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CLASSIFICATION OF NIPA FRUIT USING ARTIFICIAL NEURAL NETWORK

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Abstract - *The use of computer vision is increasing in agriculture, especially in fruit classification. The different types of fruits make classification difficult. Considering the complex appearance of the images of the fruit, selecting the most suitable data features and tuning hyperparameters is also vital. Hence, image processing is proposed since it offers a fast, efficient, and capable of replacing labor work in the harvesting process. This study was conducted to implement a classification model that uses four types (mature, immature, rejected, and damaged) of nipa fruit using an artificial neural network and to explore the different methods in the classification. There are two methods used in predicting the performance of the model, which are the largest method and the sequential method. These methods were used with four binary neural networks as base learners, which included a three-layer perceptron for each base learner consisting of (Model 1: Mature or Not-Mature, Immature or Not-Immature, Reject or Not-Reject, and Damage or Not-Damage). The largest method accuracy was 78%, the same as for the sequential method (78%). Furthermore, the results show that all the implemented methods outperform the benchmark (Human Classification) by 77%, and experiments also show that other (Multiclass) architectures developed with an accuracy of 86% outperform the remaining classifiers.*

Keywords – Artificial Intelligence, Neural Network, Classification, Nipa Fruit, Nipa Fruit Classification

INTRODUCTION

Nipa fruticans or mangrove palm is one of the Philippines' most valuable resources and one of Pangasinan's most widely used raw products, with 8000 hectares of natural nipa plantations in Region 1 producing nipa sap (Andres, 2017). It grows near coastal areas and river water with soft mud that gives the nipa nutrients to grow (Nypa Fruticans, 2021). Nipa palm plays a huge role in the business industry. In rural areas, the nipa palm's leaf is used for multiple purposes like roof thatching and varied materials like umbrellas, hats, mats, brooms, baskets, and others, and when it comes to its fruit, there are many such benefits as it can make various products like molasses, syrup, granulated sugar, vinegar, alcoholic beverages, and fuel. Furthermore, the Nipa (Sasa) is one of the things that people value and need as it has various uses in the country in terms of economics, utilization, the environment, and income generation.

According to an expert in harvesting nipa and a well-known farmer in Capandanan, Mr. Gerardo Dela Cruz Sr., farmers must learn how to classify nipa fruits to identify ready-to-harvest nipa fruits. After determining that the nipa is harvestable, farmers utilize the Nipa exercise method. The tapping of nipa sap involves an unusual kicking or beating process called "gonchanging" (Hamilton & Murphy, 1988). Farmers tread in the nipa stalk 2-3 times every week. In 30 days or up to 45 days, this approach will end. They exercise the nipa to obtain a large amount of sap. The sickling process is the reaping of the nipa stalk with the reaper after the gonchanging process, where the reaper is a type of cutting tool. In each nipa stalk, the sickling process approximately lasts 3 months then look for another harvestable nipa fruit and repeat the harvesting process.

This palm sap will exude as a fresh clear juice primarily composed of sucrose when the trunk's central growing point or upper part is incised. Every day, a severe wound on the palm is kept open to keep the sap flowing. The palm's survival is dependent on the tapper's (Usta) skill because if the daily scarring is carried out too far, the palm will die (Barreveld, 1993). Farmers will hang a bottle or bamboo tubes (traditionally) in the reaping part of the nipa to catch the liquid, which is the nipa sap, that will come out after the harvesting process. Farmers will visit the plantation daily to check the bottle or bamboo tubes and collect if it is loaded. When the farmer forgets to collect the bottle, the nipa sap might get spoiled. Nipa sap is spoiled when a bubble formed on top of the sap. The sap is collected and placed in a native earthen jar (tapayan), which is traditionally used for fermentation. This transforms the sap into a tuba, a traditional palm toddy whereas allowing it to ferment further allows Acetobacter from the air to oxidize ethanol into acetic acid. It is harvested when the acidity level reaches four or five percent. The time it takes to make nipa palm vinegar ranges from two to three weeks, though it can be done faster if a yeast starter culture is used. Since the process of harvesting nipa fruit can take months, it is important to be precise when classifying nipa fruits that are ready to harvest.

According to the residents of Lingayen, the potential of Nipa palms, particularly the economic values, was put at risk due to a lack of sufficient knowledge and limited skills among the residents, which are regarded as challenges for the application of cutting-edge production methods (Aquino L, 2019). Additionally, residents in Capandanan, Lingayen, Pangasinan are trying to have interaction in entrepreneurial activities to enhance their source of living as people experience an occasional marketable exchange of Nipa products. Consequently, residents must take the time to learn how to classify the type of nipa fruit.

Typically, harvesting is manual, thus the fruit-picker is accountable for deciding whether the nipa fruit has reached the appropriate maturity or nipa type for the harvest. For this reason, the researchers came up with this study of implementing a model that classifies nipa. A classification model, for example, might be used to classify the types of nipa fruit so that the fruit-picker would easily distinguish the harvestable nipa fruit they need. Moreover, to speed up the harvesting process and assist residents in becoming familiarized with the type of nipa fruit.

Figure 1 depicts the differences between four (4) types of nipa fruits that the researchers acknowledged and used classes for the implementation. Commonly, nipa fruits have brown to deep brown fruits borne on a spherical infructescence, 30–45 cm in diameter. Each fruit is a reversed egg shape to oblong ellipsoid, one-seeded fibrous drupe, with an angular tip, 10–15 by 5–8 cm. The seed is white in color, egg-shaped, and about 5 by 4 cm (NParks | Nypa Fruticans, 2019). Figure 1.a shows a mature nipa fruit is best to harvest and has an excellent quality of fruit that tastes like coconut. A large amount of nipa fruit can get by this type after the gonchanging process. Figure 1.b shows an immature nipa fruit. Farmers cannot harvest this type of nipa fruit since it lacks nipa sap. Figure 1.c shows rejected nipa fruit considering it only yields a small amount of nipa this is to ensure that the efforts of the farmers will not be wasted. Figure 1.d shows damaged nipa fruit which is ignored since the fruit's parts will fall to the ground at any time. Learning to classify nipa palm fruit based on physical characteristics is the most effective way to distinguish between harvestable and non-harvestable nipa fruit. Mature fruits are harvestable while Immature, Reject, and Damaged are considered non-harvestable. Moreover, it takes time and determination to learn the differences in nipa fruit features since its differences are not easily noticeable. As a result, Fruit image classification is widely used in the business world to reduce fruit loss and consumption and save time

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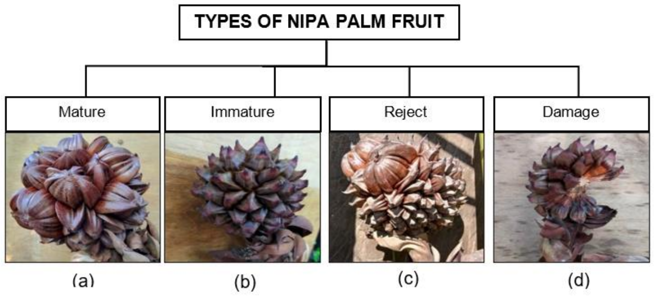

Figure 1: Visual Representation of Different Types of Nipa Palm Fruit

In the latest days, image processing has become widely adopted in a variety of fields, such as industrial image processing, medical imaging, real-time imaging, texture classification, object recognition, and so on. A further fast-growing research area is image processing and computer vision in agriculture. It is an important analyzing tool for pre-harvest to postharvest of crops. It has numerous agricultural applications. The cultivation of crops can be enhanced by technological support (Raja Sekar et al., 2018). Image classification is the process of labeling and classifying objects within an image based on the object classes. To identify what is interpreted on a given image, a computer would normally use Neural Network.

