Pineapple Sweetness Classification Using Deep Learning Based on Pineapple Images

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***Abstract*—In Thailand, the pineapple is a valuable crop whose price is determined by its sweetness. An optical refractometer or another technique that requires expert judgment can be used to determine a fruit's sweetness. Furthermore, determining the sweetness of each fruit takes time and effort. This study employed the Alexnet deep learning model to categorize pineapple sweetness levels based on physical attributes shown in images. The dataset was classified into four classes, i.e., M1 to M4, and sorted in ascending order by sweetness level. The dataset was divided into two parts: training and testing datasets. Training accounted for 80% of the dataset while testing accounted for 20%. This study's experiments were repeated five times, each with a distinct epoch and working with data that had been prepared. According to the experiment, the Alexnet model produced the greatest results when trained with balancing data across 10 epochs and 120 figures per class. The model's accuracy and F1 score were 91.78% and 92.31%, respectively.**

***Keywords*—pineapple sweetness, deep learning, Alexnet, data augmentation, balanced data, fruit classification**

I. Introduction

Pineapples are the economic crop of Thailand [1]. In 2019, pineapple production is expected to be 1.8 tons, with the majority of the crop being grown in Thailand's central region (69%) [2]. Thailand exports pineapple juice and processed pineapple worth roughly 5.5 million baht and 2.8 million baht, respectively [3]. Pineapples reign supreme among fruits [4] because of their deliciousness, health benefits, and versatility as fresh fruit, a cooking component, a juice, or a preserved food [5]. Determining pineapple sweetness is critical because customers prefer sweet pineapple over-acidic pineapple. The sweetness of pineapples is measured using a variety of methods, for example, sniffing, examining the color, freshness, and form of the leaves, texturing, or using a hand refractometer to measure. All these methods have numerous drawbacks, such as requiring skilled personnel, being unstable, and taking time. Food waste sometimes occurs because of miscalculations in the maturity of fruits and vegetables. In this study, we propose Artificial Intelligence (AI) as a solution to these issues [6–8].

AI technology can help farmers solve challenges and produce high-quality products. Cassava, for example, has always been influenced by cassava infections. Sangbamrung *et al.* [9] suggested a new approach for classifying cassava infections that used deep learning to help farmers recognize the diseases and respond appropriately. Nasir *et al.* [10] depicted a fine-tunes pre-trained model named VGG19 to classify fruits and their diseases. Furthermore, for the final classifications, they applied a relevance-based optimization strategy to select the best features from the fused vector. As a result, the accuracy increased to 99.6%. Vijayakumar *et al.* [11] proposed a deep learning method to detect dragon fruits' mellowness. To determine the harvest time, they employed a pre-trained model named RESNET 152. The specific challenge with pineapples is determining their sweetness without causing damage to the fruit. Before harvesting the crop, the ripeness and sweetness of the fruit must be verified because flavor affects product quality. For example, TIPCO used Homsuwan pineapple as a raw material to create Homsuwan pineapple juice, therefore the sweetness was determined using a refractometer, which is time-intensive and requires expertise. However, as seen in Fig. 1, the pineapple's exterior features do not explicitly reflect its sweetness. It is therefore challenging to determine their sweetness level by consideration, even for specialists. To improve pineapple production efficiency, AI plays a critical role in determining pineapple sweetness by assessing pineapple's physical characteristics. Sangsongfa *et al.* [12] used CNN-PPSM to evaluate pineapple sweetness from 4,860 pictures using deep learning. According to the findings, the accuracy of

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training and testing processes was 72.38% and 78.5%, respectively. Wan Nurul Suraya Wan Nazulan *et al.* [13] created the sweetness parameter, which was an algorithm for detecting and sorting watermelon color and shape to classify watermelon sweetness levels. They graded watermelon using K-means, with grade A denoting a high degree of sweetness, grade B denoting a medium level of sweetness, and grade C denoting a low level of sweetness. The results revealed that color and form detection had an accuracy of roughly 84.62 %. Lee *et al.* [7] created a non-invasive classifier for the sweetness levels of apples that are sweet, normal, and not sweet using a convolution neural network model. The dataset includes 1506 photos of apples' appearances as well as 130 average sweetness statistics for apples. The highest validation accuracy result obtained is 81%.

