Classification of Guava Leaf Disease using Deep Learning

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Abstract: - A higher percentage of crops are affected by diseases, posing a challenge to agricultural production. It is possible to increase productivity by detecting and forecasting diseases early. Guava is a fruit grown in tropical and subtropical countries such as Chad, Pakistan, India, and South American nations. Guava trees can suffer from a variety of ailments, including Canker, Dot, Mummification, and Rust. A diagnosis based only on visual observation is unreliable and time-consuming. To help farmers identify plant diseases in their early stages, an automated diagnosis and prediction system is necessary. Therefore, we developed a deep learning method for classifying and forecasting guava leaf diseases. We investigated a dataset composed of 1834 leaf examples, separated into five categories. We trained the dataset using four different and generally preferred pre-trained CNN architectures. The EfficinetNet-B3 architecture outperformed the other three architectures, achieving 94.93% accuracy on the test data. The results ensure that deep learning methods are more successful and reliable than traditional methods.

Key-Words: Deep Learning, Convolutional Neural Networks, Guava, Leaf Diseases

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1 Introduction

A guava's high nutritional content includes vitamins A, B-Complex, C, E, and K as well as copper, iron, magnesium, manganese, potassium, sodium, and zinc. Guavas are also high in fiber., there are many health benefits, including the prevention and treatment of cancers, skin conditions, and heart diseases, [1]. Additionally, guava is used for different types of sickness. Besides lowering blood pressure and normalizing blood sugar, it is also good for diarrhea, [2]. A large number of underdeveloped countries, including Chad, rely on guava fruit as a source of food.

It is important to note that guava plants are susceptible to various illnesses, such as canker, mummification, dot, and rust, which can reduce overall production, [3]. Even though pesticides are used on guava plants to control these diseases, they negatively affect the environment and cause economic damage to the country. It is therefore important to diagnose these diseases properly to reduce their negative impact. Guava diseases can be identified and classified by experts through manual observation that requires constant monitoring and testing. There is a significant lack of accuracy in this procedure and it is quite expensive, [4]. Guava farmers constantly lose a large portion of their production due to a lack of prevention techniques. Furthermore, many farmers are interested in learning how to prevent guava diseases and increase the production of the fruit, [5]. Consequently, farmers cannot increase guava production or improve its quality. There is a great deal of importance in diagnosing guava diseases in their early stages and correctly classifying them, [2].

Guava-producing countries must implement an automated system to detect and diagnose diseases. The system is considered the most accurate, fastest, and most cost-effective way to detect guava diseases, [2]. Deep learning approaches can be applied to the guava leaf dataset to identify guava diseases. It can assist farmers in diagnosing guava diseases early and figuring out the best pesticides, [5]. Researchers developed computer vision systems to identify and classify plant diseases as well as consider accurate solutions to plant disease problems. The proposed system uses RGB images to differentiate leaves that are healthy from those that are unhealthy, [3].

The study aims to identify guava leaf diseases, mummification, dot, canker, and rust using a deep learning model that will have a higher accuracy rate than any currently available model. These diseases will be identified quickly and accurately by the model. The model will also be used for developing prevention and control strategies for diseases, as well as providing recommendations for future studies. Finally, this study will provide agricultural scientists with valuable knowledge to further improve guava production by providing insight into guava leaf diseases.

These are the main contributions of this article:

- Four popular CNN models are trained for detecting and classifying guava leaf diseases.
- Each model's performance is evaluated and compared in terms of accuracy, precision, and recall values.

Future developments in guava leaf disease classification are discussed.

2 Related Works

A recent trend in smart agriculture has been the use of deep learning algorithms to diagnose and detect plant diseases automatically. There has been a large number of studies conducted in this area over the years, [6], [7], [8], [9].

A recent study proposed a system that used five CNN algorithms to recognize guava diseases: AlexNet, SqueezeNet, GoogLeNet, ResNet- 50, ResNet-101, and Bagged Tree (BT), [2]. Based on the results, ResNet-101 achieved decent classification performance by producing an accuracy rate of 97.74%. A recent study introduced a model to identify guava plant diseases by applying machine learning classifiers, [3]. The bagged Tree classifier achieved the best accuracy of 99% in identifying four guava diseases, namely Canker, Mummification, Rust, and Dot. A recent study proposed three CNN-based models to discover guava diseases, [5]. The experiment results show the most accurate model achieved better than the other two models with an accuracy of 95.61%. As suggested, [10], image segmentation and clustering of images can be achieved using K-means The authors applied SVM to the classifier to recognize guava diseases at an early stage with an accuracy rate of 98.17%. A recent study introduced an automated system to aid farmers in identifying guava diseases and differentiating between healthy and malady leaves, [11]. Authors adjusted machine learning algorithms including F-KNN, C-SVM, Bagged Tree, and RUSBoost Tree algorithms. C-SVM achieved the highest accuracy of 100% compared to the other classifiers.

