Research Article

Design of Machine Learning for Limes Classification Based Upon Thai Agricultural Standard No. TAS 27-2017

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Abstract
Accurately classifying the limes quality of limes according to established standards is paramount for instilling trust in farmers' trading of agricultural produce. Historically, machinery has been employed to categorize the lime quality, with dual objectives of cost reduction and error mitigation, thereby facilitating the classifying process. Nevertheless, deploying such machinery to classify limes in their fresh produce form, intended for consumer sale, has encountered limitations imposed by the stringent criteria stipulated in Thai Agricultural Standards No. TAS 27-2017, a standard derived from the Codex Standard and widely adopted by numerous countries. Considering these constraints, the presented research aims to enhance the efficiency of limes classification, adhering to the standards. The Machine Learning System is designed to recognize and categorize limes based upon their skin color and defects to achieve this goal. This system employed convolutional neural network (CNN) models in conjunction with logistic regression equations, which are unavailable in the literature. The research findings indicate that this system is proficient in accurately presenting lime images and their corresponding quality classes via a Graphical User Interface on a computer screen, achieving an accuracy rate exceeding 90%. The implications of this research extend to the agricultural sector by augmenting the efficacy of Machine Learning for classifying limes in compliance with Thai Agricultural Standard No. TAS 27-2017. Furthermore, the methodology developed in this study can find applicability in classifying other agricultural products.

Keywords: Agricultural standard, Convolutional neural network, Lime classification, Machine learning

1 Introduction

The lime, citrus fruit of global cultivation, has exhibited a noteworthy trend of expanding harvested areas over the preceding decade, a phenomenon readily discernible in Figures 1 and 2. In 2021, the global lime harvested area amounted to 1.34 million hectares, yielding a lime production volume of 20.83 million tons. Approximately 43.71% of this prodigious production emanated from three lime-producing nations: India, Mexico, and China. These nations contributed 3.55 million tons, 2.98 million tons, and 2.57 million tons of lime, respectively, as delineated in Table 1 [1]. In Thailand, the lime harvested area in this nation encompassed a cumulative expanse of 0.02 million hectares, representing a modest 0.01% of the total global lime harvested area. Moreover, the lime production in Thailand amounted to a total of 0.16 million tons, signifying 0.77% of the world's lime production. Notably, a significant portion of the lime produced in Thailand is primarily earmarked for domestic consumption.

Lime, a fruit of notable nutritional significance, is recognized for its ample supply of nutrients requisite for the sustenance of humans. Within the repertoire of lime cultivars, the cultivar Paen (Citrus aurantifolia (Christm) Swingle) holds a special place of favor among the Thai. Moreover, this versatile fruit finds application not only in the realm of dietary consumption but also extends its utility as a pivotal ingredient in pharmaceutical formulations, a principal raw material

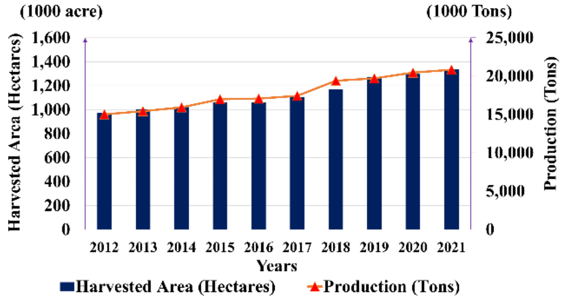


Figure 1: Global lime harvested area and lime production [1].

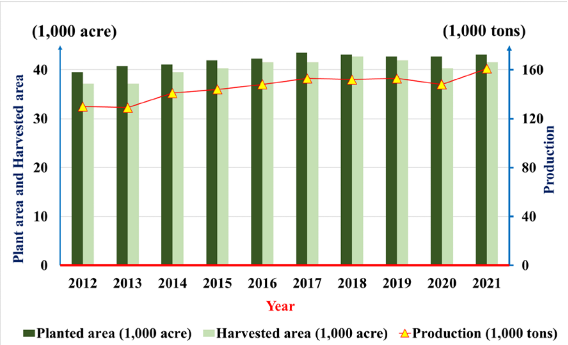


Figure 2: Lime harvested area and lime production [2].

for citric acid production, and an elemental constituent in the creation of diverse consumer products such as cleaning agents and cosmetics, among others. Given that the Paen cultivar accounts for an impressive 74.6% of the total lime cultivation area currently under the purview of agricultural practitioners [2]. It has been deemed in this research to investigate the attributes and characteristics of the Paen cultivar exclusively.