In this study, we proposed a method for determining pineapple sweetness based on its physical properties by using deep learning. The images of pineapples were employed in this study to identify biochemical properties that knew the sweetness level, and the pre-train model Alexnet was used. Alexnet is a model that learned data from Coco, which contains a wide range of fruit information. As a result, Alexnet has a high level of precision when it comes to working with fruits. The objective of this study was to create a deep learning method for classifying pineapple sweetness levels based on the physical properties of pineapples.

II. METHODOLOGY

A. Data Preparation

The input dataset was a collection of pineapple image data (Fig. 1) from [14]. The original pineapple image data comprised 42 pineapples photographed in a lab, each in RGB color and with the JPG extension. To identify target classes, the pineapple data could be grouped with the corresponding pineapple chemical data (Table I). Table I demonstrates Degrees Brix (°Bx) representing a unit of sweetness that measures the amount of sugar in a liquid (solution), as well as pineapple acidic (Acidez) refers to the amount of acid in a liquid.

Eq. (1) is used to calculate the IM (Maturity Index) value. The level of IM is exactly proportional to the sweetness of the pineapple.

$$\mathbf{IM} = \frac{\mathbf{°Brix}}{\mathbf{Acidez}} \tag{1}$$

In this study, we divided pineapple sweetness into four categories based on the IM value. as follows:

(1) Pineapple M1 represents the pineapple with IM values ranging from 0 to 19.
(2) Pineapple M2 represents the pineapple with an IM value ranging from 20 to 29.
(3) Pineapple M3 represents the pineapple with an IM value ranging from 30 to 39.
(4) Pineapple M4 represents the pineapple with an IM value of 40 or more

The M1, M2, M3, and M4 are in ascending sequence of pineapple's sweetness. We divided them into four categories based on the level of sweetness used in the real market. There were 88 pineapple images in M1, 20 images in M2, 32 images in M3, and 28 images in M4 categories.

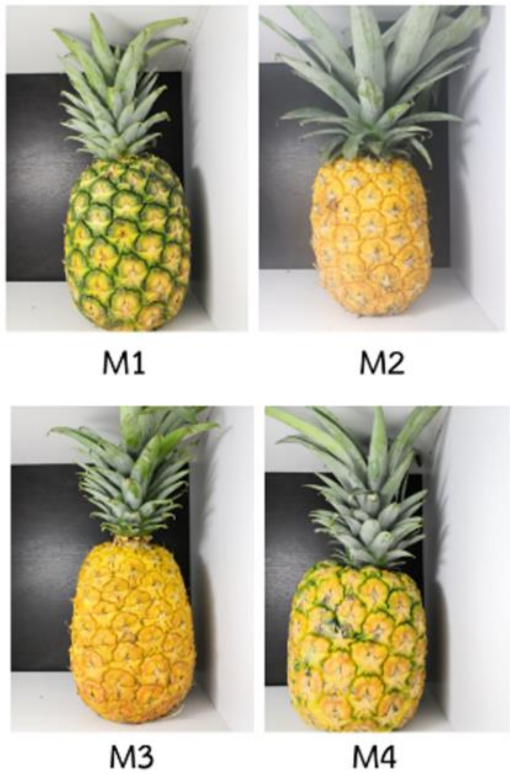

Figure 1. The pineapples are classified as M1 (least sweet), M2, M3, or M4 (most sweet).

TABLE I. EXAMPLES OF DATA ON PINEAPPLE CHEMISTRY WERE USED TO LINK THE CLASSES OF CORRESPONDING IMAGES

Acidez		pH		°Brix		
Promedio	**DE**	**Promedio**	**DE**	**Promedio**	**DE**	**IM**
0.5045	0.0081	3.3633	0.0153	16.1333	0.0577	31.98
0.7328	0.0169	3.2900	0.0100	13.4000	0.1000	18.29
0.8907	0.0092	3.2133	0.0058	15.3333	0.1528	17.22
0.7989	0.7989	3.3267	0.0058	13.4333	0.1528	16.81
0.6901	0.6901	3.2567	0.0058	12.7667	0.2082	18.50

As presented in Fig. 1, each class's pineapple image demonstrates the various physical qualities. The pineapple in the M1 class, which has the least sweet flavor, has a peel with a mixture of hues, such as green and yellow. In the M2 class, the pineapple has a slight sweetness. Its peel is simply yellow, similar to the pineapple in the M3 class. Finally, the M4 pineapple possesses traits that are similar to those of the M1 pineapple, with less green and more yellow on its skin. When it comes to the exterior qualities of pineapples, the external expression is only one of the key criteria used to determine the fruit's sweetness; the fruit's flavor is also determined by a chemical compound that is not visible from the outside.