In previous years, neural networks (NN) have grown in popularity as a computing approach for data classification and predictive applications. Neural Network is a computer-generated model of the human brain that mimics its structure and functionality. This method is also called the artificial neural network (ANN), and it can be trained to learn a complex relationship between two or more variables. One of the most appealing aspects of a Neural Network is its ability to learn patterns or relationships between given input and the desired output (Nur Badariah Ahmad Mustafa et al., 2011; Johari 2009).

Farmers will be able to utilize artificial intelligence and machine learning to help them accomplish their goal of a greater harvest by making smarter field decisions. Subsequently, the researchers intend to assist farmers by developing a model that combines Neural Network and Python to automatically classify nipa fruit based on the input image. However, the researchers decided that the model would only be used for research purposes. The model will deploy to a staging environment where the researchers and panels who will evaluate the model will have access to the implemented model. In addition, deployment in a production environment will append to the recommendations, where future researchers can utilize the implemented model for deployment so that users and farmers can use it to reduce fruit loss and consumption.

Using Neural Networks and Python language, the researchers will develop a model that will classify the type of nipa fruit. The pre-processing began with images of the nipa fruit with its stalk. Farmers would be able to easily distinguish the harvestable nipa fruit they need with the help of the model. In creating a machine learning model, it will be presented with design choices as to how to define the model architecture. Often, it is not immediately clear what the optimal model architecture should be for a given model, and thus it'd be nice to be able to explore a range of possibilities (Sayak, 2018). In these instances, it shows how the right choice of hyperparameter values affects the performance of a classification model.

According to some computer programmers who have implemented a neural network, tuning the hyperparameters is a case of trial and error since there is no exact solution or calculation in finding the perfect values for the hyperparameters to achieve an accuracy of more than 90%. The performance of the Neural Network model will vary depending on the type of data how diverse your data is, and the amount of data used by the computer programmers. King and Shellie (2016) indicated that ANN models are reliable and useful simple prediction tools in fruit analysis when dealing with non-linear data such as fruit properties. Thus, the use of Neural Networks in agriculture has increased. This frequently yields better analysis results compared to traditional statistical methods (Torkashvand et al. 2017; Sharma and Singh 2017).

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The researchers considered ANN in this study among other types of Neural networks such as Convolutional Neural networks and Recurrent Neural networks since Artificial Neural network remains dominant for concerns where datasets are limited (Meel, 2021; Bhuiya, 2020). Previous studies (Huang et al., 2021; Gholipoor & Nadali, 2019; Niedbaa, 2019; Torkashvand et al., 2017) confirmed that the artificial neural network model has been widely used in the agricultural industry and indicated to be a reliable and highly effective predicting tool with high prediction accuracy. (Fatma and Amed, 2018) researched to classify the four stages of banana maturity using different classification techniques, including the SVM classifier, naive Bayes, KNN, decision tree, discriminant analysis classifiers, and Artificial Neural networks. Compared to other supervised classification algorithms, the artificial neural network-based system has optimal performance and the highest overall recognition rate, 97.75%, among other techniques. Anatya et al. (2020) have previously used Convolutional Neural Networks (CNN) to classify five types of fruit, including banana, star fruit, mango, melon, and tomato. The classification accuracy of 1294 image data is 61 %. The retrieval of fifty (50) image data, on the other hand, has the highest accuracy of 88.93%.

OBJECTIVES OF THE STUDY

The main goal of this study is to develop a model for the Classification of Nipa Fruits as Harvestable or Non-harvestable using Neural Network that can use by those who are unable to determine when nipa fruit is ready to harvest. These lead to the specific objectives as follows:

1. To determine the data pre-processing techniques applied to the input data image.
2. To identify the neural structure in classifying harvestable nipa fruit.
3. To determine the measures for evaluating the constructed neural network.

METHODOLOGY

The research methodology refers to the methods or techniques utilized to gather, examine, and process relevant evidence. The methodology part of a research paper allows the reader to critically examine the study's overall validity and dependability.

This chapter will discuss the research methods accessible for the study and what it is appropriate for it to employ in response to the statement of the problem in Chapter 1, which is directed toward the construction of the model using neural networks. In more detail, in this section, the researchers outline the architectural design, data collection, and calendar of the activities. This benefited the researchers in systematically conducting the study and achieving their objectives.

ARCHITECTURE DESIGN

The primary goal of this study is to use a Neural network to classify nipa fruit images and evaluate the model's performance based on accuracy. This section describes the classification process. Figure 2.1 depicts the model's architecture diagram.

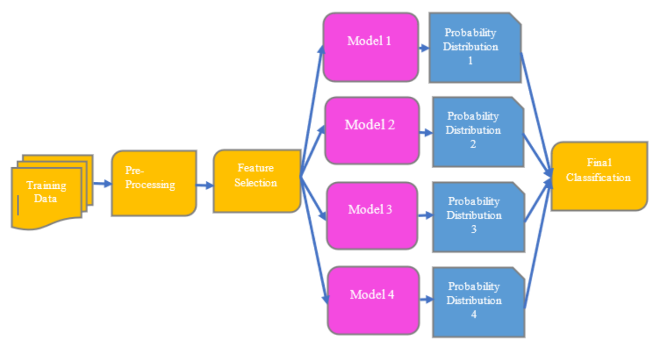

Figure 2.1: Architecture Design

INPUT DATA

Input data used was nipa images gathered around Pangasinan. There are a total of 300 images in each class. Four types of nipa images are acquired by the researchers consisting of Mature, Immature, Reject and Damage labeled as class 0, class 1, class 2, and class 3 respectively. Twenty percent of these images (60) are separated and will be used as a testing set. The remaining 80% will be used for training (240). The training data set is then augmented to generate 5748 images after acknowledging the minimum amount of input images (1437 images per class). Apart from the training and test set, another variety of images composed of 20 images in each class was prepared. All the images used were then resized to 64 by 64 pixels. Different samples of Nipa palm fruit images are shown in Figure 2.1.1. The sampled nipa fruits illustrated below are mature, immature, reject, and damaged, respectively.

Figure 2.1.1: Sample Nipa palm fruit images.