Table 1: 10 World's Biggest Producers of lime in 2021 [3]

Countries	Production (Tons)	%
India	3,548,000	17.03
Mexico	2,983,802	14.33
Mainland China	2,571,932	12.35
Turkey	1,550,000	7.44
Brazil	1,499,714	7.20
Argentina	1,378,021	6.62
Spain	1,017,360	4.88
United States of America	801,950	3.85
South Africa	665,382	3.19
Iran (Islamic Republic of)	478,972	2.30
Other	433,804	20.81
Total	20,828,937	100

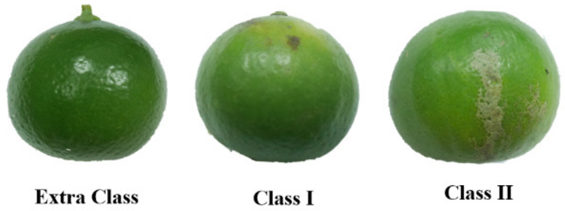


Figure 3: Lime characteristics according to quality class.

The widespread consumption of lime, a commonly enjoyed fruit, necessitates the establishment of standardized regulations to ensure the safety and acceptability of the produce and promote equitable trade. Currently, specific criteria exist for categorizing the quality of fresh lime fruit intended for commercial business, as outlined in the Thai Agricultural Standard No. TAS 27-2017 [4]. This standard draws upon the guidelines set forth by the Codex Alimentarius, an international food standards body established by the Food and Agriculture Organization of the United Nations (FAO) and the World Health Organization (WHO), which are widely recognized and accepted by numerous countries. These quality standards for lime fruits are categorized into three levels, as illustrated in Figure 3.

In categorizing limes for commercial purposes, a hierarchical classification system has been established to assess and define the quality attributes of these citrus fruits. This system consists of three primary classes, each with specific quality criteria delineated to facilitate effective classifying and marketing. The following description elucidates the criteria associated with each of these classes.

Extra Class: Limes falling within the ambit of the "Extra Class" are expected to exhibit a level of superiority. They shall be characteristic of the variety. These limes must have no significant defects except for minor superficial imperfections. These minor external defects are permissible, provided they do not compromise the overall appearance, quality, and presentation of the package of the limes. Thus, "Extra Class" limes represent the pinnacle of quality and are virtually free from noticeable blemishes.

Class I: Limes categorized as "Class I" are still commendable and represent the specific lime variety. In this class, some leeway is granted for slight defects in shape and coloring. Nonetheless, such skin defects should not exceed 5% of the fruit's surface area. Significantly, these defects must not extend to the pulp of the fruit and should not seriously detract from the overall appearance of the lime. "Class I" limes may be considered good quality, with slight aesthetic imperfections being the primary differentiating factor.

Class II: The third and final class, "Class II," comprises limes that do not meet the stringent criteria for inclusion in the higher-quality classes. Despite not attaining the quality standards of the classes, "Class II" limes are still deemed acceptable for various commercial purposes. In this class, a greater degree of defects is granted for defects in shape and coloring, with the skin defects allowed to encompass up to 10% of the fruit's surface area. Just like in "Class I," it is essential that these defects do not affect the fruit's pulp and that the limes maintain their important characteristics related to quality, keeping quality, and presentation.

The lime fruits in Class I and II should be green but may show yellow patches up to 30% of their surface. This hierarchical classification system is vital for the standardized assessment and marketing of limes, ensuring that consumers receive products that align with their expectations and quality preferences.

