IDENTIFICATION OF A LANZONES TYPE THROUGH THE CLASSIFICATION OF ITS LEAVES USING CONVOLUTIONAL NEURAL NETWORK

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Abstract—**This study experimented a program that aims to classify if a lanzones tree bears a native or duko variety based on its leaves. 216 leaves for each lanzones variety were gathered and harvested from Nagcarlan Laguna to serve as the paper's dataset. The researchers used Convolutional Neural Network (CNN) as their training model to classify the 216 leaf samples gathered from two variety of lanzones trees which then offered a 92.59% validation accuracy and a 97.84% training accuracy. Using the provided testing data set, the model's evaluation was demonstrated. This had an accuracy rate of 91.66 percent for classifying lanzones leaves.**

Keywords: Lanzones, duko, native, leaf classification, computer vision, convolutional neural network.

1. Introduction

The classification of plants has been the foundation or basis of Botany Science. It has been difficult to satisfy the needs of the researchers to quickly differentiate one leaf from another. Because of this, computer vision and intelligence systems have been given particular attention to plant recognition based on digital leaf images due to its significant implications in automatic plant identification.

Prior to the introduction of computer vision and intelligent systems to the field of botany, plant identification and recognition has been labeled tedious and often repetitive due to the taxing process of having to manually inspect the leaves one by one in order to differentiate them. The manual process of classification also causes the result of the task to be subjected to the researcher's judgment. To avoid such problem, the traditional method of distinguishing leaves was gradually replaced with a system that uses machine learning methods so the task would be a lot simpler, faster, and time-efficient.

The most common method to differentiate and identify any given plant is through the plant's leaf. Leaves are more commonly used to distinguish one plant from another. There are numerous parameters that can be applied to leaves. These parameters include the shape of the leaf and the size of the leaf, venation type, area, color, and many other factors. As a result, the leaf of the plant is extremely important for plant recognition. [4] However, due to the wide range of leaf morphology, including changes in size, texture, shape, and venation, classifying leaves using computer vision is a difficult issue for automating the identification of plant species. [1] Which is to say, this research topic is still deemed as a challenge not only to former researchers, but also to current researchers. As of the moment, there has been many topics derived from the main theme of leaf classification.

OBJECTIVE: For this academic journal, this paper's objective is to allow student researchers to explore more about graphic and visual computing thus applying what they have learned by creating a program that aims to differentiate a native lanzones leaf from a duko lanzones leaf through the use of computer vision.

Lansium domesticum Correa, also known locally as lanzones, is a round to oval, sweet, and delectable berry that grows naturally on tropical fruit trees of the Mahogany family on the Malayan Peninsula. It is a long, upright shrub that bears fruit after around 4 years after planting and keeps doing so for almost 100 years. Similar to many other plants, lanzones also got various type of fruits. The cultivars Duko, Longkong, Paete, and Jolo are favorites among farmers. From April to June, little yellow flowers are seen. These flowers eventually turn into clusters of greenish berries. Between August and November, when the fruits' skin color becomes brownish-yellow, the fruits are deemed suitable for harvesting. [11]

Natural antioxidants are abundant in lanzones. They also contain polyphenols, another natural antioxidant, in addition to some vitamin A. According to a 2006 research in "Food Chemistry," lanzones have antioxidant properties comparable to those of other tropical fruits like papayas and bananas. Foods contain antioxidants that aid your body in scavenging harmful free radicals, which can speed up aging and perhaps lead to disease. Additionally, lanzones are a good source of B vitamins, including riboflavin, often known as vitamin B2. 124 micrograms of riboflavin, or 8 to 11 percent of the RDA for riboflavin for adult men and women, which varies from 1,100 to 1,600 micrograms for women and 1,300 micrograms for men, are present in a 3 1/2-ounce dose of lanzones. B vitamins support healthy nervous system function and aid in the conversion of carbohydrates into utilizable energy.

LIMITATIONS: There are 3 limitations imposed on this research by the researchers. They are listed down below.

- The program cannot detect any diseases that may be in the leaves because it is not yet within the capabilities of the researchers and a more extended period of research would be needed in order to achieve this result.
- There was a shortage in the variety of lanzones trees thus, only 2 variety were used as datasets.
- The datasets gathered were lower than the desired amount for this study due to the need for duko/native trees.

2. Review of Related Literature

The study of leaves classification has been studied and researched by a lot of researchers.