(Two images from each class: Mature, Immature, Reject, Damage)

The accuracy of a supervised classification is hugely dependent on the training data provided by the researchers. The most reliable method for improving models is to provide better training data. The model learns from training data, and the data required for this study are images. An image is merely a collection of pixels, and each pixel has numerical values that correspond to colors. The model will learn from the images based on the numerical value of pixels.

PRE-PROCESSING

Data preprocessing is the process of converting raw data into an understandable format. It is an essential process in cleaning data to make it suitable for a classification model as the model cannot work with raw data and helps improves the model's accuracy and performance. Cropping, array conversion, and index randomization are preprocessing techniques that are used. The other possible methods are standardization or normalization, histogram extraction of RGB including histogram of grayscale images, and data augmentation.

FEATURE SELECTION

The primary goal of using this method is to get only the relevant features and omit the redundancy of input variables or filtering noise from the dataset. During this step, retrieved features are converted into feature vectors, which are then classified to recognize as the input. The goal of feature selection is to choose the crucial features to improve the performance of the classification model.

In the context of image classification, the histogram of an image typically refers to a histogram of pixel intensity values. Since there are 255 different intensities for an 8-bit grayscale image, ranging from 0 (black) to 255 (white), the histogram will graphically display 255 numbers indicating the distribution of pixels among those grayscale values. Color images can also be histogrammed — either individually for the red, green, and blue channels, or as grayscale images.

FOUR BINARY CLASSIFICATION MODEL

The researchers will develop four binary classifiers as base models for the overall structure of multiclass classification. These base models will be trained using the same data set. The first model's objective is to determine whether the nipa fruit is mature or not. The input images in this model are mature nipa fruit images labeled as 1, while 1/3 of the images in the other classes are labeled as 0; the second model’s objective is to determine whether the nipa fruit is immature or non-immature type. The input images in this model are immature nipa fruit images labeled as 1, while 1/3 of the images in the other classes are labeled as 0; the third model’s objective is to determine whether the nipa fruit is rejected or not. The input images in this model have rejected nipa fruit images labeled as 1, while 1/3 of the images in the other classes are labeled 0; and the fourth model’s objective is to determine whether the nipa fruit is damaged or not. The input images in this

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model are damage nipa fruit images labeled as 1, while 1/3 of the images in the other classes are labeled 0. Training and test sets are separated, and the model randomly selects 10% of the training set for the validation set every epoch.

PROBABILITY DISTRIBUTION

In this study, a four-base (binary) model will provide a probability and predict the outcome of a specific image, such as whether it is mature or not, immature or not, reject or not, and damaged or not. The experiment's possibility of probable outcomes is calculated using a probability distribution. These base models give a probability ranging from 0 to 1 to indicate how confident they are. These probabilities provided by the base models will then analyze in the final classification.

FINAL CLASSIFICATION

The final classification of images as mature, immature, rejected, or damaged will base on the probability output provided by four-base models. The researchers experimented with various methods for predicting the final output, such as largest probability and sequential probability, to see which method would provide the best accuracy.

DATA COLLECTION

Since there is currently no available dataset for nipa fruit images, this project includes data collection. Four (4) classes were gathered (Mature, Immature, Reject, and Damage) with different ambient noises,irrelevant adjacent objects, and light conditions. A tool used to take nipa palm fruit images is a regular cellphone camera. Data has gathered around Lingayen Pangasinan and Dasol Pangasinan and was held from November 2021 to May 2022. Mr. Dela Cruz, an expert farmer with thirty (30) years of experience in the nipa industry, assisted the researchers in annotating the nipa images. The researchers sought a second opinion from a nipa fruit expert in addition to the primary participant to assess the correctness of the labeled image data. The researchers intend to use an unstructured interview to make the interviewee feel at ease and respond freely in their native language, the Pangasinan language. Researchers also use direct observations as a fundamental and actual data collection method.

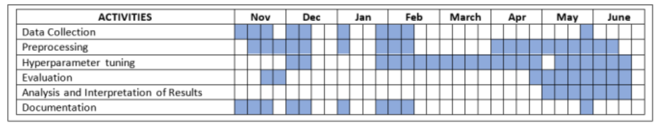

Table 2.3: Timetable of Activities

CALENDAR OF ACTIVITIES

Table 2.3 shows a Gantt chart of the activities. Each bullet represents approximately one week of activity.

RESULTS AND DISCUSSION

This chapter discusses the data pre-processing techniques applied to input data images, the deep neural structure in classifying nipa, and the measures for evaluating the constructed neural network.

Data Pre-processing Techniques Applied

To deal with the complexity of the images, the researchers used image cropping to reduce image noise in the background of nipa fruit. The researchers manually cropped the images into uniform squares, then resized them to 64 by 64 pixels. The data are shuffled randomly, and the data was split in the ratio of 8:2 (80% for training and 20% for the test set).
The other preprocessing techniques applied are:

A. *DATA AUGMENTATION*

Since there are lesser amounts of data images gathered during data collection, the researchers used data augmentation techniques to have more data to train. For each class, there are 240 training data before the process, and 1437 training data after the process. Rotating, flipping, zooming, and adjusting brightness on images of nipa fruits are among the data augmentation techniques used to improve learning capability and to have more training data since adding more data is a possible technique to prevent the model from overfitting.

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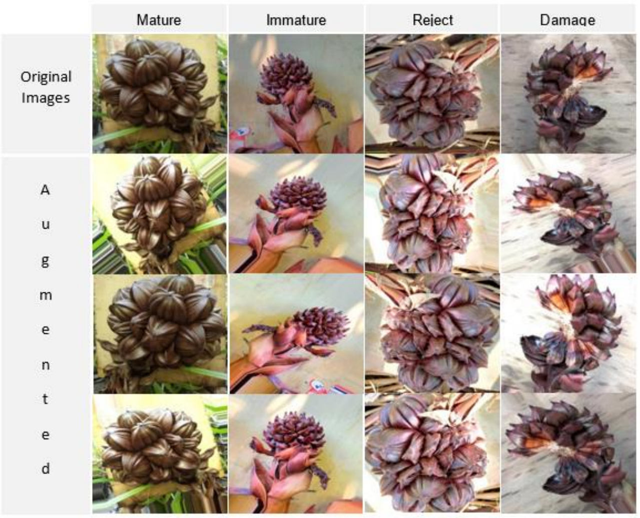

Figure 3.1.2: Sample Augmented Nipa Fruits Images

Figure 3.1.2 shows augmented samples for each of the four classes. Each augmented image is a combination of techniques used. The first row shows the original images such as mature, immature, reject, and damaged images. The next three rows depict augmented images to increase the number of images.

B. FEATURE SELECTION

A digital image consists of three-color channels (RGB), the smallest indivisible segments of an image are called pixels, and each pixel has a strength that is often referred to as pixel intensity (Das, 2021). Figure 3.1.3.a illustrates how machines read images, while Figure 3.1.3.b shows how the researchers will prepare the training data so that the model can recognize and accept the data, allowing the researchers to implement the model successfully.

