artificial selection of disease spot features, make plant disease feature extraction more objective, and improve the research efficiency and technology transformation speed. This review provides the research progress of deep learning technology in the field of crop leaf disease identification in recent years. In this project, we present the current trends and challenges for the detection of plant leaf disease using deep learning and advanced imaging techniques. We hope that this work will be a valuable resource for researchers who study the detection of plant diseases and insect pests.

Shoibam Amritraj, Nitish Hans, C. Pretty Diana Cyril, An Automated and Fine- Tuned Image Detection and Classification System for Plant Leaf Diseases, 2023.

Plant leaf disease detection is the process of discovering and diagnosing diseases that damage the plant leaves. This can be done using a variety of approaches including visual inspection, laboratory tests, computer vision techniques etc. Plant leaf diseases must be detected and categorised in order to take corresponding countermeasures to manage and control them for healthy and high-yielding crops. In this contemporary Deep Learning era traditional object detection methods have become obsolete due to limitations such as the need for manual crafted features, lack of robustness, and inability to handle large datasets. Deep learning-based approaches are more robust, can account for differences in brightness, interference, and perspective, and can automatically learn features from enormous datasets. These techniques are practical because they can efficiently process large datasets in a brief time frame. Several research studies have developed expert and automatic disease detection methods. Most of this research is limited to one or two plant species and a few disease types. In this research study, we presented a computer vision approach applying the state-of-the-art YOLO algorithm with our own dataset consisting of 8 different classes of plant leaf diseases caused by fungi, bacteria, viruses and pests. Our system achieved promising results and effectively predicted the diseases with the bounding boxes and class probabilities. Overall, this research project provides a solution for plant disease detection using YOLOv5 and contributes to the development of automated agricultural management systems.

Rafia Mumtaz, Muhammad Deedahwar Mazhar, Embedded AI for Wheat Yellow Rust Infection Type Classification, 2023.

Wheat is the most important and dominating crop in Pakistan in terms of production and acreage, which is grown on 37% of the cultivated area, accounting for 70% of the total production. In order to minimise this loss, the accurate and timely detection of rust disease is crucial instead of manual inspection. Towards this end, we propose a system to detect wheat rust disease and classify its infection types into four classes, including healthy, resistant, moderate (moderately resistant to moderately susceptible), and susceptible. The wheat rust dataset is collected indigenously from the National Agricultural Research Centre, Islamabad. A pre-trained U2 Net model is used to remove the background and extract the leaf containing the rust disease. Subsequently, two deep learning classifiers, including the Xception model and ResNet-50 are applied to classify the stripe rust severity levels, where the ResNet-50 model outperformed with the highest accuracy of 96%. This research presents a comparison between two state-of-the-art deep learning classifiers in terms of accuracy, memory utilisation, and prediction time, which will assist the research community in selecting the most appropriate model for plant disease detection. Moreover, to assess the external validity, the performance of these classifiers is compared with the existing technique using a publicly available dataset, which confirms the validity of the results. Additionally, an intelligent edge computing rust detection device has been developed, where the trained ResNet-50 model is deployed, which facilitates the farmers to monitor the rust attack.

III. METHODOLOGY

The first step in plant disease detection is to collect a dataset of plant images that include healthy plants as well as plants affected by various diseases. These images serve as the input for training the machine learning model. Preprocessing is crucial to prepare the images for analysis. This may involve resizing, normalisation, and augmentation techniques to ensure uniformity and improve the model's ability to generalise.