Currently, the classification of limes, per the abovementioned standards, predominantly relies on human visual assessment. In this method, the classification outcome is contingent upon the subjective judgment of classifiers, which can introduce the potential for misclassification. Arises because different classifiers may interpret the same defect or abnormality in distinct ways, resulting in discrepancies and inaccuracies in classification outcomes.

According to data derived from Sandia National Laboratories in the United States [5] and insights provided by the eminent figure in the domain of quality assurance, Dr. Joseph M. Juran Tarantino [6], it is evident that a 100% reliance on visual inspection yields an effectiveness or accuracy rate of approximately 87%. In the most unfavorable of conditions, a highly skilled and experienced inspector may still encounter an error rate as high as 20% to 30%. Consequently, a compelling rationale exists for using machine-based classification tools. This adoption aims to mitigate errors, reduce time expenditure, and ultimately minimize the costs associated with the classification of limes.

A recent empirical investigation employing machine-based methodologies for the classification, quality control, and detection of abnormalities in fruits revealed that Convolutional Neural Networks (CNN) demonstrate remarkable efficacy in training machines to proficiently discern various attributes, defects, and discrepancies among fruit specimens. Consequently, CNN models are extensively employed for the comparative analysis of distinct fruit characteristics and the identification of irregularities, thereby facilitating fruit classification, quality assessment, and the detection of defects attributed to diseases and insect infestations. Multiple studies have harnessed CNN models for these purposes, such as Behera *et al.* [7], who utilized the Visual Geometry Group 19 (VGG19) model to discriminate among three stages of papaya ripeness, achieving an exemplary classification accuracy of 100%, Jahanbakhshi *et al.* [8] successfully employed CNN to classify sour lemons based upon apparent defects, attaining a classification accuracy rate of 100%. Suketha *et al.* [9] leveraged the Residual Neural Network model to organize vegetables and fruits, achieving a commendable accuracy rate of 95.83%. Similarly, Yuesheng *et al.* [10] employed the GoogLeNet model to classify spherical vegetables and fruits, reporting training and test accuracy rates of 96.88% and 96%, respectively.

Moreover, Naranjo-Torres *et al.* [11] conducted a comprehensive review of agricultural research between 2015 and 2020, where CNN models were predominantly employed in classifying fruits and vegetables through image-processing techniques. The review identified several CNN models that were commonly employed in these studies, including proprietary models, VGG, AlexNet, GoogLeNet, ResNet, and LeNet, with the proportional utilization rates in various investigations being 29.2, 25.0, 16.7, 12.5, 12.5, and 4.2%, respectively. In light of the popularity and effectiveness of VGG, AlexNet, GoogLeNet, and ResNet in such research endeavors, these four CNN simulation models have emerged as pivotal choices for scholars seeking the most suitable CNN model for application in their research pursuits.

In the context of the research investigation, mathematical models were employed to ascertain the classification and quality assessment of various fruits, focusing on crucial fruit attributes such as fruit density, skin color, and skin defects. A notable observation in this research was the frequent utilization of regression equations. For instance, Kumar [12] employed Logistic Regression for fruit classification, and the outcomes of this analysis indicated that fruits could be classified with an exceptional degree of accuracy, achieving training and testing accuracy rates of 99.43%. Furthermore, Ivanovsk *et al.* [13] employed Multiple Linear Regression to predict the density of peat, with results demonstrating a heightened predictive accuracy in this regard.

This research aims at the examination of the classification of external characteristics of lime skin. The study incorporates the utilization of regression equations and integrates a Convolutional Neural Network (CNN) model to classify lime quality based on specific quality parameters.

2 Literature Review

2.1 *Machine learning*

Machine learning, denoted by the reference [14], constitutes a pivotal subdomain within the interdisciplinary realms of Artificial Intelligence (AI) and computer science. This multifaceted discipline leverages data-driven techniques and sophisticated algorithms to emulate and replicate the cognitive processes underlying human learning. Over time, it iteratively refines its predictive accuracy, culminating in the establishment of mathematical models that exhibit the most superior predictive performance. Such mathematical formulations are indispensable constituents of data analysis and machine learning workflows, contributing substantively to creating predictive models capable of simulating the decision-making capacities of human agents within computational systems.