The researchers used pixel representation and extracted histogram values as features. The RGB

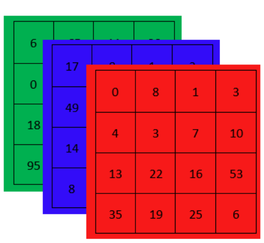

Figure 3.1.3.a: RGB color channels of an image

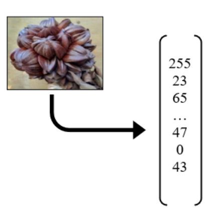

Figure 3.1.3.b: Image to Vector

image with grayscale can be represented by

$$Histogram\,(x,y)^{RhisGhisBhis+GRhis} = Rhis + Ghis + Bhis + GRhis$$

The histogram of intensity image red, green, blue, and grayscale is represented as

$$Histogram(x,y)^{RhisGhisBhis+GRhis}$$

where the number of levels is on a scale of 0 to 255. The researchers concatenated the histogram values of red, green, and blue channels with Grayscale (Nahid & Kong, 2018). Afterward, the Histogram has 1280 array length, and the Pixel values have 12288 array length. These two (2) features are concatenated to form 13568, which is used in the model's input layer. Figure 3.1.3.c demonstrates the Histogram feature extraction process. The researchers used this method to add features to the model that could help the model become more familiar with raw input images and improve its performance.

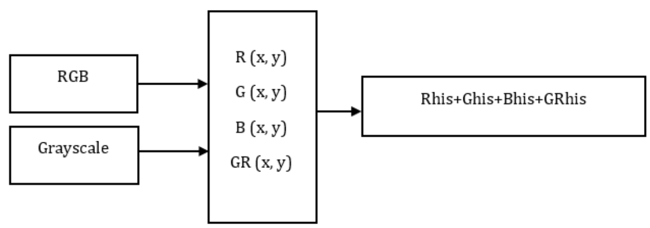

Figure 3.1.3.c: Histogram process

C. STANDARDIZATION

The pixel value of the red, blue, and green channels (RGB) ranges from 0 to 255. The researchers then used standardization to scale the feature (value of pixels), since the datasets used are images, every row of the dataset is then divided by the maximum value of RGB pixel. Standardization is a scaling technique and is used to improve the performance of the model.

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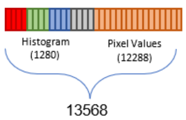

Figure 3.1.3.d: Image Structure

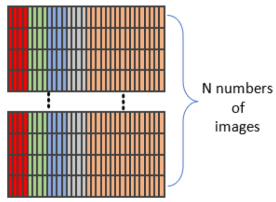

Figure 3.1.3.e: Dataset Structure

Figure 3.1.3.d visualizes a structure of an image where the feature Pixel representation and Histogram are concatenated to form a 13568-array length that serves as the input of the model. ¬Figure 3.1.3.e visualizes the dataset structure, which contains 5748 photos to be fed to the model.

Classes	Total raw images	Training images	Augmented images	Test images
Mature	300	240	1437	60
Immature	300	240	1437	60
Reject	300	240	1437	60
Damage	300	240	1437	60
Total	**1200**	**960**	**5748**	**240**

Table 3.1.3 Final Dataset Count

Table 3.1.3 shows the final dataset count of images used in the model. Training, testing, and augmented images were included in each of the four classes. The dataset in each class is divided into two sets: a training set of images, which contains 80% of the total images (240 training sets), and a testing set of images containing the remaining 20% (60 image samples). In addition, each class has 1437 augmented images.

STRUCTURE AND TRAINING OF NEURAL NETWORK

Artificial neural networks are designed to mimic the behavior of neurons in the human brain. It can execute perceptual and cognitive tasks in a relatively short time. In this study, every base model is a multilayer perceptron using ReLU as the hidden layer activation function and sigmoid as the output layer activation function. One hidden layer back propagation artificial neural network (BP-ANN) model was implemented using Keras API for the classification of nipa fruit. The concept of this BP-ANN is the data from the input layer will not only be fed to the output layer, but it will also pass through from the output layer to the input layer. The architecture of the neural network model is shown in Figure 3.2 which has 13568 nodes in the input layer, 10000 nodes in the hidden layer, and 1 node in the output layer with a learning rate of 0.00005 and 50 epochs with a batch size of 32.

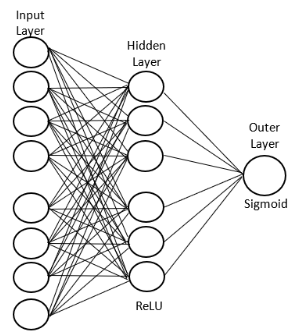

Figure 3.2: Base Model Architecture Diagram

Adam was used as the optimizer since it is one of the best algorithms that is most widely used in machine learning. The inputs for these models are RGB pixel representations of the dataset images that are flattened into a 1D array and a color histogram of each color channel that is extracted from each image. These RGB pixel representations and color histograms are concatenated into a single array and serve as the input features of each training dataset.
The researchers then decided to use two methods for the final classification: the largest and the sequential method. These methods will base on the probability output of the base models. Test sets serve as the basis for the overall performance of the model. In the Largest Method, the highest probability prediction among all the models will be the final prediction while in Sequential Method, this method will ask the four-based model sequentially and the first who satisfies the condition (probability > 0.85) first will be the final classification. If none of the four-base models satisfy the condition, the final output will be the one that has the highest probability.

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The researchers used two devices in training the Neural Network. The first device used in training the program is MateBook D14 and its CPU is AMD Ryzen7 3700U with Radeon Vega Mobile Gfx 2.30 GHz and installed RAM of 8GB (6.94 Usable) with AMD Radeon™ RX Vega 10 Graphics. The other device used is ASUS ROG Zephyrus Duo 15 SE GX551 and its CPU is AMD Ryzen9 5900HX 8-Core, 16-thread 3.3GHz with Turbo Boost (up to 4.6GHz) and installed RAM of 32GB DDR4 3200MHz with GPU of NVIDIA GeForce RTX 3080 Laptop GPU. However, due to the initial code design of the base models, the training took a considerable amount of time. Each model averages 2hours of training time per 100 iterations. Due to this, the researchers then opted to use the Keras platform to implement the base models. Models implemented using Keras take advantage of the installed GPU in the device to hasten up computation and thus, shorten training time.

MEASURES FOR EVALUATING THE CONSTRUCTED NEURAL NETWORK

The main performance evaluation factors of the classification process are Precision, Recall, and Accuracy. Computations of these factors are from the numerical measure which are true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The classification is TP if a particular image is predicted as Class X and has an actual value of Class X. If the classification of an image is not class X and is indeed not of class, then it is deemed TN. It is deemed FP, if an image is predicted as class X but is not class X. Consequently, if an image is predicted as not class X but its actual value is class A, then it is considered an FN classification (Zhu W., et al, 2002).

