Grape Disease Detection Using Federated Learning

Student name 1, s123456, Student name 2, s123456, Student name 3, s123456, Names are to be centered in Times (or Times Roman) 12-point nonboldface. Leave two blank lines before your Abstract

***Abstract*—Early detection of diseases that harm grape leaves will enable essential safeguards to be taken where financial monitoring value will not be negatively impacted. A noteworthy cause of several bacterial infections on grape leaves is environmental change. The early diagnosis of grape leaf diseases is important for sustaining top-notch production capabilities. In this researc, authors have used a dataset of enormous number of grape leaves where four categories are available. Before feding the dataset into the model, authors have applied numerous preprocessing techniques where data augmentation is also performed. The authors of this study use the VGG16, InceptionV3, and MobileNetv2 CNN architectures to detect these types of cases. The systems become more reliable and resilient as a result of the incorporation of federated learning. Different evaluation metrics have been used to track how well different architectures work. Later, the hyperparameters of these models underwent fine-tuning. Experimental result shows, MobileNetv2 has the significant number of F1-score with lower amount of elapsed time. The number of trainable parameters are also lesser in MobileNetV2 where k-fold cross validation has also been applied. The results of the improved model has been interpreted using LIME Explainable Artificial Intelligence (XAI) algorithm. The heatmap shows, the fine-tuned MobileNetV2 outperforms the state-of-the-art architectures with a significant level.**

***Index Terms*—Grape leaf, XAI, VGG16, InceptionV3, MobileNetV2, Trainable parameters**

I. Introduction

THE occurrence of diseases in the fruit leaves is a common phenomenon. The growth of a particular region's agricultural products has a significant impact on the world economy [1]. Fruit import and export are directly related to the development of a nation's finances, especially In these circumstances, grapes have a considerable effect [2]. Typically, grape trees are seen growing in areas with only a little heat. The ideal places to cultivate grapes are in tropical and subtropical climates [3]. The grape tree is susceptible to numerous diseases caused by a prodigious amount of bacteria and fungi [4].Due to many grape tree diseases, growers frequently suffer losses [5]. In order to prevent further harm, a system that can identify grape leaf diseases early on is needed. In this field, though some research has been done using machine learning, deep learning architectures are not very common [6-8].In terms of classifying and segmenting images, computer vision is rapidly expanding [9]. The output of grapes may be hampered if fruit leaf infections are not identified earlier. Here, computer vision plays a key role in the early detection of many disorders.Three Convolutional neural network (CNN) designs have been trained and verified using picture datasets to carry out such tasks, making it simple to identify diseases [10]. Three well-known CNN architectures that have already been trained using Imagenet to perform well on picture datasets are VGG16, InceptionV3, and MobileNetV2. The authors evaluated how well these models worked and afterwards adjusted every hyperparameter of the suggested architecture to improve the evaluation even further. The sections of the papers are organized in such a manner where Section II contains the recent research in this field. The detailed methodology has been described in Section III. The experimental result and result interpretability has been discussed in Section Iv. The final outcome along with the future of this research have been discussed in Section V.

II. Literature Review

CNN is frequently used to identify various fruit leaf diseases. In [11], writers discovered many fruit leaf illnesses, with the majority of the photos falling under the category of mango and banana. The performance of CNN architectures has been compared using a variety of evaluation measures [12], with VGG16, InceptionV3, and MobileNetV2 being the most extensively utilized. Disease affected leaves also can be detected from image segmentation. According to Roy et al. [13], picture segmentation can be useful for spotting illnesses in fruit leaves. There are many preprocessing strategies used here, but adding filters is the most important one [14]. Two further deep learning architectures that may identify differences in photos are Unet and En-UNet [15]. Images that were originally in RGB format are first converted to grayscale. Binarization and thresholding are two significant techniques that have also been utilized. Machine learning (ML) models are consistently outperforming Deep Learning (DL) architectures. Another distinctive web-based technique has been proposed in [16] where diseases are significantly detected. The Support Vector Machine (SVM) has been used to classify the mean as the major factor. Various surveys have been carried out in the subject area. The publication [17] suggests a survey in which various fruit leaf diseases have been divided into categories. The pinnacle works have also been mentioned for diagnosing illnesses. The article concentrated mostly on algorithms that use genetic techniques. Swarm optimization with SVM has been proposed in [18] where the usage of deep learning techniques are limited. These integrated techniques fail in some evaluation metrics. Pomegranates are another fruit that significantly contributes to the global economy. In [19] detection of the pomegranate leaf disease system has been proposed. The morphological analysis makes it possible to pinpoint the climate-related problems with this problem. In such circumstances, neural networks have been widely used. Neural networks are effectively used for texture and feature analysis [19]. The use of an unsupervised technique has been made [20] Multiple illness photos are integrated into one dataset by Smith et al., where K means clustering, in order to detect mango leaf diseases [20]. Using a supervised learning dataset, the study examined the effectiveness of Random Forest and Naive Bayes. Numerous properties have been retrieved, the majority of which are environmental in nature. There is no usage of result interpretability in the advanced study in this area. Taking this research gap into account in this research, authors have proposed a system that can detect grape leaf disease instantly. For training purposes, three fine-tuned CNN architectures have been applied where evaluation metrics are observed properly. The integration of federated learning allows this system to work in any server globally without any extensive interactions between machines. The research shows that Fine-tuned MobileNetV2 has the most significant results where it has outperformed the state-of-the-art deep learning architectures.

III. Proposed Methodology

IV. Results

V. Discussion and Summary

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