When the amount of data in each class was considered, the researcher discovered that the image data had an uncorrelated amount of data. The M1 class had substantially higher images than the other classes, which was the main cause of the unbalanced dataset problem. The problem has a significant impact on the model's learning ability. Therefore, we utilized a technique called Data Augmentation to enhance the amount of picture data by rotating the image by 90 degrees, 180 degrees, and 270 degrees. Finally, the amount of data in each class was roughly the same. As illustrated in Fig. 2, we added around 120 images per class, for a total of 488 images that should be enough for classification.

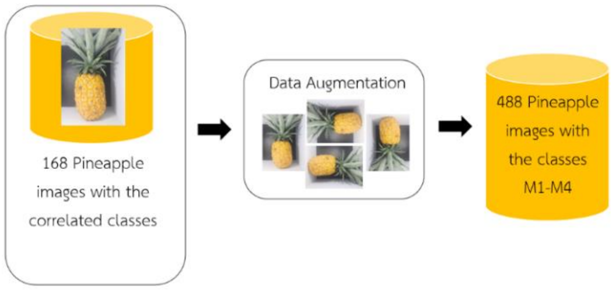

Figure 2. Data preparation.

B. Method

Once the data preparation was completed, the obtained dataset was separated into 80% for the training dataset and 20% for the test dataset. The data separation is created using balanced data criteria. The training dataset was then fed into Alexnet, a pre-trained model constructed from A Convolutional Neural Network (CNN) with 25 layers and eight levels of depth that can accept input sizes of 227×227×3.

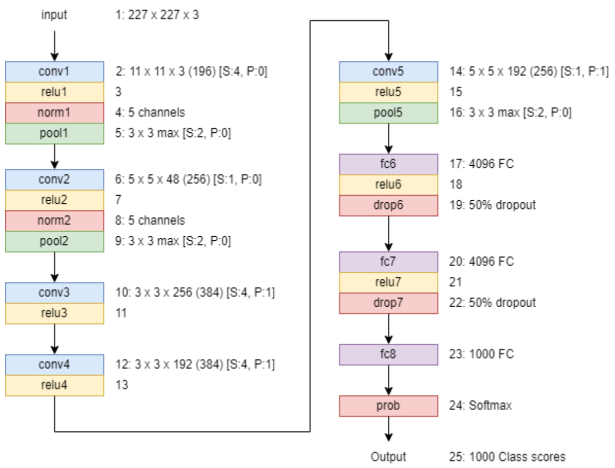

Figure 3. The structure of Alexnet [15].

The framework of Alexnet (Fig. 3) is divided into two parts: Feature learning and Classification. Feature learning takes data from the input and extracts the information needed for feature identification or classification. Classification is the procedure for categorizing data. The following are the sub-levels of feature learning:

- The image's attributes are extracted by the convolutional layer.
- The most relevant properties from the data are extracted by the pooling layer. Alexnet employs a 3×3 maximum pooling size, with only the highest value retained.
- ReLU is a function that converts negative values to zero; thus, ReLu is always greater than or equal to 0.
- A normalization layer can be used to adjust the data range to the appropriate extent.
- A fully connected layer connects all neurons on one layer to all neurons on the other.
- The dropout layer is used to randomly reject Neurons at each layer of a Neural Network. To solve overfitting and overparameterization models, this strategy reduces the dependency on neural networks.
- The Softmax layer is a function that accepts a vector of real numbers as input and produces a probability as an output.