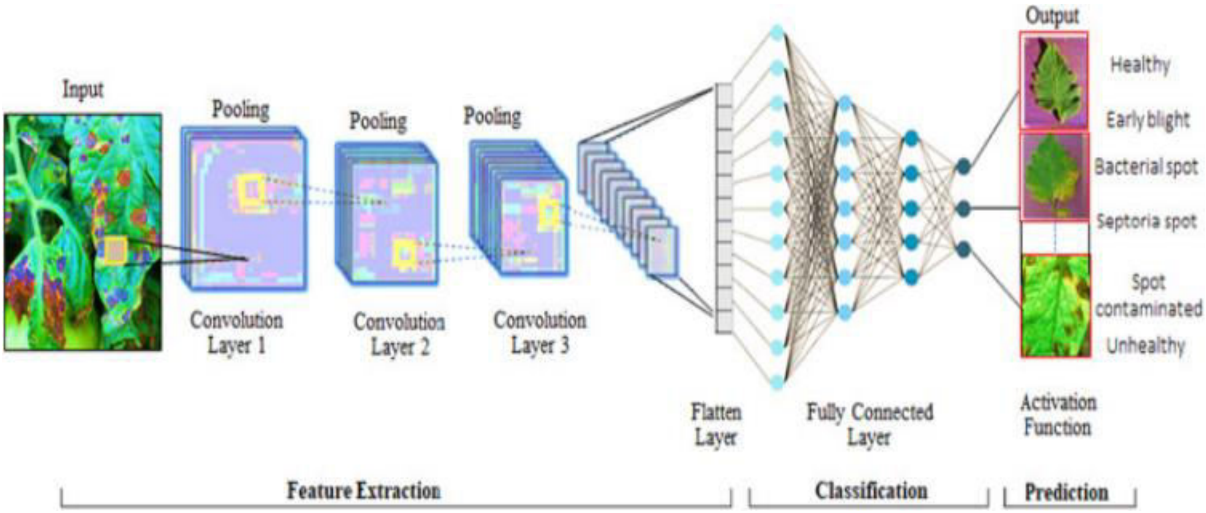

Fig1. The architecture of the proposed system

Feature extraction is the process of capturing important characteristics of the images that are relevant for disease detection. In plant disease detection, features can include colour, texture, and shape characteristics of the leaves. Classification is the task of categorising an input image into one of several predefined classes (e.g., healthy or diseased). In the context of plant disease detection, this step involves training a classification model using the extracted features from the images. Sequential models, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, can be used to capture sequential patterns in the data. In the context of plant disease detection, these models can be applied to sequences of images taken over time to track the progression of a disease. LSTM networks are particularly well-suited for sequence modelling tasks due to their ability to maintain long-term dependencies in the data. By analysing sequences of images taken over time, sequential models can help identify patterns that indicate the progression of a disease. This information can be valuable for farmers and agronomists to take timely action to prevent the spread of the disease. Sequential models can be integrated with traditional classification models to improve the accuracy of disease detection. For example, the output of a sequential model can be used as an additional feature for a classification model, enhancing its ability to distinguish between healthy and diseased plants. Once trained, the model can be deployed in a real-world setting where it can continuously monitor plants for signs of disease. By regularly analysing new images, the model can provide timely alerts to farmers, allowing them to take proactive measures to protect their crops. While sequential models show promise for plant disease detection, there are several challenges that need to be addressed. These include the need for large and diverse datasets, the interpretability of the models, and the scalability of the approach to different plant species and diseases.

IV. RESULTS AND DISCUSSION

WEB APPLICATION:

This module offers a user-friendly interface to upload leaf images for disease detection. TensorFlow particularly focus on training and inference of deep neural networks. Convolutional Neural Network (CNN) is a type of deep neural network architecture commonly used for tasks involving image recognition, classification and segmentation. Keras is a high-level deep learning API, that provides an easy-to-use interface for building, training and deploying neural network, including CNNs. The Sequential model is one of the key components of Keras and is particularly well-suited for building simple neural network architectures where layers are stacked sequentially.

ALERT:

This module implementing an internet-based messaging services such as application programming interfaces (APIs) provided by messaging platforms (e.g., Twilio, Nexmo) allows the software to send SMS messages directly to farmers' mobile numbers over the internet.