A recent study suggested deep learning for recognizing guava plant diseases such as Algal leaf spot, whitefly, and rust diseases, [12]. The experiment results on the dataset show an average accuracy of 98.74%. A recent study developed an automated system to detect guava diseases and early detection of plant leaves, [13]. Based on the experiment results, they achieved an accuracy of 98.96% using ResNet. A recent study proposed a deep learning-based mobile application to detect plant diseases using a phone's camera, [14]. The system uses VGG architecture to classify the major grape diseases. The VGG models were able to achieve an accuracy rate of 98% on the test data. Additionally, many types of research done using the EfficientNet model have achieved significant accuracy results. A variety of types of plant village datasets were used in these studies to identify plant diseases, [15].

3 Materials and Methods

3.1 Dataset

The guava plant dataset is publicly available on Kaggle. Five major categories of guava are represented in the dataset: Canker, Mummification, Dot, Rust, and Healthy. In total, 1,834 images are included in the dataset. The dataset is divided into three major categories: training, validation, and testing directories. There are 1239 images in the training set, 457 images in the validation set, and 138 images in the testing set. Each of these images in the training set belongs to a different class; 696 images are canker, 150 images are mummification, 149 images are dot, 149 images are rust, and 95 are healthy images. The distribution of the data is presented in Figure 1.

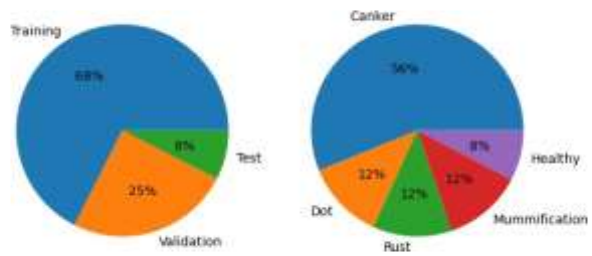

Fig. 1: Distribution of the data

3.2 Data Processing

Image pre-processing is an important step for reducing noise and improving differential shading in images. In addition, it is necessary to resize the image in deep learning architectures to increase their accuracy. The images in the dataset are 512 x 512 pixels in size. We resized the images to 224 x 224.

3.3 Data Augmentation

Data augmentation is a technique used to increase the size and diversity of a dataset by generating new images from existing ones. This is done by applying a variety of transformations to the images, such as rotation, translation, cropping, and adding noise. Increasing the size and diversity of the training dataset can prevent overfitting and improve the model's generalization ability, [16].

3.4 CNN Architectures

3.4.1 Visual Geometry Group (VGG)

The VGG architecture is a straightforward and efficient CNN design, which has been applied to a variety of image recognition tasks, including object detection, segmentation, and object classification, [17]. The structure comprises convolutional layers stacked on top of each other, followed by fully connected layers and max-pooling layers. The convolutional layers function using 3 x 3 filters, preserving spatial information in images. The feature maps are downsampled by the max pooling layers to reduce the network's parameter count and avoid overfitting. The images are then classified into distinct categories by fully connected layers. The VGG architecture has two principal variations, namely VGG-16, comprising 16 layers, and VGG-19, featuring 19 layers. It is the number of convolutional layers that distinguishes the two architectures, with 13 in VGG-16 and 16 in VGG-19. The sample images from the guava leaf disease dataset after augmentation are presented in Figure 2.

Fig. 2: Sample images from the guava leaf disease dataset after augmentation

3.4.2 Residual Network (ResNet)

The ResNet is designed to handle the issue of vanishing gradients, which are caused by excessive weights in a neural network, resulting in learning difficulties, [18]. Residual connections are proposed to resolve this issue. A residual connection is a path that skips one or more layers of the network, thus allowing the earlier layers' output to be added directly to the output of the later layers. This helps the network learn better, even when it's deep. Depending on the application, the number and layout of residual blocks will differ. ResNet-50, for instance, consists of 50 residual blocks, each consisting of three convolutional layers.