Precision indicates what percentage of positive predictions have been correct. This demonstrates how accurate the model is in classifying images. Eq 1 shows the equation for precision.

$$\frac{TP}{(TP + FP)}. \qquad (1)$$

Recall indicates what percentage among all positive samples were correctly predicted as positive by the classifier. It is also known as the True Positive Rate (TPR), Sensitivity, and Detection accuracy. This demonstrates how accurate the model is in classifying images. Eq 2 shows the equation for recall.

$$\frac{TP}{(TP + FN)}. \qquad (2)$$

F1-score merges precision and recall together into a single metric. It is arithmetic means of precision and recall. Eq 3 shows the equation for F1-score.

$$2 * \frac{Precision * Recall}{Precision + Recal}. \qquad (3)$$

Precision, Recall, and F1-score are used to evaluate classification models. Accuracy indicates the model's overall performance, which is the percentage of total samples correctly identified by the classifier. Eq 4 shows the equation for accuracy.

$$\frac{(TP + TN)}{(TP + TN + FP + FN)}. \qquad (4)$$

		Predicted Class			
	Classes	Class 1	Class 2	Class 3	Class 4
Actual Class	Class 1	TP	FN	FN	FN
	Class 2	FP	TN	TN	TN
	Class 3	FP	TN	TN	TN
	Class 4	FP	TN	TN	TN

Figure 3.3: HEATMAP

(Visualization of Confusion Matrix)

The predicted values after training are tallied and presented in a form of a confusion matrix. The model will compute the performance based on the prediction. See Figure 3.3 to understand the concept of the confusion matrix plotted as a heatmap. This will assist the researchers in visualizing the results and understanding the outcome of the model's prediction.

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PERFORMANCE OF THE BASE MODELS

The models are evaluated using test sets. The test set consists of 60 nipa fruit images in each class. Figure 3.3.1.a to figure 3.3.1.d visualize a summary of each model's predicted results, while the given tables assess whether the performance is accurate or requires further refinement, such as hyperparameter tuning.

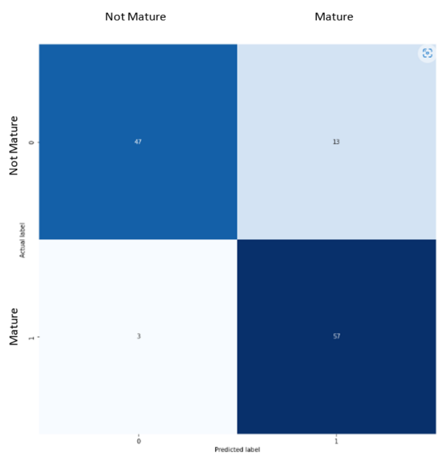

Figure 3.3.1.a: Heatmap for Mature Test Set (Model 1)

Figure 3.3.1.a visualizes the values of the confusion matrix from the model 1 performance. The diagonal elements represent outcomes that have been accurately classified. Incorrectly classified outcomes are depicted on the off diagonals of the confusion matrix. The heatmap shows that out of all the predicted values, 57 images of the Mature class are correctly classified while 47 of the Not-Mature images are correctly classified.

Prediction			Performance			
Class	Not-Mature	Mature	Precision	Recall	F1-Score	Support
Not-Mature	47	13	0.94	0.78	0.85	60
Mature	3	57	0.81	0.95	0.88	60
Accuracy					0.87	120
Macro Avg			0.88	0.87	0.87	120
Weighted Avg			0.88	0.87	0.87	120

Table 3.3.1.a: Classification Report for Model 1

Table 3.3.1.a shows that out of 60 Not-Mature test images, 47 of them are labeled correctly. From there, the computed precision is 94% and 78% for recall in the "Not-Mature" class. Since precision and recall have been obtained, the F1 score can be calculated using the arithmetic mean. The F1 score calculated is 85%. On the other hand, out of 60 mature test images, 57 of them are labeled correctly. From there, the computed precision is 81% and 95% for recall of the "Mature" class. Since precision and recall have been obtained, the F1 score can be calculated using the arithmetic mean. The F1 score calculated is 88%. The final accuracy acquired for model 1 is 87%.

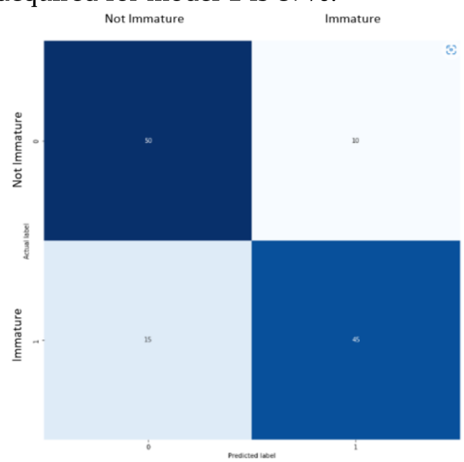

Figure 3.3.1.b: Heatmap for Immature Test Set (Model 2)

Figure 3.3.1.b visualizes the values of the confusion matrix from the model 2 performance. The diagonal elements represent outcomes that have been accurately classified. Incorrectly classified outcomes are depicted on the off diagonals of the confusion matrix. The heatmap shows that out of all the predicted values, 45 images of the Immature class are correctly classified while 50 of the Not-Immature images are correctly classified.

Prediction			Performance			
Class	Not-Immature	Immature	Precision	Recall	F1-Score	Support
Not-Immature	50	10	0.77	0.83	0.80	60
Immature	15	45	0.82	0.75	0.78	60
Accuracy					0.79	120
Macro Avg			0.79	0.79	0.79	120
Weighted Avg			0.79	0.79	0.79	120

Table 3.3.1.b: Classification Report for Model 2

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Table 3.3.1.b shows out of 60 Not-Immature test images, 50 of them are labeled correctly. From there, the computed precision is 77% and 83% for the recall in the "Not-Immature" class. Since precision and recall have been obtained, the F1 score can be calculated using the arithmetic mean. The F1 score calculated is 80%. On the other hand, out of 60 immature test images, 45 of them are labeled correctly. From there, the computed precision is 82% and 75% for recall of the "Immature" class. Since precision and recall have been obtained, the F1 score can be calculated using the arithmetic mean. The F1 score calculated is 78%. The final accuracy acquired for model 2 is 79%.

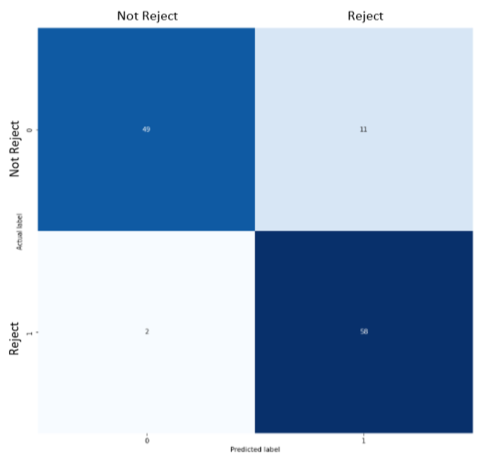

Figure 3.3.1.c: Heatmap for Reject Test Set (Model 3)

Figure 3.3.1.c visualizes the values of the confusion matrix from the model 3 performance. The diagonal elements represent outcomes that have been accurately classified. Incorrectly classified outcomes are depicted on the off diagonals of the confusion matrix. The heatmap shows that out of all the predicted values, 58 images of the Reject class are correctly classified while 49 of the Not-Reject images are correctly classified.