III. Experiment and Results

A. Experiments

The goal of this study was to develop a deep learning approach for classifying pineapple sweetness levels based on physical attributes. We conducted five experiments with two sets of data as follows:

- Experiment 1 employed Alexnet with five epochs without any data augmentation (data A).
- Experiment 2 employed the Alexnet six epochs, with 80 images per class for data augmentation (data B).
- Experiment 3 employed the Alexnet 12 epochs, with 80 images per class in the data augmentation (data B).
- Experiment 4 employed the Alexnet 11 epochs, with 120 images per class in the data augmentation (data C).
- Experiment 5 employed the Alexnet 10 epochs, with 120 images per class in data augmentation (data C).

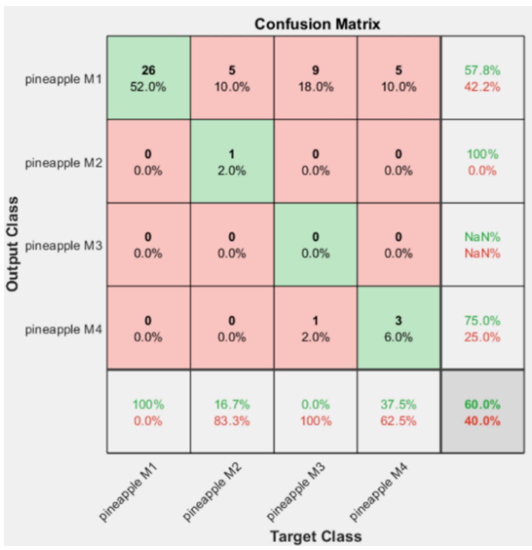

Figure 4. Experiment 1's confusion matrix.

Experiment 1 employed Alexnet with five epochs without any data augmentation (data A). Each class's images were divided into 20%. Class M1 had 26, class M2 had six, class M3 had 10, and class M4 had eight images. The training of the model is affected when the amount of data in each class is uncorrelated. As seen in Fig. 4, the model had a 60% accuracy rate.

Experiment 2 employed the Alexnet six epochs, with 80 images per class for data augmentation (data B). Fig. 5 shows the total model evaluation accuracy when test data B was utilized to evaluate a trained Alexnet model of five epochs.

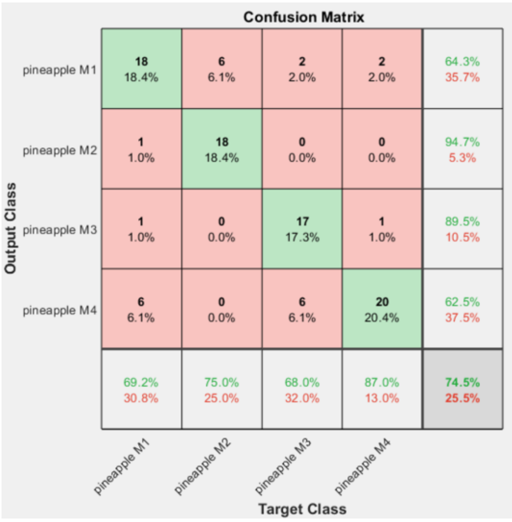

Figure 5. Experiment 2's confusion matrix.

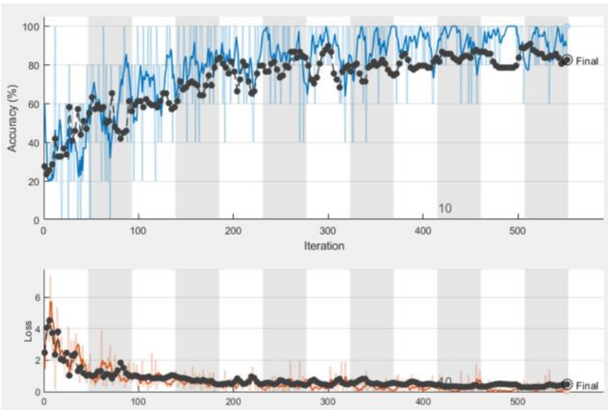

Figure 6. Experiment 3's training process.

Experiment 3 employed the Alexnet 12 epochs, with 80 images per class in the data augmentation (data B). As the result, the accuracy of the model's prediction was 82.65%. However, The Alexnet model performed best at epoch 11 when looking at the trained model performance (Fig. 6). Then, experiment 4 was conducted.