3.4.3 Inception V3

The Inception structure contains repeated blocks entitled inception modules, [19]. Each inception module works with a convolutional feature map as input and generates several smaller feature maps of varying sizes. Various sizes of feature maps permit the inception module to capture diverse image details. These inception modules are organized hierarchically, with each module constructed upon the preceding module's output. This permits the architecture to acquire more intricate representations of the input image as it moves deeper.

The Inception V3 model has 22 layers, encompassing 9 inception blocks. The initial 13 layers are convolutional, with the subsequent 3 being fully connected. The ultimate layer is a softmax layer that gives the probability of every class.

3.4.4 EfficientNet

The main idea behind EfficientNet is to achieve better performance by balancing three different scaling dimensions: depth, width, and resolution, [20]. In traditional CNN architectures, these dimensions are often scaled together, which can lead to excessive computational requirements without significant performance gains. The EfficientNet approach, however, uses a compound scaling method that carefully determines the optimal balance between these dimensions, resulting in networks that are both efficient and accurate.

EfficientNet includes several different models with different scaling coefficients. The most commonly used models are EfficientNet-B0, EfficientNet-B1, EfficientNet-B2, EfficientNet-B3, EfficientNet-B4 and EfficientNet-B5. Of all the models in the family, the EfficientNet-B0 is

the smallest and most efficient. It has a width multiplier of 1.0, a depth multiplier of 1.0, and a resolution multiplier of 224. The EfficientNet-B5 is the largest and most accurate model in the family. It has a width multiplier of 6.0, a depth multiplier of 1.0, and a resolution multiplier of 1280.
The characteristics of the four architectures are compared in Table 1 and the architectures are shown in Figure 3.

3.5 Performance Metrics

Classification algorithms are assessed using a range of performance metrics to determine their efficacy in making precise predictions on labeled datasets. The selection of metrics depends on the particular issues at hand and the trade-offs that are deemed necessary, [23]. Classification algorithms are evaluated using the following performance metrics:

Accuracy: This is the most basic metric, which shows the proportion of accurately predicted instances to the total number of instances. Nevertheless, it may not be appropriate when datasets have an imbalanced distribution.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP + TN}}{\boldsymbol{TP + TN + FP + FN}} \tag{1}$$

Precision: It concentrates on the number of true positive predictions made by the model out of all positive predictions. It aids in evaluating the model's ability to prevent false positives. Precision is calculated as:

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP}} \tag{2}$$

Table 1. Comparison of VGG16, ResNet50, InceptionV3 and EfficientNet-B3

	VGG16	ResNet50	InceptionV3	EfficientNet-B3
Year	2014	2015	2015	2019
Top-1 Accuracy	71.30%	74.90%	77.90%	81.60%
Top-5 Accuracy	90.10%	92.10%	93.70%	95.70%
Parameters(M)	138.40	25.60	23.90	12.30
Depth	16	107	189	210