The mathematical principle of machine learning applies the Categorical Cross Entropy equation in Equation (1) to calculate the pixels in the image that are utilized to predict the image classification [14].

$$Categorical\ Cross\ Entropy = \sum_{i}^{N} \frac{CE_i}{N} \tag{1}$$

The evaluation of the image classification accuracy of the machine learning algorithm is calculated from the classification accuracy percentage and the confusion matrix according to Equation (2).

$$ACC = \frac{n_{corr}}{n} \times 100 \tag{2}$$

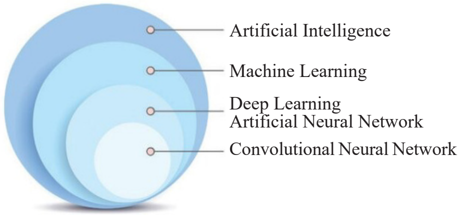


Figure 4: CNN is a subset of Deep Learning Neural Networks [16].

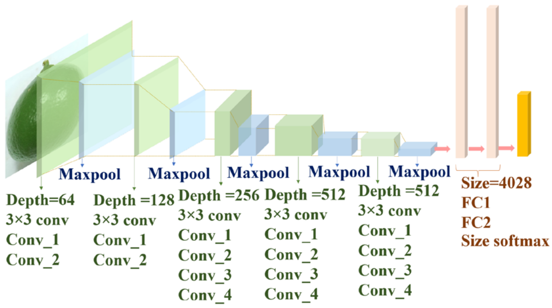


Figure 5: Architecture of CNN model.

Where "*n*" is the number of all possible examples for a given problem, and "n_{corr}" is the number of correctly classified examples by the current theory. The classification accuracy can be interpreted as the probability that a randomly selected "n_{corr}" from "*n*" is correctly classified.

2.2 *Convolutional neural network*

The Convolutional Neural Network (CNN), as denoted in reference [15] and Figure 4, represents a fundamental component within deep learning, specifically designed to examine data characterized by a grid-like structure. In the CNN architecture, individual layers comprise a series of interconnected neurons, fostering intricate interlayer connections, while the layers themselves possess a three-dimensional structure, as depicted in Figure 5 (as discussed in reference [16]. This inherent three-dimensional layering is a distinctive feature of CNNs, rendering them well-suited for image data analysis tasks. The primary objective of employing CNNs is to harness the computational power of computers to accomplish the recognition and differentiation of objects contained within images. In essence, these networks are instrumental in the automated identification and classification of objects, thereby facilitating complex image analysis tasks.

Therefore, the Convolutional Neural Network models are applied to find the difference between lime images and design the limes classification system in this research.

2.3 *Ordinal logistic regression*

Ordinal Logistic Regression [17] is a statistical method used to refer to a regression model in which the dependent variable has a multinomial distribution independent of each other and has a continuous sequence of data characteristics. The distance of each successive sequence does not have to be the same sequentially, with the requirements being that 1) the regression coefficients of each group of models must be equal, 2) the analyzed independent variable data is qualitative, 3) the quantitative data is covariate variable, and 4) there are more than two conditions applied as criteria for grouping. Therefore, the Ordinal Logistic Regression method is appropriate for this study. The form of a mathematical equation is in the Equation (3).

$$\ln\left(\frac{\pi_i}{1-\pi_i}\right) = \alpha_i + \beta x + + \beta_2 x_2 + \ldots + \beta_i x_i \quad (3)$$

Where π_i is the cumulative probability of group i,

α_i is the constant of variables group i,

i is the sequence of dependent variables 1, 2, 3, …, $j-1$,

β_x is $\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i$; β is the sequence of the regression coefficient.

3 Materials and Methods

The design of the lime classification system, according to Thai Agricultural Standard No. TAS 27-2017, using machine learning in this research follows the methods outlined below.

3.1 *Research methodology*

This research investigates the design of a lime classification system based on quality classes. The application of the Convolutional Neural Network model and the mathematical model in Ordinal Logistic Regression is employed to classify limes according to the quality criteria outlined in Thai Agricultural Standards No. TAS 27-2017, as well as those falling below this standard. The classification results are presented through a Graphical User Interface. In this context, the study is divided into five phases, as illustrated in Figure 6.

