Classification of Guava Diseases from Guava Fruits and Leaves Using Deep Learning Techniques

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***Abstract*—Guava is a good source of nutrients for people all over the world. In addition, it also contributes to the agriculture economy as well. But like all other plant diseases, guava diseases have become a big concern for guava production and the economy around it. Furthermore, improper diagnosis of these guava diseases may drive farmers to use pesticides inappropriately or excessively. So, if we could correctly classify the diseases, it would result in massive benefits in terms of productivity, and quality. Therefore, correctly classifying the disease is crucial for both the economy and food value. In this paper, we suggest a Deep Learning-based guava disease classification model. The proposed framework uses the concept of Transfer Learning (TL) and Ensemble learning to classify guava diseases from the high-resolution (24M pixels) images of guava fruits and leaves. We trained a few pre-trained GoogleNet and EfficientNet models with the cost-sensitive loss function - Focal Loss. Then ensemble the best performing models to classify guava diseases. With the proposed framework, we could able to get an accuracy of 75.2% in the test set, where the test set contains 33% of the dataset (101 samples).**

***Index Terms*—Transfer Learning, Classification, Guava Disease, Deep Lerning**

I. Introduction

Guava is a very popular, and nutrients rich tasty fruit. It plays an important role in the agriculture-based economy of many countries around the world. There are many things that can contribute to the economical loss of guava production. But among them, guava diseases are the major factor for the reduction of guava production and the resulting financial losses. Particularly, Dot, Canker, Mummification, and Rust are terrible guava diseases that can reduce the overall guava production. So, classifying these guava diseases accurately and timely is very important. However, most of the time these guava diseases are not correctly classified owing to a lack of proper knowledge and time-consuming methods, particularly for those who grow guava plants on the rooftops. Though experts in this field can classify guava diseases based on symptoms, it needs regular manual observation and testing, both of which can be error-prone and expensive. As a result, a low-cost, simple, and efficient approach for the classification of guava diseases is essential.

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Some studies have been performed with Image Processing, Deep Learning, and Machine Learning-based methods aimed at classifying guava diseases from guava images. But most of the works were focused on the traditional Machine Learning algorithms with a large dataset. Only a few efforts have been made for CNN-based fruit or plant disease classification. Especially there is no research previously done that focused on classifying guava diseases from a very small dataset that contains both guava fruits and guava leaves.

The objective of this research is to find an efficient Deep Learning model for classifying guava diseases from both guava fruits and guava leaves. The dataset used in the research is very small (306 samples) and each image contains 24M pixels (6000x4000) with a resolution of 300 dpi. The training set contains only 164 images (54% of the dataset), which enforces the model to learn the important features to classify an image. Moreover, the Focal Loss [2] made sure that the model learns to classify the images that are hard to classify. We have built some separate models to classify guava diseases by fine-tuning GoogleNet and EfficientNet. Later, we ensembled some best-performing models to finally classify guava diseases from images. With this proposed model, we could able to classify 75.2% of images in the test set.

II. Relevant Work

For the classification of plant diseases, several methods have been proposed. But in the past, most researchers worked with traditional machine-learning techniques, especially in the field of agriculture. However, the scenario is changing in recent years, as there has been an increasing number of research aimed at classifying plant diseases with Deep Learning.

To classify guava diseases, a CNN-based model was proposed by Al Haque et al [3]. In their research, they have developed a model to classify guava diseases and healthy guava - anthracnose, fruit rot, fruit canker, and disease-free guava. They have trained three different CNN models and found 95.61% accuracy in the third model. In another research, Ahmad Almadhor et al [1] have proposed a model to recognize four guava diseases against healthy fruits. In their proposed framework, they applied the ΔE color difference image segmentation to separate the infected areas. Then upon extracting rich informative feature vectors they classified guava diseases by advanced machine-learning classifiers like KNN, Bagged Tree, Boosted Tree, Cubic SVM, etc. They could able to achieve an accuracy of 99% by the Bagged Tree classifier.

Namrata Sagvekar et al [7] have used CNN technique to detect and classify disease from plant leaves. They have achieved an accuracy of 96.02% with 38 different classes (plants). S. Krithikha Sanju and Dr. B. L. Velammal has analyzed some State-of-the-Art Machine Learning Techniques to detect and classify plant diseases from the plant leaves using Image processing and pre-trained models [4]. Here, they compared some popular Deep Learning models like DenseNet, GoogleNet, MobileNet, VGG16, etc to identify and classify plant leaf disease automatically. Using the Siamese convolutional neural network (SCNN) model with several Transfer Learning models, LACHGAR et al [6] have classified plant diseases on the publicly available "Plant Village" dataset. With their proposed approach, they have achieved an accuracy of 96.77% on the test partition.