In 2018, Ali et. Al. developed a method that is easy to use and effective in terms of calculation. It is based on the fusion of two texture feature types, Local Binary Pattern (LBP) and Bag-of-Features (BOF). These characteristics are used as inputs to a multi class Support Vector Machine or (SVM)-based decision-making model. On a database of leaf picture downloads that is open to the public, the proposed approach is assessed. The testing findings show that their suggested strategy is the most effective method for identifying plants. [5] Relevant technologies, like digital cameras, smartphones, and remote database access, are now widely accessible and have significantly improved image processing and pattern recognition. Automated species identification is getting closer to being a reality, Wäldchen et. Al. stated. [7]

In the following year, in an effort to identify plants, Kaur, Surleen, and Prabhpreet used four steps: image acquisition, pre-processing, feature extraction, and classification. Photos from the Swedish leaf collection, which includes 1,125 images of 15 different species, were used in the study. After pre-processing with a Gaussian filtering algorithm, the features of texture and color have been retrieved. Finally, classification was performed using a Multi class-SVM, which had an accuracy of over 93.26 percent and was intended to be improved. [3]

Simultaneously, Upadhyay et. Al. developed an automated plant identification method using a computer-based technology. Leaf structure is used to extract the vein feature, which is a derived feature. Digital scanners are used to capture leaf photos at the initial stage. Following that, morphological features are extracted to serve as the classification stage's input. [4]

Another study is being conducted in the same year by Qadri et. Al. and their study's goal was to evaluate the machine vision (MV) approach's capability for categorizing eight citrus varietals. Eight different citrus types' leaves were depicted, including grapefruit, Moussami, Lemon, Kinow, Local Lemon, Fuetrells, and Malta Shakri. These were captured using a digital camera in an open space without the use of a sophisticated laboratory setup. A multi-feature dataset composed of binary, histogram, textural, spectral, rotational, scalability, and translational (RST) invariant properties was created from the dataset of acquired digital images. [9]

2 years after 2019, Qadri et. Al. made another study that aims to examine how well the computer vision (CV) method can categorize eight canola variants. CON-I, CON-II, CON-III, Pakola, Canola Raya, Rainbow, PARC Canola Hybrid, and Tarnab-III were the eight canola cultivars shown in the input photographs. These photographs were taken with a digital camera on an open, sunny day without the use of a sophisticated lab equipment. The artificial neural network included first-order histogram characteristics, second-order statistical texture features, binary features, and spectral features of three bands: blue (B), green (G), and red (R) (ANN). For classification, a 10-fold stratified cross-validation method was employed. The best outcomes with accuracy levels between 95 percent and 98 percent were seen when the classifier was fed data from regions of interest (512 512). [10]

And before the mentioned year ends, in order to identify the herbal, fruit, and vegetable plants that are accessible in Sri Lanka using their leaves, Dissanayake and Kumara analyzed the performance of various machine learning algorithms and chose the best method to be utilized for further development of a smartphone application. The Multilayer Perceptron algorithm's accuracy and loss curves were used to determine the classification accuracy of the algorithms. Support Vector Machine, Multilayer Perceptron, Random Forest, K-Nearest Neighbors, and Decision Tree algorithms' respective classification accuracy rates are 85.82 percent, 82.88 percent, 80.85 percent, 75.45 percent, and 64.39 percent. The Support Vector Machine and Multilayer Perceptron algorithms performed satisfactorily, according to the findings. [8]

In the year 2021, a study conducted by Tavakoli et. al. focuses on creating an automatic discriminative method that is established on convolutional neural network for the purpose of categorizing 12 distinct cultivars of common beans that is a part of three various species. The method used in this study was assessed by classifying the three various species as level I, level II, and level III. Level I being the cultivars from the same species, level II being cultivars from different species, and level III based on images from the leaf foreside and backside. The presented method for this study provides a dependable procedure for identification of different plant cultivars. [12] Another similar study that is based on convolutional neural network was conducted by Koklu et. al. that aims to classify grapevine leaves. The deep learning-based classification in this study was managed with the use of grapevine leaves images. Images of 500 vine leaves that is a part of 5 different species were captured using a special self-illuminating system. The result of the deep learning-based classification shows a success rate of 97.60 percent. It was determined that the selection of characteristics increased the success rate of the classification. [14]

In the same year, in an effort to solve the problematic manual identification of leaves of the vast range of medicinal plants that are available in India, Pushpa and Athira conducted a study to recognize and classify various species of plants based on the textures and geometric features of their leaves. The most relevant characteristics of leaf such as shape, texture, geometry, color, and vein patterns are used for plant recognition. The images of leaf are preprocessed to enhance the image and to remove noise in the first stage of procedure and for the next stage, the geometrical and texture characteristics are computed. The selected geometric and texture characteristics attained a 96 percent accuracy. [15] SVM or support vector machine is also utilized in a study conducted by Yigit et. al. in which 637 healthy leaves that consists of 32 various plant species are used where 22 visual characteristics of each leaf are successfully extracted by utilizing image processing. [13]

3. Methodology

3.1. Data Gathering

For this study, leaves from two varieties of Lanzones, namely duko and native, were gathered from Nagcarlan Laguna. Upon gathering, a total of 216 leaf samples for each variety were collected. The samples for each variety were divided into two and captured under natural sunlight using two different smartphones, the Xiaomi Mi 10 with 108 megapixels and the Huawei Nova 3i with 16 megapixels, at noon time (1:00 p.m.–4:00 p.m.). All acquired images are in jpg format and were later used as the dataset for this study.