MONITORING:

This module implements real-time monitoring using live web cameras. Higher resolutions like (1280 x 720 Pixels HD) which offer great detailed and clarity, which can be advantageous for capturing and analyzing the discoloration, lesions, or abnormal growth patterns. It indicate the presence of disease that are not readily noticeable to the naked eyes.

DATASET:

This module consisting of images of tomato leaves affected by seven common diseases, including Early Blight, Light Blight and Septoria Leaf Spot, along with healthy leaves, for disease classification tasks. It focused on Tomato leaf diseases, including Target Spot, Bacterial Spot and Tomato Yellow Leaf Curl Virus, collected from multiple sources for research on deep learning-based disease detection algorithms.

ALGORITHM:

Convolutional Neural Networks (CNNs), a type of deep learning algorithm primarily used for image recognition and classification tasks. CNNs are inspired by the structure and function of the human brain's visual cortex, where individual neurons respond to stimuli in a restricted region of the visual field.

HOW IT WORKS

Image Classification: One of the most common applications of CNNs is image classification, where the goal is to categorise images into predefined classes or categories. CNNs can learn hierarchical representations of features from raw pixel data and effectively classify images into various classes. This application is widely used in areas such as object recognition, face recognition, and scene classification.

Object Detection: CNNs are also widely used for object detection tasks, where the goal is to detect and localise objects of interest within an image. CNN-based object detection models can simultaneously predict the presence of multiple objects in an image and provide bounding boxes around them. Applications include autonomous driving, surveillance systems, and medical imaging for tumour detection.

Semantic Segmentation: Semantic segmentation involves assigning semantic labels to each pixel in an image, effectively partitioning the image into different regions based on their semantic meaning. CNN-based semantic segmentation models can segment images into meaningful regions such as objects, backgrounds, and boundaries. This application is essential in fields like medical imaging for organ segmentation, autonomous navigation, and satellite image analysis.

Medical Image Analysis: CNNs have made significant advancements in medical image analysis tasks such as disease diagnosis, lesion detection, and medical image interpretation. CNN-based models can analyse medical images such as X-rays, MRI scans, and histopathology slides to assist healthcare professionals in diagnosing diseases, identifying abnormalities, and planning treatments. This application has the potential to revolutionise healthcare by improving diagnostic accuracy and efficiency.

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OUTPUT:

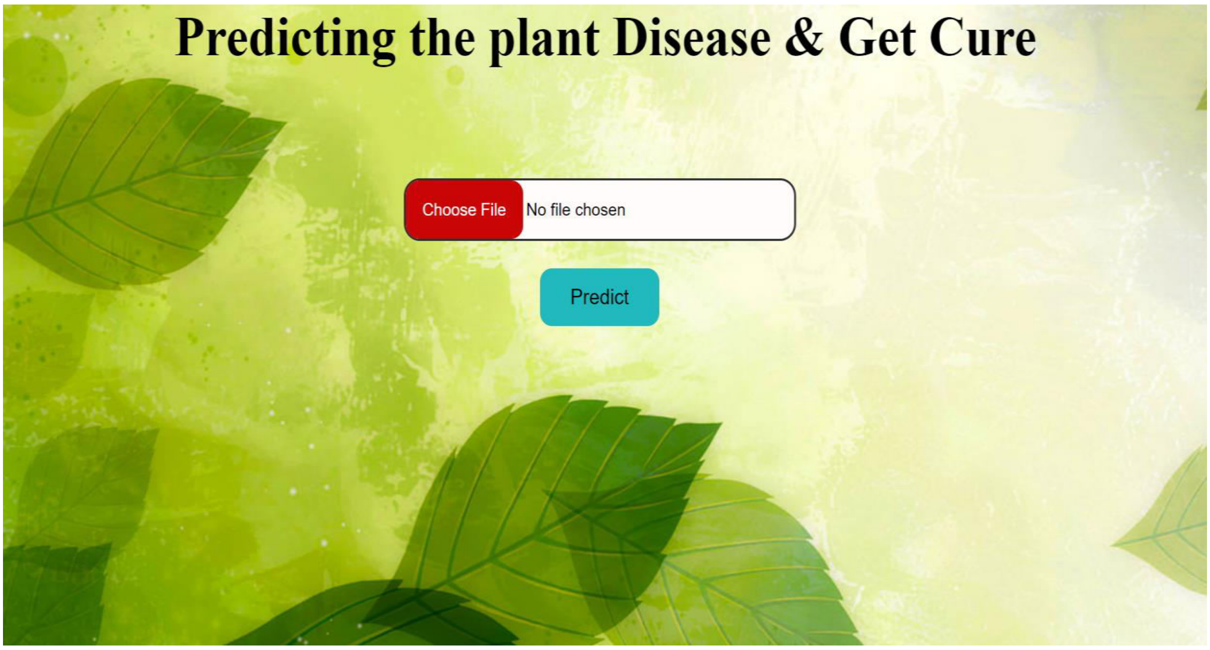

Fig2. Home Page

Fig3. Predict Leaf Disease Sample

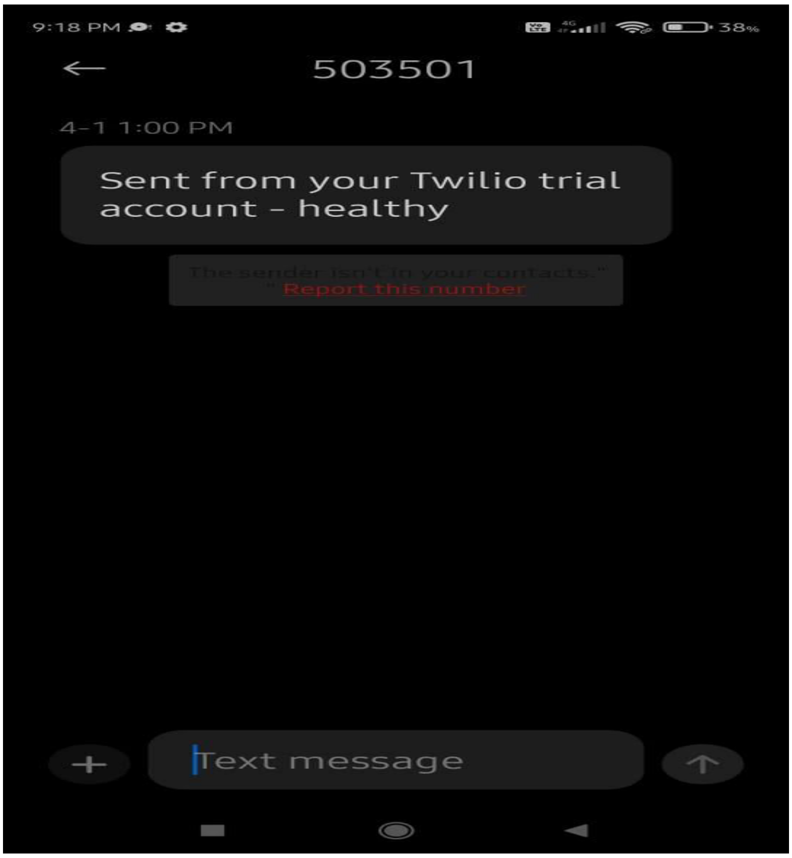

Fig4. Message via SMS

V. CONCLUSION

In conclusion, utilising convolutional neural networks (CNNs) with sequential models is a promising approach for plant disease detection. By leveraging these advanced deep learning techniques, researchers and developers can create accurate and efficient models for identifying diseases in plants, such as tomatoes. The availability of datasets like TOM-715 and Tomato-Leaf-Disease further enhances the development process, providing rich and diverse sets of images for training and testing. Ultimately, the use of CNNs with sequential models has the potential to significantly improve agricultural practices, enabling farmers to detect and manage plant diseases more effectively, leading to higher crop yields and enhanced food security.

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