As illustrated, some researches have been conducted by researchers to classify guava diseases from either guava fruits or guava leaves, but no research was previously done that classifies guava diseases from both guava fruits and guava leaves. Here, in our research, we have fine-tuned several pre-trained models and ensemble them to classify guava diseases from both guava fruits and leaves.

III. Methodology

Our proposed framework uses Transfer Learning and Ensemble Learning for guava diseases classification from guava fruits and leaves images. The research procedures are:

A. Image Preprocessing

For training, validating, testing, we transformed the images with some transformation techniques. Such as resize images to model requirements (256x256), center crop (224x224), normalize (mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]) etc. Besides, as the training set contains only 164 images, we performed some data augmentation in the training images like random horizontal flip with a probability of 50% and random rotation ranging from -30° to +30°. No data augmentation was performed on the test set except some transformation as required by pre-trained models.

B. Focal Loss

$$FL(p_t) = -\alpha_t(1-p_t)log^{\gamma}(p_t) \quad (1)$$

Here,

$$p_t = \begin{cases} p & ify = 1 \\ 1-p & otherwise \end{cases}) \quad (2)$$

While training our model, to minimize the error, we have used a loss function called Focal Loss. It is a cost-sensitive loss function that resolves the problem of an imbalance dataset and forces the model to learn the hard examples. In order to force the model to learn the hard examples, Focal loss adds a modulating factor to the cross entropy loss. This modulating factor decreases the loss contribution from easy examples and keeps quite the same as cross entropy loss contribution for the hard samples. Equation 1 formulate the calculation of Focal loss and Fig. 1 shows how the variation of modulating factor changes the loss contribution for a sample. If the hyperparameter gamma is set to 0, Focal loss acts as the original Cross entropy loss function. Because setting the gamma (γ) = 0 makes the modulating factor = 1.

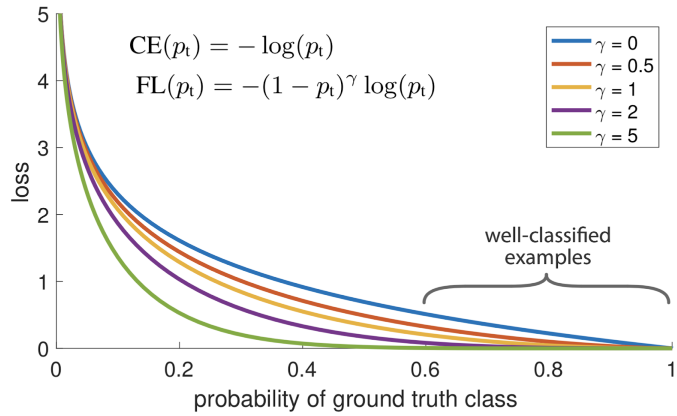

Fig. 1. Focal Loss with various gamma values

C. Transfer Learning and Ensemble Learning

Transfer learning is a popular machine learning method that allows a model to use the previously learned knowledge in a different task. It was inspired by human's capability to inherit or transfer knowledge across many tasks. In our proposed framework, we have also fine-tuned some models using the pre-trained GoogleNet and EfficientNet (B0 and B1). Both of these models are pre-trained on the very famous ImageNet dataset. As the ImageNet dataset contains 1000 classes, the pre-trained models classify images into 1000 classes. So, we have to change the last layer of the models. Both of these models have performed quite well, especially with the Focal loss function.

After training some individual models, we selected the best performing 10 (n) models and ensemble them in one model. In the ensemble model, all the scores predicted by all the trained models are added, and then the softmax function calculates the probability for each class as Fig 2. A guava fruit or leaf image is classified as the class with the highest probability calculated by the softmax. For the optimization of our models, we have used the Adam optimization algorithm, which is an extension to SGD (Stochastic gradient descent). Adam stands for Adaptive Moment Estimation. In order to converge faster, it uses the combination of Momentum and Adaptive Learning Rates.

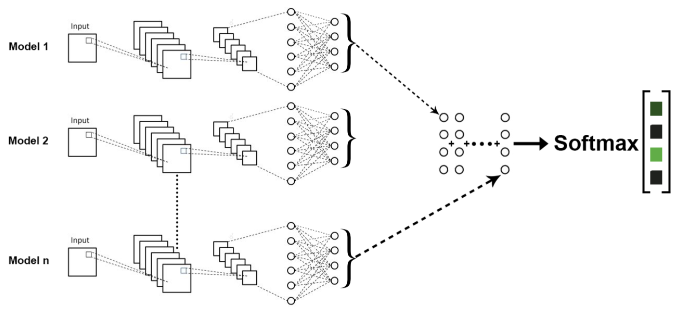

Fig. 2. Ensemble of n number of best performing trained models.

