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Grape Disease Detection Using Federated Learning

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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 research, authors have used a dataset of an enormous number of grape leaves where four categories are available. Before feeding 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 have been interpreted using the 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

Generally 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 [4]. 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 [5]-[7].In terms of classifying and segmenting images, computer vision is rapidly expanding [8]. 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 [9]. 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.

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II. Literature Review

CNN is frequently used to identify various fruit leaf diseases. In [10], 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 [11], 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. [12], 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 [13]. Two further deep learning architectures that may identify differences in photos are Unet and En-UNet [14]. 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 [15] 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 [16] 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 [17] 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 [18] 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 [18]. The use of an unsupervised technique has been made [19] Multiple illness photos are integrated into one dataset by Smith et al., where K means clustering, in order to detect mango leaf diseases [19]. 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. Research Methodology

The workflow of this research is presented in Figure 1.

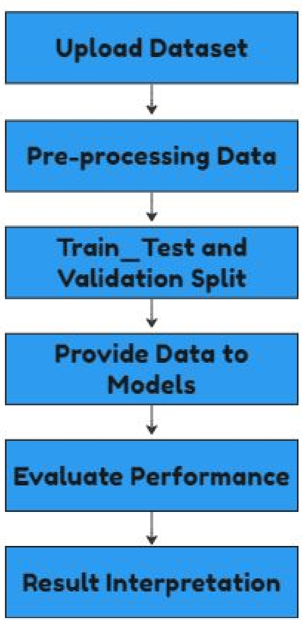

Fig. 1. Proposed Workflow of this research

At first a dataset of 6000 images was uploaded. Numerous preprocessing steps have been adopted. The dataset is later splitted into three sets namely Train, Test and validation set. After that, the train set and the validation set is provided to the model for recognizing diseases of four classes. Three CNN architectures have been considered for training purposes. FInally, their performance has been observed using some performance metrics. Finally the achieved result has been interpreted using the LIME XAI model.

In this research, authors are focused on proposing an automated system for detection of grape leaf disease detection. In this section, all the required methodologies utilized in this research will be discussed.

A. Dataset Description

For training purposes, the dataset is a vital factor. The dataset used here consists of 6000 images of grape leaves. There are four classes of data:

i) Grape healthy
ii) Grape-Esca (Black-Measles)
iii) Grape-Black-Rot
iv) Grape-Leaf-Blight

These are the four types of images available in this dataset.

Figure 2 represents some of the images that are available in the trained and validation dataset.

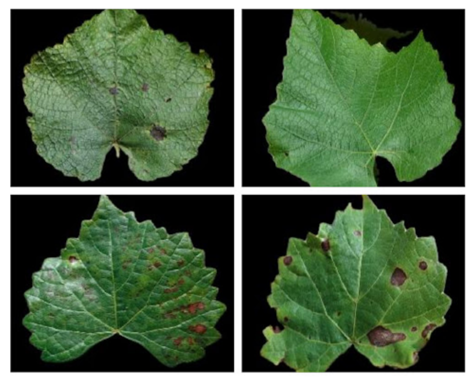

Fig. 2. Images of 4 types of diseases in the dataset

B. Preprocessing of Images

The acquired dataset is obtained from numerous sources where all the images are in different shapes. The first step of preprocessing includes resizing them into a permanent shape. The shape that has been utilized in this dataset is 126 X 126. The background is converted into totally dark as there are differences in lighting in individual images. Resizing allows us to reduce the amount of computational complexity. After reducing the size, the next step is to remove noise from the image. There are multiple filters available for noise removal among them Gausian filters allow blurring the background of the image along with extracting features precisely. For this purpose, Gausian filters have been applied to all the images in the training and validation images. After performing the preprocessing part, segmentation is performed in the background part where the utilized algorithm is GMM (Grabcut segmentation algorithm). The primary task of this algorithm is to label the foreground and background pixels.

Later, data augmentation is performed where multiple image processing techniques have been adopted. For augmenting the dataset, keras.ImageDataGenerator has been utilized. Table I represents the value of the numerous operations of the data augmentation.

Operation	Scale	Rotation	Zoom In	Shift Right	Vertical flip	Horizontal flip
Value	1/255	45	Yes	Yes	Yes	Yes

TABLE I
DATA AUGMENTATION PARAMETERS DESCRIPTIONS FOR THIS RESEARCH

C. Description of the CNN Architectures

We have used three CNN architectures namely VGG16, MobileNetV2 and InceptionV3 where all the parameters are fine-tuned. These models are pretrained on Imagenet dataset for data detection and recognition. Description of all models are described in the below sections.

1) VGG 16: In terms of Convolutional neural network architectures Visual Geometry Group (VGG) was introduced in 2014. The model is globally renowned for image segmentation and recognition purposes. Almost 13 convolutional layers are available inside this model. Keras has been utilized in the background of tensorflow for this purpose. At first three fully connected layers are available in the model. In this research, the base layer has been removed where the size of the kernel size is 2 X 2. As the model has been trained in millions of labels of images where there are only 4 labels in this image dataset. In the base layer, all the hyperparameters are fine-tuned. The fine-tuning is processed identically for all the models in the same way. The fine-tuning parameters for all the models are described in Table II.