Figure 1. Leaf Samples

3.2. Schematic Diagram

The schematic diagram proceeds through different steps. First is image acquisition. This is the process by which the data was acquired, specifically the Lanzones leaf images. Second is the training, validation, and test data split. This step is where the data was divided for training, validation, and testing. The third step is image resizing and gray-scale conversion. This was applied to all leaf images. The fourth is data augmentation. Data augmentation was applied to increase the size of the training data set. Fifth is feature extraction. This is the process by which the model was created and trained. The sixth step is classification. This is where the model was tested using the test data set. Lastly, the process of fine tuning the parameters was applied to attain the desired accuracy before proceeding to interpretation.

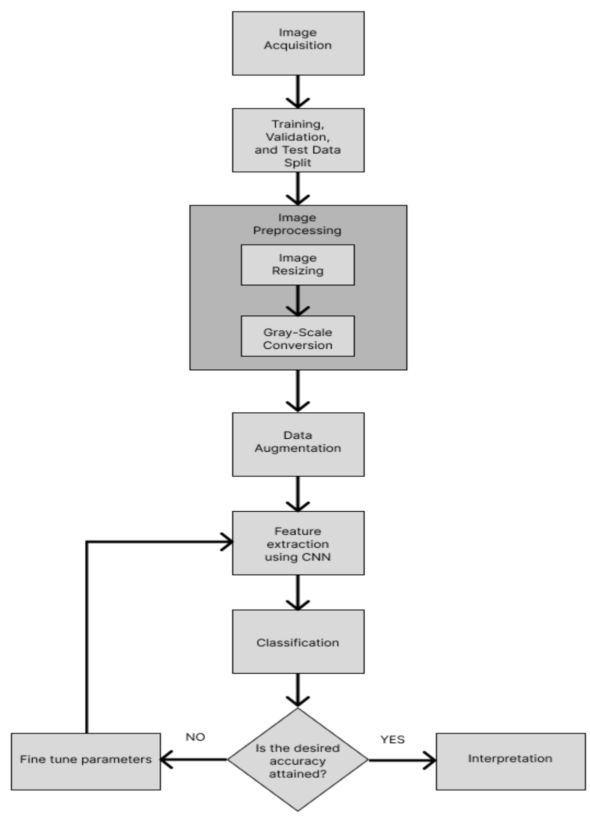

Figure 2. Schematic Diagram

3.3. Image Pre-processing

For image pre-processing, all images were resized to 200x200 and then converted to gray-scale.

3.4. Data Augmentation

Data augmentation was performed to increase the size of the training data set, which is 162 images. Rotation and flipping were applied for each image while also applying flipping to the rotated version of each image. With this process, the training data set was increased from 162 to 648 total images.

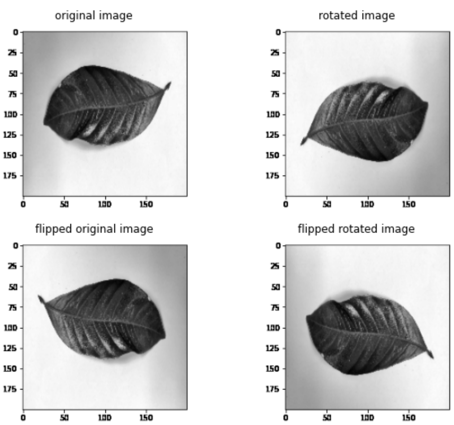

Figure 3. Augmented Image Samples

3.5. Training, Validation, Test Data sets

Data is separated into 3 Data sets; training data set, validation data set, and test data set. Training data set and validation data set is used for the training of the model and using the validation data set to evaluate the trained model accuracy. Lastly, the test data set will be used for prediction on the trained model, which will evaluate the test data set's accuracy.

3.6. Training Model

The researchers used Convolutional Neural Network (CNN) for their training model, to classify the type of Lanzones. The researchers used Keras with Python to create the model as well as training the model. The model was created on a Sequential Class with the parameters of 20 epochs, a batch size of 32, and used binary cross entropy for the loss function.