Prediction			Performance			
Class	Not-Reject	Reject	Precision	Recall	F1-Score	Support
Not-Reject	49	11	0.96	0.82	0.88	60
Reject	2	58	0.84	0.97	0.90	60
Accuracy					0.89	120
Macro Avg			0.90	0.89	0.89	120
Weighted Avg			0.90	0.89	0.89	120

Table 3.3.1.c: Classification Report for Model 3

Table 3.3.1.c shows that out of 60 Not-Reject test images,49 of them are labeled correctly. From there, the computed precision is 96% and 82% for recall in the "Not-Reject" class. Since precision and recall have been obtained, the F1 score can be calculated using the arithmetic mean. The F1 score calculated is 88%. On the other hand, out of 60 rejected test images, 58 of them are labeled correctly. From there, the computed precision is 84% and 97% for recall of the "Reject" class. Since precision and recall have been obtained, the F1 score can be calculated using the arithmetic mean. The F1 score calculated is 90%. The final accuracy acquired for model 3 is 89%.

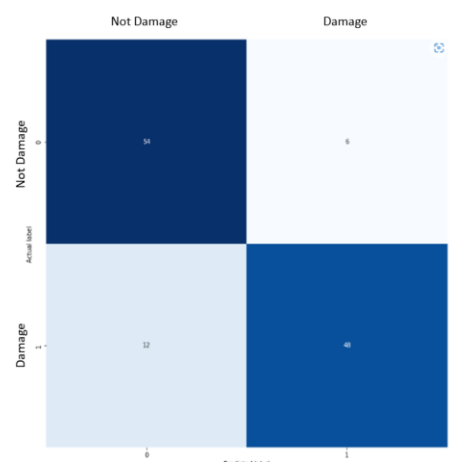

Figure 3.3.1.d: Heatmap for Damage Test Set (Model 4)

Figure 3.3.1.c visualizes the values of the confusion matrix from the model 4 performance. The diagonal elements represent

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outcomes that have been accurately classified. Incorrectly classified outcomes are depicted on the off diagonals of the confusion matrix. The heatmap shows that out of all the predicted values, 48 images of the Damage class are correctly classified while 54 of the Not-Damage images are correctly classified.

Prediction			Performance			
Class	Not-Damage	Damage	Precision	Recall	F1-Score	Support
Not-Damage	54	6	0.82	0.90	0.86	60
Damage	12	48	0.89	0.90	0.84	60
Accuracy					0.85	120
Macro Avg			0.85	0.85	0.85	120
Weighted Avg			0.85	0.85	0.85	120

Table 3.3.1.d: Classification Report for Model 4

Table 3.3.1.d shows that out of 60 Not-Damage test images, 54 of them are labeled correctly. From there, the computed precision is 82% and 90% for recall in the “Not Damage” class. Since precision and recall have been obtained, the F1 score can be calculated using the arithmetic mean. The F1 score calculated is 86%. On the other hand, out of 60 damage test images, 48 of them are labeled correctly. From there, the computed precision is 89% and 90% for recall of the “Damage” class. Since precision and recall have been obtained, the F1 score can be calculated using the arithmetic mean. The F1 score calculated is 84%. The final accuracy acquired for model 4 is 85%.

PERFORMANCE OF THE OVERALL MODEL

The researchers use two architectures for evaluating the overall performance of the model such as Largest Prediction and Sequential Prediction.

Figures 3.3.2.a depicts the summary of predicted results and Tables 3.3.2.a shows the performance of the architectures.

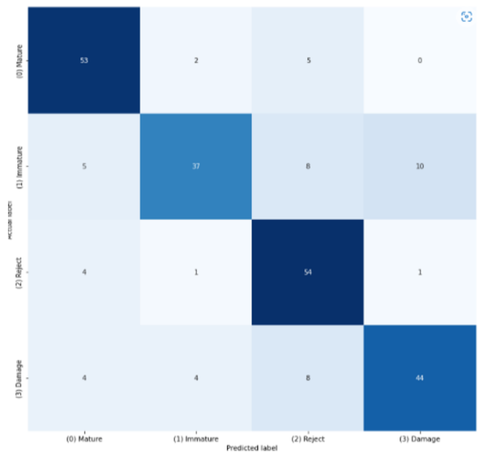

Figure 3.3.2.a: Largest prediction Heatmap

The heatmap in Figure 3.3.2.a provided the summary of predicted results of the largest prediction according to the confusion matrix. Heavy colored diagonal indicates that the model has impressive performance. Furthermore, out of 240 test set images, 188 predictions were correct. In the heatmap, if the diagonal part is heavy colored, meaning the model predicts 50% above the test set correctly.

Prediction					Performance				
Class	Mature	Immature	Reject	Damage	Precision	Recall	Accuracy	F1-Score	Support
Mature	53	2	5	0	0.80	0.88	0.78	0.84	60
Immature	5	37	8	10	0.84	0.62		0.71	60
Reject	4	1	54	1	0.72	0.90		0.80	60
Damage	4	4	8	44	0.80	0.73		0.77	60
Average					0.79	0.78		0.78	240

Table 3.3.2.a: Classification Report of Largest Prediction

Table 3.3.2.a shows the evaluation performance of the largest probability model. The model predicted 66 images as "Mature," and 53 of them are correctly predicted. From there, the performance computed in precision is 80% and 88% for the recall of the "Mature" class. Since there are a total of 60 images in each class, the F1 score is 84%. Afterward, 44 images are labeled as "immature," and 37 of them are correctly predicted. From there, the performance computed precision is 84% and 62% for the recall of the "Immature" class. Since there are a total of 60 images in each class, the F1 score is 71%. Then, 75 images were rejected, and 54 of them are correctly predicted. From there, the performance computed precision is 72% and

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90% for the recall of the "Rejected" class. Since there are a total of 60 images in each class, the F1 score is 80%. Then, 55 images are tagged as "damage," and 44 of them are correctly predicted. From there, the performance computed precision is 80% and 73% for the recall of the "Damage" class. Since there are a total of 60 images in each class, the F1 score is 77%. Using the summary predicted results, the model can compute the main performance evaluation factors of the classification and the final accuracy for the final model is 78%.

Figures 3.3.2.b depicts the summary of predicted results and Tables 3.3.2.b shows the performance of the architectures.