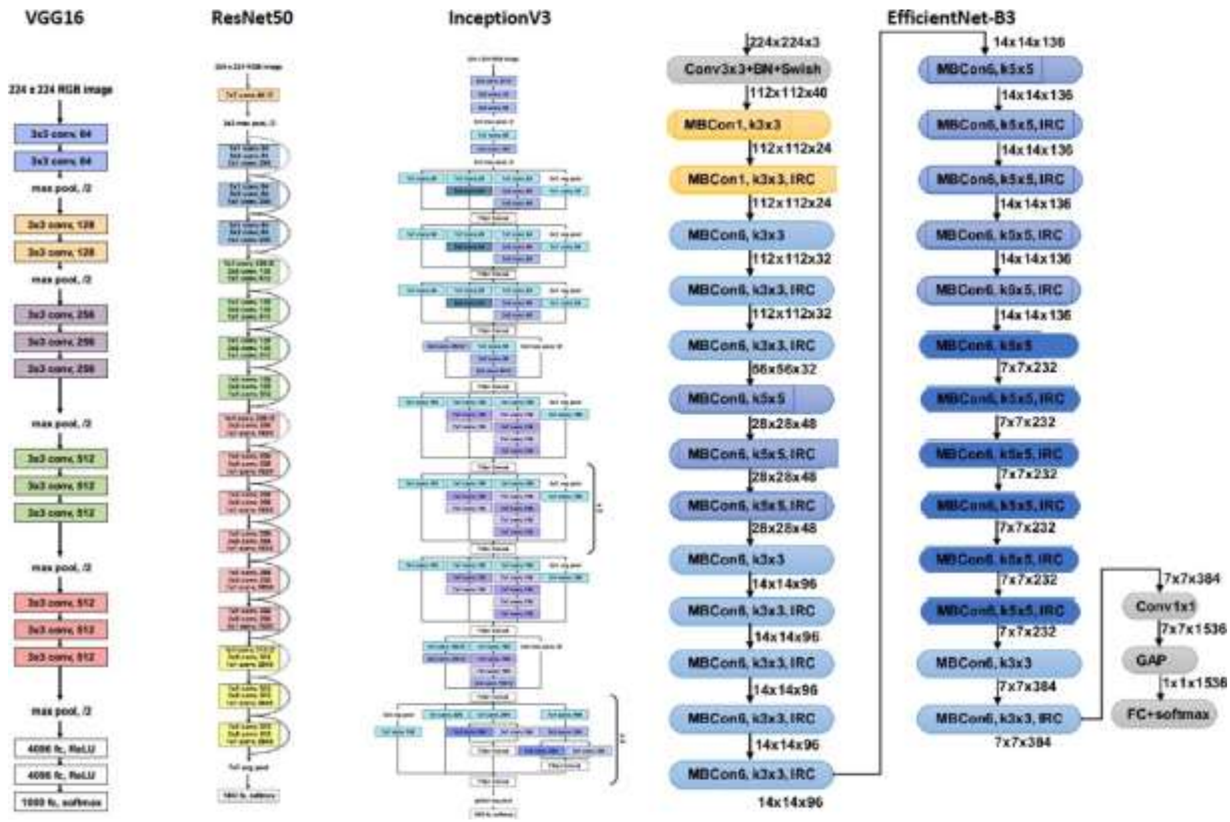

Fig. 3: Architectures of VGG16, ResNet50, InceptionV3 and EfficientNet-B3, [21], [22]

Recall: It is a useful metric for understanding how well the model captures all instances of the positive class. It measures the number of true positive predictions out of all actual positive instances and is calculated as:

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP} + \boldsymbol{FN}} \tag{3}$$

F1-Score: It is the harmonic mean of precision and recall. It offers equilibrium between the two metrics and proves to be particularly valuable when handling datasets that lack balance. The F1-Score is determined by using the formula:

$$\boldsymbol{F1 - Score} = \frac{\boldsymbol{2 * Precision * Recall}}{\boldsymbol{Precision + Recall}} \tag{4}$$

4 Results and Discussions

It takes a lot of human labor to detect and classify diseases in guava leaves using traditional methods. It is difficult to differentiate between disease types due to their similar shape, texture, and color. Recently, many studies have been published showing that both traditional and deep learning methods successfully classify different leaf disease types, [24], [25], [26]. This section presents the results of deep-learning models for the classification of guava leaf diseases. We trained four different and commonly used CNN architectures on the Guava image dataset for this purpose. Graphs showing the accuracy and loss of each CNN architecture for training and validation data can be found in Figure 4, Figure 5, Figure 6, and Figure 7.

The confusion matrix and overall performance of the EfficientNet architecture, which produces the most accurate results, are presented in Figure 8 and Figure 9.