Through extensive modification of the parameters of the model the researchers learned that having the epochs higher than 20 makes the model starts to overfit and having the epoch less than 20 makes the accuracy decrease into an undesired amount. The batch size have been tested with different the values from 8 to 64, and a batch size of 32 yields the best result. Binary cross entropy for the loss function since the expected output will be 1 or 0 and in this case, Duko or Native.

	Number of Data	Description
Training Data set	648	Training data set and Validation data set has an 80/20 split. The 80% is the Training data set and the 20% is the Validation data set
Validation Data set	162	
Test Data set	108	
Total Number of Data:	918	

Figure 4. Data Sets

3.7. Deep Learning Architecture

The researchers used 3 Convolution Layers, The hyper-parameters of the first convolution Layer has 32 number of kernels, a 5x5 kernel size, and activated using Rectified Linear Units (ReLU) and has a Pooling layer with a pool size of 2x2. The second and third convolution layer has almost the same specifications as the first convolution layer but instead of having 32 number of kernels, it is changed to 64 number of kernels for both second and third convolution layer. After the addition of convolution layers we include a flatten layer, a dense layer of 64, a dropout with a value of 0.65 in that order. Lastly, for our output layer we have a dense layer of 1 with a sigmoid activation since we are doing a binary classification.

3.8. Training Model Accuracy

The researchers used the validation data set to evaluate the trained model's accuracy. The accuracy is determined by:

$$\text{accuracy} = \frac{\text{true positive} + \text{true negative}}{\text{total number of predictions}}$$

4. Results and Discussion

This section evaluates the performance of the proposed methodology to classify the type of Lanzones. The trained model was analyzed, and the researchers assessed how accurate it was at making predictions.

4.1. Plot Graph of Accuracy and Validation Accuracy

The model was evaluated during the training process which is represented by Figure 5. In the early phases of training, the training accuracy is greater than the validation accuracy. The validation accuracy increased as the training progressed to the 5th epoch. At 12th epoch, the validation accuracy begins to slightly decline while the training accuracy continues to improve steadily. The model provided a 97.84% training accuracy and a 92.59% validation accuracy.

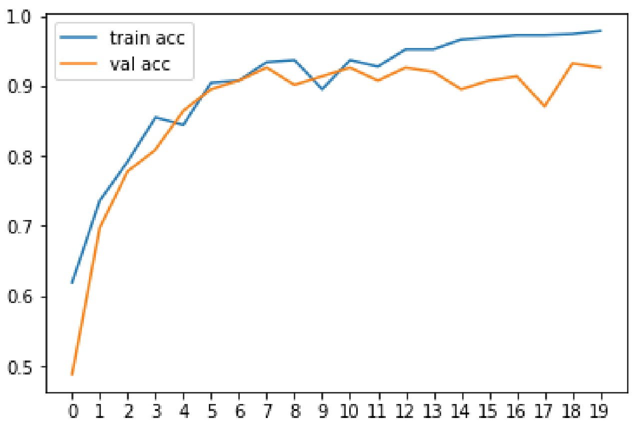

Figure 5. Plot Graph at 20th Epoch

4.2. Results of Test Accuracy

The model was evaluated using the provided testing data set, which is shown in Figure 6. The accuracy of the model to classify Lanzones is 91.66%. The model examined 59 Duko leaves and 49 Native leaves. Based on the given testing data sets, there are 99 correct predictions out of 108. There are 7 incorrect predictions with the Duko leaves and 2 incorrect predictions with the Native leaves.

Type of Lanzones	Correct Prediction	Incorrect Prediction	Total Prediction
Duko	52	7	59
Native	47	2	49
Total	99	9	108

Figure 6. Results of Model Testing

5. Conclusion

This study has focused its scope towards the classification of the variety of Lanzones leaves, namely duko and native. The 216 leaf samples that have been gathered were used as a dateset for a Convolutional Neural Network (CNN) Training Model. It is through this study that the researchers has come to the conclusion that an epoch higher than 20 would cause the model to overfit while having an epoch less than 20 would cause the accuracy to decline to an undesirable amount. The training accuracy is higher than the validation accuracy in the early stages of training.

As the training moved forward to the 5th epoch, the validation accuracy improved. At the 12th epoch, the training accuracy starts to consistently increase while the validation accuracy starts to significantly drop. The model offered a 92.59% validation accuracy and a 97.84% training accuracy. The evaluation of the model was shown in Figure 6 through the usage of the provided testing data set. This wielded the result of having a 91.66% accuracy rate of classifying lanzones leaves. There were 99 out of 108 accurate classifications, 7 incorrect classification of duko while 2 incorrect classification of the native leaves.

The researchers would recommend future researchers to test out a different training model with different set or variety of lanzones leaves. Future researchers may also use more than 2 variety to test out whether the accuracy rate would still remain within the range of 91.66% and higher if the datasets variety were to be increased.

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