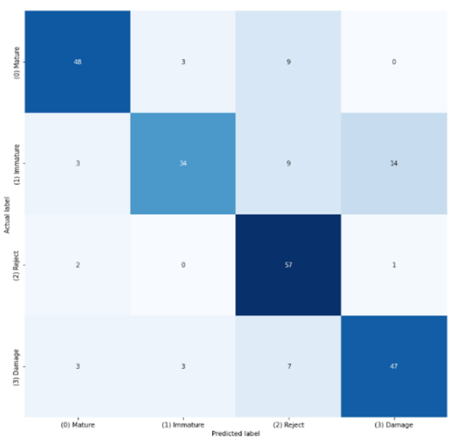

Figure 3.3.2.b: Sequential prediction Heatmap

The heatmap in Figure 3.3.2.b provided the summary of predicted results of sequential prediction according to the confusion matrix. Heavy colored diagonal indicates that the model has impressive performance. Furthermore, out of 240 test set images, 186 were correctly predicted. In the heatmap, if the diagonal part is heavy colored, meaning the model predicts 50% above the test set correctly.

Prediction					Performance				
Class	Mature	Immature	Reject	Damage	Precision	Recall	Accuracy	F1-Score	Support
Mature	48	3	9	0	0.86	0.80	0.78	0.83	60
Immature	3	34	9	14	0.85	0.57		0.68	60
Reject	2	0	57	1	0.70	0.95		0.80	60
Damage	3	3	7	47	0.76	0.78		0.77	60
Average					0.79	0.78		0.77	240

Table 3.3.2.b: Classification Report of Sequential Prediction

Table 3.3.2.b shows the evaluation performance of the sequential probability model. The model predicted 56 images as “Mature”, and 48 of them are correctly predicted. From there, the performance computed precision is 86% and 80% for recall of the “Mature” class. Since there is a total of 60 images in each class then the F1 score is 83%. Afterward, 40 images as “Immature”, and 34 of them are correctly predicted. From there, the performance computed precision is 85% and 57% for recall of the “Immature” class. Since there is a total of 60 images in each class then the F1 score is 68%. Then, 82 images as “Reject”, and 57 of them are correctly predicted. From there, the performance computed precision is 70% and 95% for recall of the “Reject” class. Since there is a total of 60 images in each class then the F1 score is 80%. Then, 62 images as “Damage”, and 47 of them are correctly predicted. From there, the performance computed precision is 76% and 78% for recall of the “Damage” class. Since there is a total of 60 images in each class then the F1 score is 77%. Using the summary predicted results, the model can compute the main performance evaluation factors of the classification and the final accuracy for the final model is 78%. The need for additional preprocessing features, or insufficient datasets contribute to low accuracy.

HUMAN CLASSIFICATION

A human classification was utilized as a benchmark. The researchers selected random people who classified forty (40) images in benchmarking form through google forms. To avoid guessing or being uncertain in classifying, the participants were given a brief discussion about the types of nipa palm fruit to help participants understand what and how to discern between distinct types of nipa fruits. The images used in the benchmarking came from the test set.

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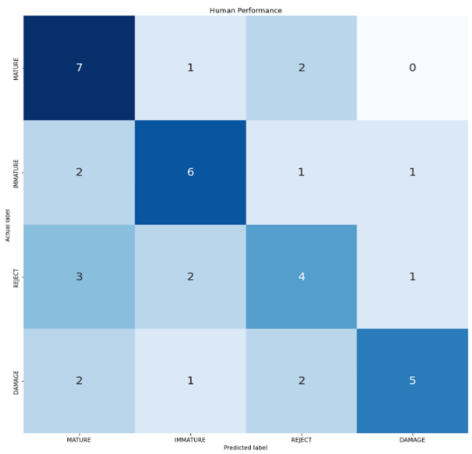

Figure 3.3.3: Heatmap for Human Classification

The heatmap in Figure 3.3.3 provided a neutral prediction since the diagonal part is dominant in dark color. Furthermore, out of 800 test set images, the diagonal with darker colorings has 436 correct predictions.

	Prediction				Performance				
Class	Mature	Immature	Reject	Damage	Precision	Recall	Accuracy	F1-Score	Support
Mature	7	1	2	0	0.50	0.70	0.75	0.58	10
Immature	2	6	1	1	0.60	0.60	0.80	0.60	10
Reject	3	2	4	1	0.44	0.40	0.73	0.42	10
Damage	2	1	2	5	0.71	0.50	0.83	0.59	10
Average					0.56	0.55	0.78	0.55	40

Table 3.3.3: Human Classification

As shown in table 3.3.3, the overall average accuracy of random participants' responses is 77%. This implies that humans' performance in classifying nipa is quite poor. When it comes to harvesting, it is indeed critical to choose the right approach to maximize output while minimizing losses. Many farmers struggle with harvesting and processing crops. They must know the exact harvest time because the harvesting period and duration has an impact on the quality, durability, transportation, and storage of harvested crops. The capacity of a farmer to harvest and handle his crops successfully could make an enormous difference between financial success and failure (Folnović, 2021).

OTHER ARCHITECTURE

A multiclass classifier was implemented by the researchers as an alternative architecture. The Multiclass classifier is a single model that will simultaneously classify the researchers' input data, and the output will be interpreted after the process is completed. It was implemented for the possibility that this architecture might get higher accuracy than the proposed architecture. The Multiclass Architecture Diagram was depicted in Figure 3.3.4.a.

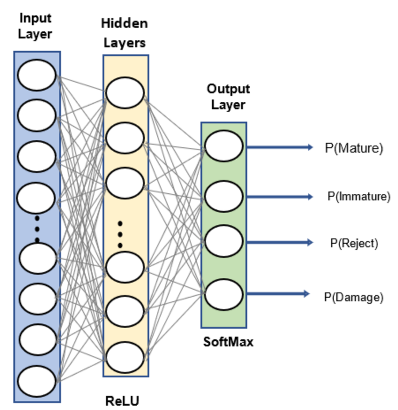

Figure 3.3.4.a: Multiclass Architecture Diagram

In constructing a Multiclass Neural Network, the researchers implemented a four-layer perceptron with ReLU as the activation function in the hidden layers and SoftMax as the activation function in the output layer. The input features used are Pixel Representation and color histogram. The network has 13568 nodes on the input layer, 10000 nodes on the hidden layer, and 1 on the outer layer, a learning rate of 0.00005, and 50 epochs with a batch size of 32.

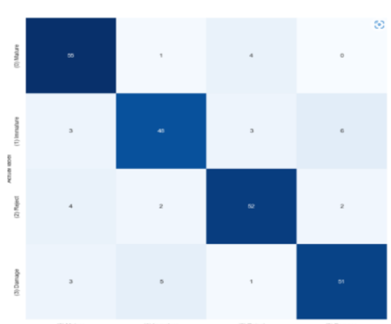

Figure 3.3.4.b: Multiclass Architecture Heatmap

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The heatmap in Figure 3.3.4.b provided a consistent heavy color in the diagonal part where 206 images were correctly predicted. Therefore, this architecture shows a satisfactory performance in classifying nipa palm fruit.