Fine-tuned parameter name	Value
Regularizer	L1
Rate of learning	0.0001
Optimizer	Adam Stochastic gradient descent
Loss	Categorical cross entropy
Number of epoch	15
Binarizer	Yes

TABLE II
FINE-TUNED PARAMETERS FOR THE BASE LAYERS FOR THIS RESEARCH

2) InceptionV3: There are numerous deep convolutional deep learning architectures proposed by Google. InceptionV3 was initially recognized as GoogleNet. We have applied the fine-tuned version of InceptionV3 where fine-tuned parameters are described in Table II. In total, there are 48 layers available in the model and 5 fully connected layers have been utilized here. Factorized vectorization is also applied in the InceptionV3 model where weight decay is used for ignoring overfitting. To reduce the number of trainable parameters there are numerous techniques that have been integrated here. The Inception module is the primary reason for the model to be efficient in terms of image segmentation and detection. Batch normalization has been applied in this model for training images. This feature normalizes the input with the output so that they can be extracted easily and efficiently. Dropout has been applied in order to reduce overfitting along with reducing computational complexities.

3) MobileNetV2: For classifying images, MobileNetV2 works incredibly well. MobileNetV2 is a compact deep learning model based on CNN that uses TensorFlow to determine the image's weight. A fresh trainable layer is then put to MobileNetV2 after the base layer has been removed. The model runs on the gathered data and identifies the characteristics of our photographs that are most connected. 19 layers of bottlenecks make up MobileNetV2 [20]. ResNet-10 is used in the base model of OpenCV, which was added [21]- [22]. For the purpose of identifying the front of a fruit image, Caffemodel from OpenCV is employed. The necessary information is then extracted and sent to the layer of the fruit classifier. Machine learning overfitting is a serious issue.

We employed the Dropout layer to avoid overfitting our model to the dataset. With MobileNetV2, we eliminated the base layer (include top=False). The images have been altered. Our model uses a pool size average pooling operation (7,7) and has 256 hidden layers. In the fully connected layer, softmax activation function is used, whereas ReLu activation function is utilized in the hidden layer. In the fully connected layer, softmax activation function is used, whereas ReLU activation function is utilized in the hidden layer. For greater precision, a learning rate of 0.001 is established. The stochastic gradient descent approach developed by Adam aids the model in comprehending picture characteristics.

D. Federated Learning for this Research

Federated Learning is a machine learning paradigm in which the model is trained locally on each device after the training data is dispersed across several devices rather than being collected in one location. The global model is then delivered back to the devices for additional training after the updates from each device have been combined on a central server. In this research, data is trained in multiple devices from numerous devices. The Google Cloud has been utilized for this purpose. The sensitivity of data allows training on multiple cloud servers. The whole training process has been performed in three devices where on an average nine hours have been spent in the training process.

E. Result Interpreting Using LIME

Explainable AI is used to interpret the result where most dominant features from the images have been extracted. Local Interpretable Model Agnostic Explanations have been used for interpreting the result. By causing changes to the initial input data and creating fresh samples, the local approximation is produced. The model is then updated using these samples to produce a fresh set of predictions. The final predictions are then used to train a more straightforward, understandable model (like linear regression) that roughly mimics the behavior of the original model in the immediate vicinity of the prediction.

IV. EVALUATION METRICS

For this research, authors have focused on using three main comparisons, namely F1-score, elapsed time and number of trainable parameters. The equation for F1-score is stated below:

$$F1 - score = 2 * Precision * recall / precision * recall \quad (1)$$

Apart from that, the result has been interpreted by the LIME XAI and classification report for the most efficient models has been provided as a proof of efficiency.

V. Experimental Result Analysis

After completing the whole training process the experimental result has been observed. Three criterias are taken into account mainly to evaluate the performance of these models. The parameters are:

i) F1-Score
ii) Trainable parameters
iii) Elapsed time

At first the comparison of F1-score between the trainable parameters have been made. Figure 3. shows the comparison of these models. From there it can be observed, the maximum average accuracy has been achieved by MobileNetv2 where 10 fold cross validation has been applied. The result also demonstrates the second better performing model is the InceptionV3. VGG has the lowest amount of F1-score in comparison to the two previous models.