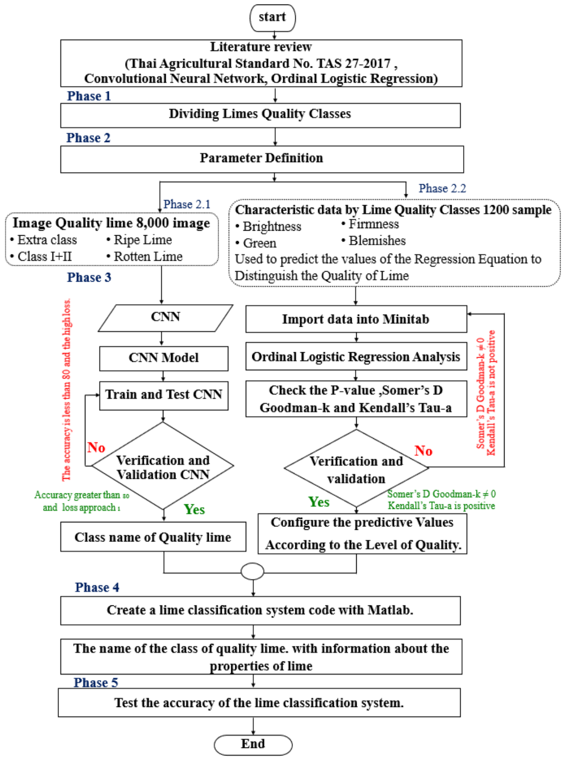


Figure 6: Design of Machine Learning for Limes Classification based upon Thai Agricultural Standard No. TAS 27-2017.

3.2 *Phase 1: Dividing limes quality classes*

In the process of categorizing the limes into four distinct groups, they have been identified, considering their prevailing trading conditions within the broader market context. These delineated categories are as follows.

Extra Class Limes: Representing the zenith of lime quality, this classification pertains to limes bearing vivid green hues devoid of discernible skin defects. Class I and Class II Limes Encompassing limes of commendable quality, these categories include specimens characterized by fruit exhibiting either green or greenish-yellow pigmentation. Permissible

Figure 7: Examples of lime in each group.

variations within this category comprise the presence of yellow patches, which collectively should not exceed 30% of the fruit surface area, or the existence of minor skin defects, provided that such defects do not exceed a cumulative total of 10% of the fruit surface area.

Ripe Limes: This grouping pertains to limes that have transitioned to a yellow hue.

Rotten Limes: Limes that have deteriorated to the extent of acquiring a brownish discoloration are classified within this category, as illustrated in Figure 7.

3.3 *Phase 2.1: Preparing lime image dataset*

All lime images being tested in this research have the same size of 500 × 500 × 3 pixels and the same white control system. These images are taken in a studio box with a shooting brightness of 2,000–2,400 LUX or in a closed room with no external light and only fluorescent lighting. The cameras used in this research are the iPhone 7 mobile phone camera with a resolution of 12 megapixels and a digital camera with 16 megapixels. Keep the ISO setting the same throughout the shooting, as shown in Figure 8.

This research divides the lime images in each quality class into two sets. The first set of images is used to train the Convolutional Neural Network models, and the second set is used to test the trained models. The proportion of lime images in set 1 and set 2 is 80 with 20, respectively. The total number of lime images used for training and testing in this research was determined from the experiment by letting Convolutional Neural Network models classify lime images in Extra Class, Class I, and Class II that have similar skin color or have different skin defects. It has been found that 1,600 lime images are required to train the model effectively for accurate classification of lime images according to the quality classes, achieving an accuracy of 90%. Therefore, the number of lime images in each quality class is set at 2,000. These images, comprising the first set, are used to train