Experiment 4 employed the Alexnet 11 epochs, with 120 images per class in the data augmentation (data C). The accuracy of the experiment was found to be 89.73%. According to the findings in Fig. 7, switching to the Alexnet 10 epochs resulted in higher accuracy values.

Experiment 5 employed the Alexnet 10 epochs, with 120 images per class in data augmentation (data C). As a result, the accuracy was enhanced to 91.78 %, with an F1 score of 92.31%, as illustrated in Fig. 8. Note that the F1 score indicates how well the model can average precision and recall.

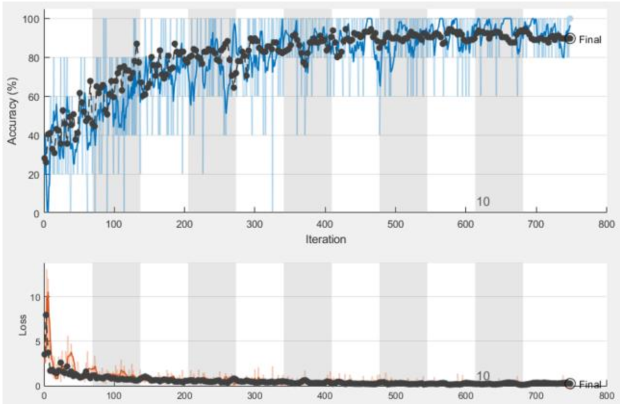

Figure 7. Experiment 4's training process.

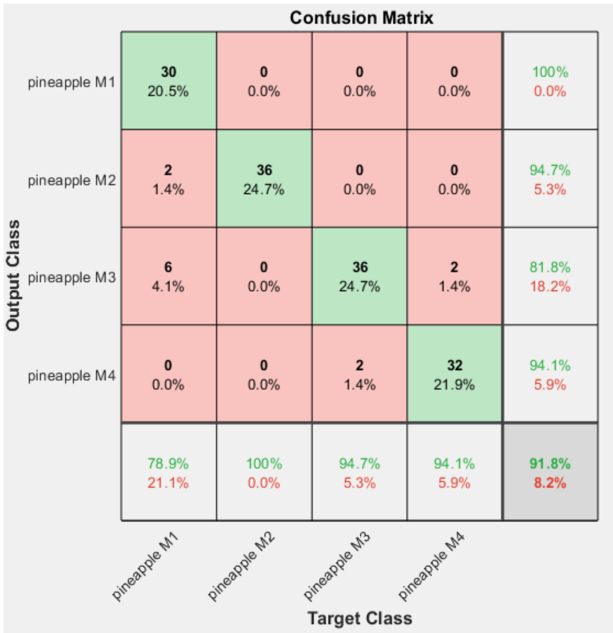

Figure 8. Experiment 5's confusion matrix.

IV. Discussion

The objective of this study was to develop a classification method to distinguish the pineapple sweetness level by analyzing the pineapple's physical properties using Alexnet. Five experiments were designed to discover the best model for classifying pineapple sweetness. The Alexnet was used in each experiment, but the number of epochs was variable. The experiment used two sets of data: 1) Data A, which had not been augmented and was unbalanced, and 2) Data B, which had finished data augmentation and was balanced.

From the experimental results in Experiment 1, we found that the experimental data were unbalanced, with the amount of training data affecting the model's accuracy and performance. As shown in Fig. 4, M1 was the class with the largest amount of data. The true positive of M1 was extremely high compared to the true positive of the M1, M2, and M3 classes due to a short amount of data. The model had a low recall value for predicting these classes. The True positive value for the M3 class in the model was zero, indicating that the model was unable to predict the M3 class. The problem of unbalanced data can be solved by balancing the amount of data in each class. Additional data can be gathered from other sources or by employing the Data Augmentation approach.

In Experiment 2, we trained five epochs with the model that works with balance data and achieved a 74.6% accuracy rate. The model's performance using balancing data was improved, but not good enough due to its low precision. As a result, the number of training epochs had been increased to 12, increasing the accuracy by 82.65%. Experiment 2 and Experiment 3 showed that the number of training epochs had a considerable impact on the model's learning efficiency. The model can learn better with a larger number of epochs.