D. Hyperparameters

There are some hyperparameters in our model. We tweaked them as need. We have used a batch size of 64 most of the time but also tried 32 and 48 as batch sizes. The learning rate was set to 0.001 and sometimes 0.0015. We have two hyperparameters in the Focal loss - alpha (α) and gamma (γ). We have tried a variety of combinations for both of them. The alpha (α) value ranges from 0.1 to 1, while the gamma (γ) value ranges from 0 to 5. Among them, we found the combination of alpha (α) = 0.25 and gamma (γ) = 2 as the best performing combination.

IV. Experiments

A. Dataset

In our research, we have used “A Guava Fruits and Leaves Dataset for Detection and Classification of Guava Diseases through Machine Learning” dataset [8]. The dataset includes 306 images where target diseases are Dot, Canker, Mummification, and Rust. Each image has a dimension of 6000x4000 (24M pixels) with 300 dpi. These images were captured from the tropical regions of Pakistan under the supervision of Prof. Dr. Ikramullah Lali. And all the images, Dot (76), Canker (78), Mummification (83), and Rust (70), were labeled manually by the domain specialists. For our research purpose, We have split the dataset as 54% (164 images) for the training set, 13% (41 images) for the validation set, and 33% (101 images) for the training set. We also made sure data is stratified, which means data is balanced for all the partitions.

TABLE I
Dataset Partition

Disease	Total	Train	Validation	Test
Canker	0.251634	0.25000	0.243902	0.257426
Dot	0.248366	0.25000	0.243902	0.247525
Mummification	0.271242	0.27439	0.268293	0.267327
Rust	0.228758	0.22561	0.243902	0.227723

B. Evaluation metrics

- Accuracy: Accuracy measures how many observations were correctly classified. It count both positively and negative ly classified samples.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}) \qquad (3)$$

- F1-score: F1-score combines both precision and recall into one metric by calculating the harmonic mean between the two. Here, precision is the ratio between the True Positives (TP) and all the Positives and recall is the measure of a model correctly classifying True Positives.

$$F1-score = \frac{2*Precision*Recall}{Precision+Recall}) \qquad (4)$$

V. Results and Discussion

We got an accuracy of 75.2% with our proposed model. It did quite well considering the fact that the dataset is very small and the training partition contains 164 samples only. Moreover, the model does not just classify the guava fruit disease or guava leaf diseases, it can classify guava diseases from both images of guava fruits or guava leaves. Also, it can classify all four guava diseases very well as illustrated in the confusion matrix (Fig.3) generated by the ensemble model on the test set.

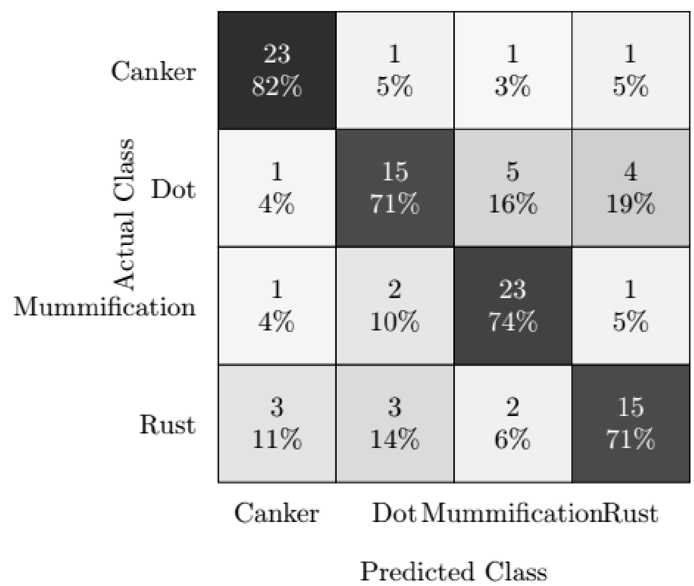

Fig. 3. Confusion Matrix generated by the ensemble model on the test set.

VI. Conclusion

In this research, we have proposed a Deep Learning model to classify guava diseases from images. Here we have trained our model with the pre-trained models and ensemble the best performing models for the final classification. As the dataset is imbalanced and varies a lot we have used a cost-sensitive loss function. In addition, as the training set contains very little data, we performed various augmentation techniques to oversample the dataset. Though there have been some researches to classify guava diseases from images of either guava fruits or guava leaves, our proposed framework is the first approach to classify guava diseases from both guava fruits and guava diseases. And with a comparatively small training set, our model could able to correctly classify 75.2% of the test set . With other techniques such as label smoothing and knowledge distillation, this research can be extended to perform more efficiently.

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