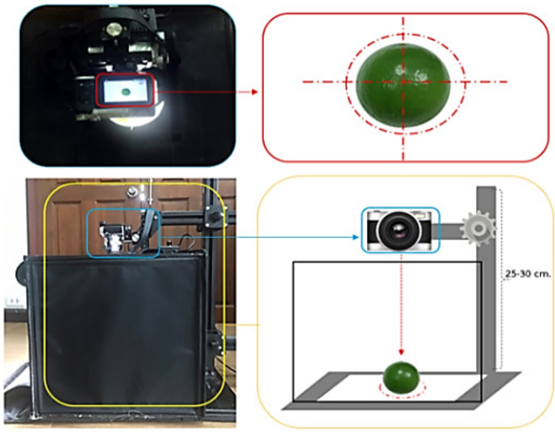


Figure 8: Photographing and positioning the lime by using a studio box.

the Convolutional Neural Network model, utilizing 1,600 images (80% of all lime images in each group). Lime images in the second set are intended to test the ability of the trained Convolutional Neural Network models, utilizing 400 images (20% of all lime images in each group). Therefore, in this research, 8,000 lime images are used to both train and test the Convolutional Neural Network models, facilitating the classification of 4 lime groups according to quality classes.

However, all limes images used for training and testing such subjects must have the white edge of the background removed as much as possible. It can help the model to detect differences better, as in Figure 9.

3.4 *Phase 2.2: Finding lime characteristics values*

The determination of lime quality, according to Thai Agricultural Standard No. TAS 27-2017 involves assessing various characteristics such as skin color, skin brightness, fruit density, and the size of skin defects, which serve as criteria for directly classifying the quality of limes. Therefore, the limes of each quality class are used to measure the numerical values of characteristics affecting the quality of limes in each quality class to determine the lime quality classes according to the above standards. The test results are obtained by taking 300 samples of limes to determine these characteristic values with the following methods.

1) The Color Meter application measures the CIELAB color chart [18], which assesses food color,

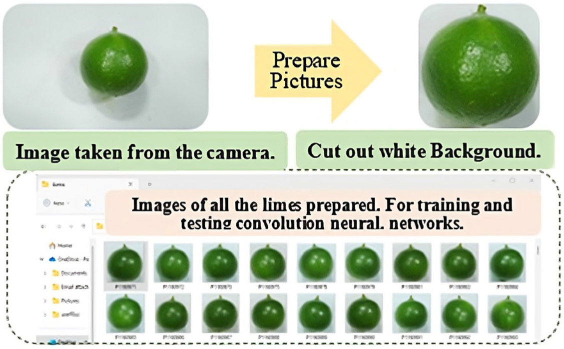


Figure 9: Preparation of research images.

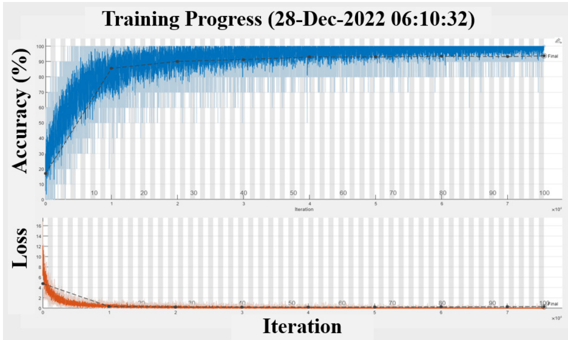


Figure 10: Training image Convolution Neural Network Models.

encompassing skin brightness, including green and yellow values. This tool helps determine the freshness level based on the color of the lime skin.

2) The Effegi Fruit Pressure Tester is employed to measure the density of limes.

3) The size of skin defects is assessed by measuring the area of the defects, and the results are summarized in Tables 2 and 3.