In Experiment 4, The number of epochs had been increased to 11. Experiment3's training process was examined, and it was discovered that a result at epoch 11 generated better outcomes than a result at epoch 12. In addition, the number of images per class had been increased to 120. According to the findings, the accuracy was enhanced to 89.73%. The model training is affected not only by the proper number of epochs but also by the amount of data. When there is enough data, the models can learn data patterns to become more comprehensive.

Experiment 5's findings revealed that the performance results were good after reducing the number of epochs to ten and working with a balanced dataset of 120 images per class. The model had an accuracy of 91.78% and an F1 score of 92.31%. When compared to the findings of [14], the outcomes of this experiment were superior, although the amount of data in this study was 10 times lower than in the previous study. We simply needed to add pineapple pictures to the pre-trained model because it already had some learning to classify fruit images.

Compared to the results of the existing [12] and this studies, Sangsongfa *et al.* developed a deep learning based-prediction model using CNN to predict the pineapple sweetness from images. The majority of the research settings were similar to ours, but they underlined the importance of experimenting with varied image resolutions. Their investigation gathered the pineapple photographs by photographing them in a lab and then cropping the zoomed-in pineapples that clearly showed pineapple buds (Fig. 9). Moreover, they used a refractometer to measure the sweetness and kept them as a training dataset. In this study, we collected the data from the existing study [14]. Ours and theirs were comparable after looking at the data aspects, including the approach they utilized, which was based on CNN. Therefore, ref. [12] was a good fit for comparison with our research. As the experimental results, the compared study [12] provided 80.15% accuracy; meanwhile, ours received 91.78% accuracy, as shown in Table II. Our proposed method produced considerably superior results since we used the entire picture of pineapples as the data input, which included important pineapple attributes such as buds and leaves. When farmers use a refractometer to determine the sweetness of a pineapple, they must first rip it. However, as part of this study, we did not injure the pineapples to determine their sweetness level, instead of relying solely on their physical appearances. As a result, our technology assists farmers in improving the performance of a quality control process while also reducing processing time and labor.

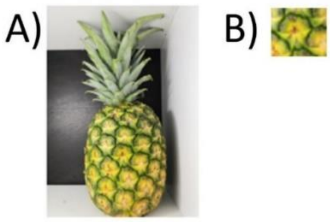

Figure 9. A) The image used in this study; B) The image used in the compared study [12].

TABLE II. RESULTS FROM THE COMPARED STUDY [12] AND OUR STUDY

Metric	The compared study [12]	This study
ACC Test %	80.15%	91.78%

A limitation of this study is that the model works effectively with yellow pineapple data acquired in the lab with uniform color and light and no backdrop considerations. As a result, for this model to be useful in farming, it is important to establish the ability to distinguish the pineapple from the backdrop during the data preprocessing step.

V. CONCLUSION

Here, we used Alexnet to analyze pineapple photos to build a method for classifying the sweetness level. We created five experiments, each with a different number of epochs and data. Experiment 5 with 10 epochs working with balanced data and each class having 120 images yielded the best Alexnet model option. The model had an accuracy of 91.78% and an F1 score of 92.31%. This study can be expanded in the future to produce a more accurate model by expanding the quantity of the data and the number of epochs in applications. This technique can be adapted to other income crops for rapid and easy fruit classification based on physical factors without the need for additional tools to quantify sweetness.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

The suggested notion was conceived by Sarunya Kanjanawattana and Suchada Weeragulpiriya. Worawit Teerawatthanaprapha and Sarunya Kanjanawattana established the theory and carried out the approach. The analytical methods were confirmed by Sarunya Kanjanawattana and Gun Bhakdisongkhram. Sarunya Kanjanawattana encouraged Worawit

Teerawatthanaprapha to investigate the findings of this work. Sarunya Kanjanawattana, Panchalee Praneetpholkrang, Gun Bhakdisongkhram, and Suchada Weeragulpiriya collaborated on the final manuscript and discussed the findings.

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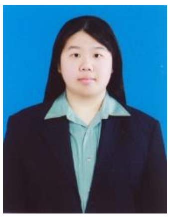

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