Prediction					Performance				
Class	Mature	Immature	Reject	Damage	Precision	Recall	Accuracy	F1-Score	Support
Mature	55	1	4	0	0.85	0.92	0.86	0.88	60
Immature	3	48	3	6	0.86	0.80		0.83	60
Reject	4	2	52	2	0.87	0.87		0.87	60
Damage	3	5	1	51	0.86	0.85		0.86	60
Average					0.86	0.86		0.86	240

Table 3.3.4: Classification Report of Multiclass Architecture

Table 3.3.4 shows the evaluation performance of the Multiclass architecture. The model predicted 65 images as "Mature", and 55 of them are correctly predicted. From there, the performance computed precision is 85% and 92% for recall of the "Mature" class. Since there is a total of 60 images in each class then the F1 score is 88%. Afterward, 56 images as "Immature", and 48 of them are correctly predicted. From there, the performance computed precision is 86% and 80% for recall of the "Immature" class. Since there is a total of 60 images in each class then the F1 score is 83%. Then, 60 images as "Reject", and 52 of them are correctly predicted. From there, the performance computed precision is 87% and 87% for recall of the "Reject" class. Since there is a total of 60 images in each class then the F1 score is 87%. Then, 59 images as "Damage", and 51 of them are correctly predicted. From there, the performance computed precision is 86% and 85% for recall of the "Damage" class. Since there is a total of 60 images in each class then the F1 score is 86%. Using the summary predicted results, the model can compute the main performance evaluation factors of the classification and the final accuracy for the final model is 86%.

COMPARISON OF FINAL MODELS AND HUMAN CLASSIFICATION

The primary objective of model comparison is to find the model with the best performance that accurately predicted the types of nipa fruits. The researchers aim to at least achieve a high accuracy that outweighs the accuracy of human classification. Table 3.3.5 shows the performance comparison for every architectural type which includes the largest Probability Prediction performance, sequential probability prediction performance, human classification performance, and multiclass architecture performance.

	Precision	Recall	Accuracy	F1-Score
Largest Probability Prediction	79%	78%	78%	78%
Sequential Probability Prediction	79%	78%	78%	77%
Human Performance	56%	55%	78%	55%
Multiclass Architecture	86%	86%	86%	86%

Table 3.3.5: Comparison of Performances

The table shows that the Multiclass Architecture classifier has the highest precision value which is 86%, the highest Recall value which has 86%, and the highest F1 score which has 86%. Furthermore, the highest accuracy of the Multiclass Architecture classifier is 86%. Thus, this indicates that it has the best performance among the other architectures and outweighs the benchmark of Human Classification with 77% accuracy.

CONCLUSION AND RECOMMENDATION

This chapter summarizes the findings of the study, as well as the conclusion to the problems concerned with the development of the Model (Classification of Nipa Fruit using Artificial Neural Network). This section also provides recommendations for future interests, such as expanding the study as a new research direction or conducting additional experiments.

This study aimed to develop a model that classifies nipa fruits as Harvestable or Non-harvestable using Neural Networks. Specifically, it sought to answer the following questions:

1. What data pre-processing techniques should be applied to input data images?
2. What deep neural structure can be used to classify harvestable nipa fruit?

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3. What measure can be used to evaluate the constructed neural network?

The following were the findings of the study:

1. The data preprocessing techniques applied to the input data images are data annotation (renaming image data, cropping, and resizing annotated data, conversion from the list to array, randomizing, conversion to a vector), data augmentation (cropping, rotating, adjusting brightness, and flipping are some of the most frequent techniques used in expanding the data capacity of nipa fruit images), Feature Selection (standardization, and histogram extraction).

2. The neural structure being used in classifying nipa fruit includes the largest probability classifier, a sequential probability classifier, and multiclass architectures. The model with the highest probability of all the predictions will be the final prediction in the largest probability classifier. The sequential probability classifier will ask the four-based model sequentially, and whoever satisfies the condition (probability > 0.85) will be the final prediction. If none of the four-base models satisfy the condition, by default, the highest probability will be the final prediction. The multiclass classifier simultaneously classifies the input images where the highest probability among the others will be the final prediction.

3. The measures being used in evaluating the constructed neural network are precision, recall, f1 score, and accuracy. The accuracy obtained at the largest prediction probability is 78%. The accuracy obtained in sequential prediction probability is 78%. The accuracy obtained in the multiclass architecture is 86% which outweighs the benchmark on human classification which has 77% accuracy.

Based on the findings, the researchers, therefore, conclude that:

Technology has become widely used in different fields, especially in agriculture. Utilizing image classification or image processing techniques in fruit classification provides a fast, accurate, and capable of replacing labor work. The researchers strive to contribute to this technological advancement by implementing a Neural Network model. Thus, this research aims to create a classification model that can classify the types of nipa fruit using an artificial neural network.

The architecture used is designed to receive an n by m matrix (where n is the number of features and m is the number of items). The needed inputs are images of nipa fruits where the researchers pre-process the data and have a 1D array for the model to recognize. The slowness of the first proposed neural network from scratch is due to the large amount of computation that only uses the CPU. Since the largest and sequential probability architectures cannot give high accuracy, the researchers then decided to use the Keras platform to implement all the models in which the training time has lessened since it also uses the GPU of the device.

The researchers compared the performance of various architectures including the largest probability classifier has an accuracy of 78%, the Sequential probability classifier has an accuracy of 78%, and the Multiclass classifier has 86%. Results showed that all the implemented architectures outweigh the benchmark of 77%. Therefore, the multiclass architecture gave the highest accuracy. The accuracy and performance of the model are relative; sometimes 60% is more acceptable when compared to randomness. It is acceptable based on where it is compared (randomness). Adding more image data and features and performing other pre-processing techniques might help the model to have higher accuracy.

The following recommendations were made based on the above findings and conclusions:

1. Nipa Fruit Classification is crucial research that needs to be explored and will have more research, especially since Nipa palm is one of the most important crops in the Philippines. As a result, the researchers recommend having more resources and research

regarding Nipa fruit classification so that its development will have a significant effect on the sector of agriculture and improvement on the quality of nipa fruit and (Sasa) Vinegar available in the marketplace.

2. In the fruit classification model, the researchers recommend applying a more complex deep learning neural network and using this model as your benchmark.

3. The researchers recommend that the size of the dataset must increase as much as possible, as the dataset has a significant impact on the performance of any learning model.

4. The researchers recommend that the model be also deployed in a production environment where the model can be transmitted and accessed by end-users in the form of mobile applications or the form of software.

5. The researchers recommended that more features be added to train neural network models since it has a major effect on the overall performance that may have been achieved.

6. The researchers recommend that this type of study regarding nipa fruit classification can use the computer vision capabilities of artificial neural networks to assist in the harvesting process. However, the model can be enhanced to do even more.

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