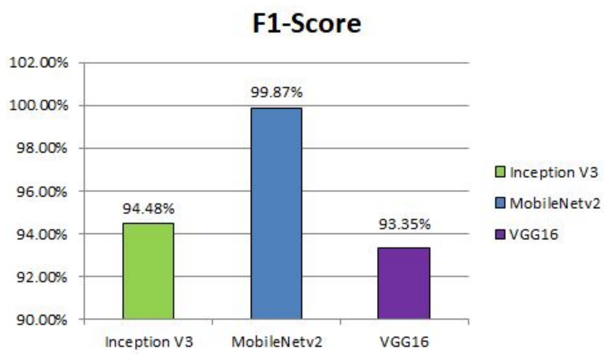

Fig. 3. F1-score comparison between models

After comparing the F1-score, the next step is to compare the number of trainable parameters of the proposed models. It has been observed that trainable parameters are an important criteria as training time becomes higher the more trainable parameters. Figure 4 shows the relative number of trainbale parameters associated with individual models after fine-tuning.

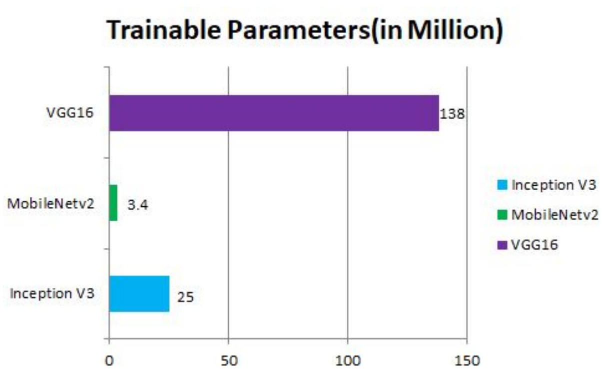

Fig. 4. Trainable parameters associated with each models

From Figure 4, it has been observed VGG16 has the maximum amount of trainable parameters which is almost 25 millions. On the other hand, the minimum amount of trainable parameters has been shown by the MobileNetV2 model where the amount of trainable parameters is approximately 3.4 millions. Finally, when we are talking about InceptionV3, the amount of trainable parameters of InceptionV3 is 25 millions. So, in the case of trainable parameters, the MobileNetV2 model has the lowest amount of trainable parameters.

Third comparison between models is included to compare the elapsed time for training. Figure 5, shows the elapsed time by the models for training on images in numerous datasets. As mentioned earlier, the models are trained in multiple devices. The reporting time by the cloud servers has been stated in Figure 5. From there it can be observed VGG16 has the highest amount of training time as the number of trainable parameters are very high. On the other hand, the elapsed time for MobileNetv2 in the training phase is lower than other two models and it has shown more accuracy. So, in three cases, MobileNetV2 has shown more prominent results than the other two models. The classification report for MobileNetV2 model is also shown in Table III. From there it can be observed, the model has performed significantly in 4 classes of data. The report shows that the model is well capable of handling data from different labels. Federated learning allows the whole procedure to be smooth and obtain a great result.

Many of the other models used in this study fared worse than the MobilenetV2 architecture did. The mask in an image can be recognized by this model. The whole results are described in Table III.

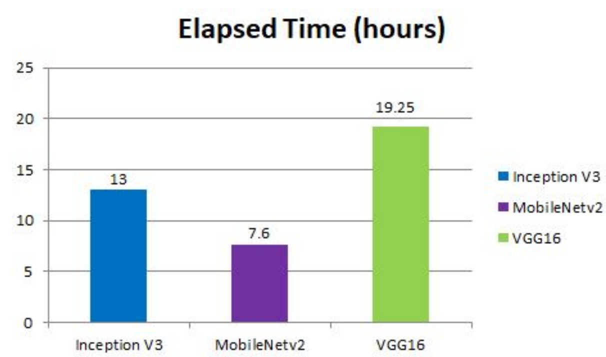

Fig. 5. Elapsed Time Comparison by the evaluated models

Class Name	Precision	Recall	F1-score
0	99.46%	99.47%	99.73%
1	99.04%	99.30%	99.27%
2	99.10%	98.38%	98.12%
3	98.50%	99.36%	99.95%

TABLE III
Classification report shown by MobileNetV2

Finally the result has been interpreted using the LIME XAI model where it can extract the most dominant features from the images. Figure 6 shows the image interpretability of the

LIME. From there the most dominant features are highlighted and the background is dark.

Fig. 6. Result Interpretation Using LIME Explainable AI

VI. Conclusion and Future Work

In this research, we have made an attempt to propose an automated system that can identify grape leaf diseases from the tree. Three types of diseases and healthy images have been considered for training and validation purposes. In total 6000 images were available in the dataset and three deep CNN architectures have been trained, validated and tested on these images. The models are fine-tuned for getting the maximum accuracy from these models. From the experimental results it has been observed the maximum accuracy has been shown by MobileNetV2 model with lesser amount of trainable parameters and elapsed time. Federated learning has been deployed in order to train images from multiple servers. The elapsed time is also another important criteria that has been observed during the training phase. The MobileNetV2 has shown an average accuracy of 99.37% where 10 fold cross-validation has been adopted by the authors. This research will be able to identify diseases of grape leaves at an earlier stage so that necessary steps can be taken at an earlier future. In the near future, we are focused on applying transformer models in order to detect grape disease more efficiently along with more variants of fruits.

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