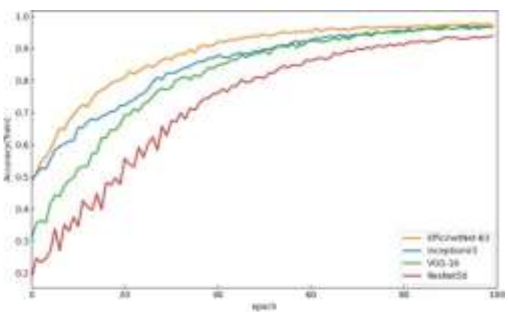

Fig. 4: Training accuracy for all architectures

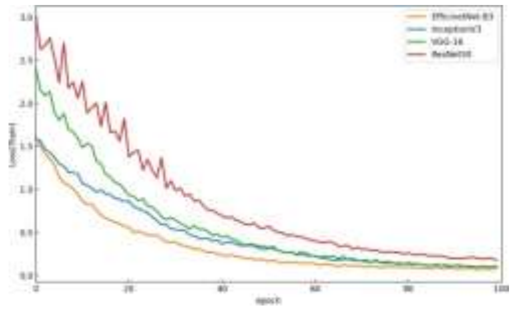

Fig. 5: Training loss for all architectures

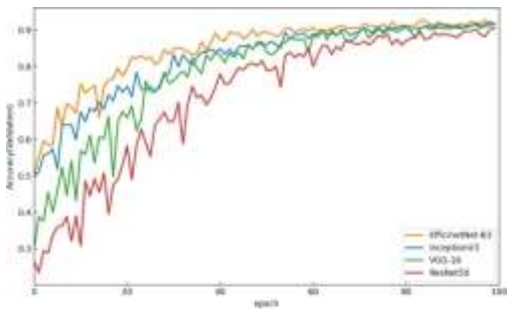

Fig. 6: Validation accuracy for all architectures

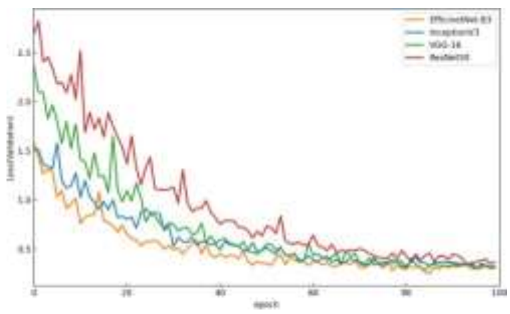

Fig. 7: Validation loss for all architectures

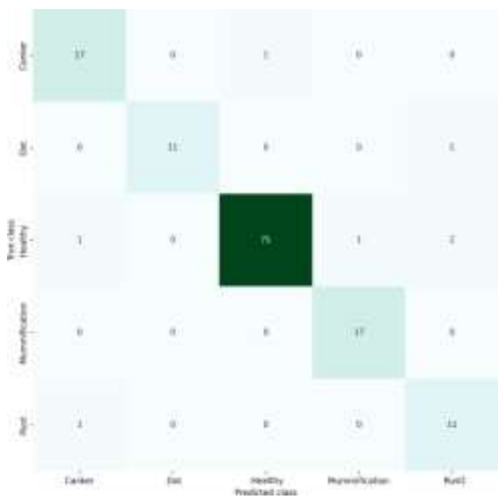

Fig. 8: Confusion matrix of EfficientNet-B3 on the test dataset.

According to the graphs, EfficientNet-B3 produces the most accurate results, while ResNet produces the least accurate results. In this study, EfficientNet achieved 97.83 % accuracy on the training set, 92.73 % accuracy on the training set, and 94.93 % accuracy on the test set. Therefore, the results obtained by applying deep learning methods to the detection of diseases of the guava leaf is very successful and reliable. These results demonstrate the high classification performance of the deep learning model, suggesting its suitability for practical applications in guava leaf disease detection. The model, therefore, can be used for disease surveillance and control in guava plants. The Confusion matrix of EfficientNet-B3 on the test dataset is presented in Figure 8. Similarly, the Precision, Recall, and F1-Score values for all classes are presented in Figure 9.

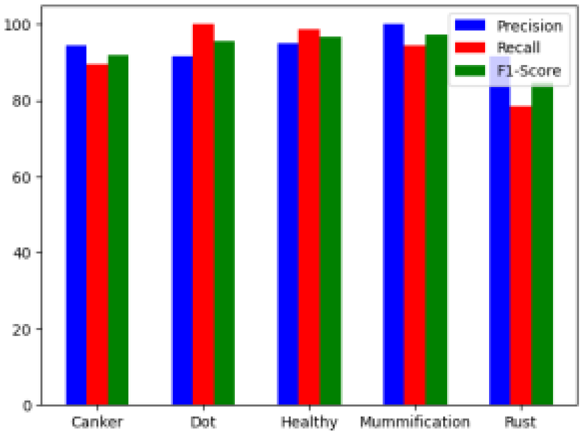

Fig. 9: Precision, Recall, and F1-Score values for all classes

5 Conclusions and Future Works

Plant diseases should be detected timely and accurately so that agricultural products can be produced more efficiently and with higher quality. Therefore, early detection of guava diseases is a widely applicable measure to reduce economic loss. In this study, we propose a deep-learning solution using VGG-16, Inception V3, ResNet50, and EfficientNet-B3 classifiers to detect guava diseases. The models showed successful results in performance metrics such as accuracy, precision, recall, and F1-score. Based on the results of the four CNN architectures trained, EfficientNet produced the most reliable and accurate results. Farmers will be able to detect guava leaf disease in real-time on their smartphones without needing any cloud services by integrating the proposed model into mobile devices. Our future goal is to enable consumers and producers to access healthier products by designing systems to detect diseases on the leaves of fruits and plants. Despite its beneficial and influential contributions, this study does have some limitations. The quality and diversity of the training dataset are key factors influencing the model's performance. Future work should involve the collection of a larger dataset that spans a wide range of guava varieties, geographical regions, and seasons to further improve the performance of the algorithm.

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