Table 2: Characteristic values in each lime quality class containing CIELAB color chart of lime skin and lime pulp density values

Characteristic	Characteristic Values in each Lime Quality Class			
	Extra Class	Class I and Class II	Ripe Lime	Rotten Lime
Brightness (L*)	42.0 to 48.9	42.0 to 48.9	49.0 to 75.9	30.0 to 36.0
Green (–a*)	–30.0 to –19.0	–18.9 to –12.0	–11.9 to –6.0	–7.0 to 12.0
Yellow (+b*)	18.0 to 30.9	31.0 to 36.9	over 43.0	33.0 to 38.0
Density (kg/cm^2)	130.0 to 103.9	127.0 to 108.9	89.7 to 73.9	80.0 to 72.0

Table 3: Calculated values of skin defect size

Calculation Order	Lime Quality Classes	Skin Color	Skin Defects Size
4	Extra Class	Green	0%
3	Class I and Class II	Green	0.01%–10%
2	Ripe	Yellow	0%–100%
1	Rotten	Brown	0%–100%

Source; Skin defect size information from Thai Agricultural Standard for Limes (TAS 27-2017) [2].

3.5 *Phase 3.1: The appropriate convolution neural network models*

Once the information has been prepared, the image data can be trained with the Convolutional Neural Network Algorithm to allow the model to learn different images of each lime quality class by calculating mathematical equations from the image pixel values. The algorithm can show accuracy and learning efficiency results during training through Validation Accuracy graphs, as shown in Figure 10.

The Convolutional Neural Network models suitable for this research are selected from 6 Convolutional Neural Network models popular in research [9]: Own Models, VGG, AlexNet, GoogLeNet, ResNet, and LeNet.

This research tests these six Convolutional Neural Network models for their ability to classify limes according to Thai Agricultural Standard No. TAS 27-2017. The goal is to select the top 4 models that can classify limes with an accuracy rate of more than 80%, ensuring the Model can classify limes more accurately than human visuals [6]. The Convolutional Neural Network models that meet the conditions are VGG19, AlexNet, GoogLeNet, and ResNet50.

Following the training process, VGG19, AlexNet, GoogLeNet, and ResNet50 have acquired the capability to classify limes into four distinct classes: Extra Class, Class I, Class II, Ripe Lime, and Rotten Lime. Models that train using the same lime images, 1,600 per group, totaling 6,400 images (80% of the total images). The models are then tested on their ability to classify these four groups of lime images with a set of lime images they have never trained

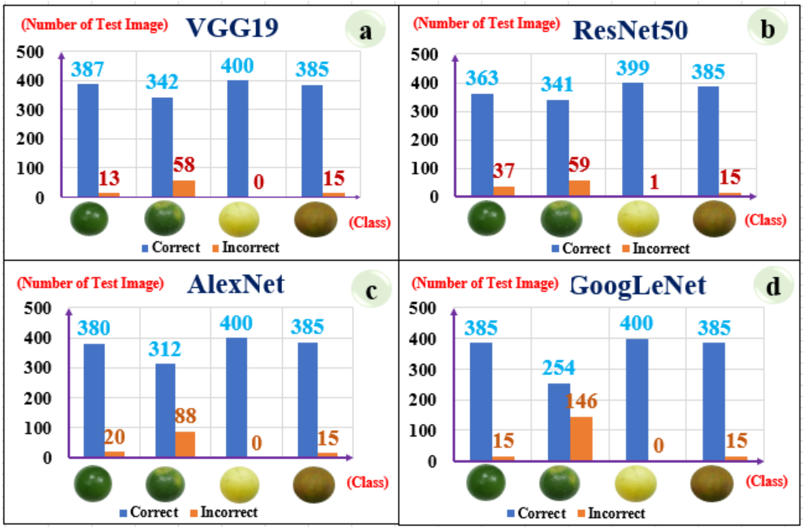


Figure 11: Lime classification results of VGG19 (a),GoogLeNet (b), AlexNet (c), and ResNet50 (d).

before. There are 400 images per group, totaling 1,600 images (20% of the total number of images) set aside for testing. The goal is to find the model with the highest ability to classify limes and choose this model to design the lime classification system.

The training and testing results of the classification of 8,000 lime images using VGG19, AlexNet, GoogLeNet, and ResNet50, following the mentioned method, indicate that these four models yield the following results in lime classification for each quality class.

In the context of lime quality classification, examining several state-of-the-art deep learning models reveals notable distinctions in their respective misclassification rates. The performance of the VGG19, ResNet50, AlexNet, and GoogLeNet architectures is evaluated across four distinct quality classes of limes: Ripe Lime, Rotten Lime, Extra Class, and Class I and Class II.

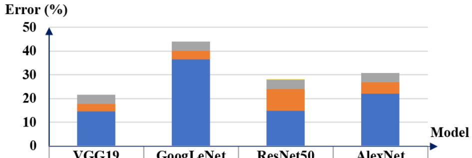
In the case of Ripe Limes, it is observed that VGG19, ResNet50, and AlexNet exhibit no instances of misclassification, thereby demonstrating their capability to accurately classify limes within this category. On the other hand, GoogLeNet, while proficient, records a slight misclassification rate of 0.25% in the same category. The assessment of Rotten Limes yields consistent results across the four considered models, as all of them maintain a low misclassification rate of 3.75%, signifying their reliability in distinguishing between sound and deteriorated limes.

In the Extra Class category, VGG19 stands out with a notably lower misclassification rate of 3.25% compared to GoogLeNet, AlexNet, and ResNet50, which display misclassification rates of 3.75%, 5%, and 9.25%, respectively. This distinction underscores the superiority of VGG19 in accurately categorizing limes in this specific quality class.

In the final classification scenario, encompassing Class I and Class II limes, VGG19 once again outperforms its counterparts, exhibiting a misclassification rate of 14.5%, in contrast to ResNet50, AlexNet, and GoogLeNet, which indicate higher misclassification rates of 14.75%, 22%, and 34.5%, respectively. This outcome underscores the enhanced accuracy of VGG19 in discerning between different quality classes of limes within this combined category.

Overall, this analysis demonstrates that the choice of machine learning architecture has an impact on the accuracy of lime quality classification, with VGG19 consistently outperforming its peers in several critical quality classes. These results show that VGG19 has a high number of correct lime classifications and a lower misclassification rate for lime quality class compared to AlexNet, GoogLeNet, and ResNet50. Additionally, the results indicate that VGG19, AlexNet, GoogLeNet, and ResNet50 can distinguish limes of very different colors well, as shown in Figures 11 and 12.

In comparing the training and testing results of VGG19, AlexNet, GoogLeNet, and ResNet50 for lime



	VGG19	GoogLeNet	ResNet50	AlexNet
Ripe	0	0	0.25	0
Rotten	3.75	3.75	3.75	3.75
Extra class	3.25	3.75	9.25	5
Class I + Class II	14.5	36.5	14.75	22

Class I + Class II Extra class Rotten Ripe

Figure 12: Limes classification mistakes of VGG19, AlexNet, GoogLeNet, and ResNet50.

classification, it is evident that VGG19 achieves the highest accuracy in classifying lime quality classes. According to the training results, VGG19 exhibits a Validation Accuracy of 93.68%, outperforming GoogLeNet, ResNet50, and AlexNet, which show rates of 92.61%, 90.58%, and 89.39%, respectively. Regarding testing results, VGG19 demonstrates an Accuracy Quality Class of 94.62%, surpassing ResNet50, AlexNet, and GoogLeNet with rates of 92.93%, 92.04%, and 88.18%, respectively.

Furthermore, VGG19 exhibits a high Average Prediction Class of 97.24%, while ResNet50, AlexNet, and GoogLeNet have rates of 95.43%, 94.91%, and 94.76%, respectively, as depicted in Table 4. An example illustrating the calculation of Validation Accuracy, Accuracy Quality Class, and Average Prediction Class for the VGG19 model is provided below, following the steps specified in Equations (4)–(6).

$$\%Validation\ Accuracy\ (VGG19) = \frac{Number\ of\ Correct\ Predictions\ on\ Validation\ Set}{Total\ Number\ of\ Predictions\ on\ Validation\ Set}\times 100 = \frac{5{,}996}{6400}\times 100 = 93.68 \quad (4)$$

$$\%Accuracy\ Quality\ Class\ (VGG19) = \frac{The\ Number\ of\ test\ images\ that\ the\ CNN\ model\ correctly\ predicted}{Total\ number\ of\ images\ tested}\times 100 = \frac{1514}{1600}\times 100 = 94.62 \quad (5)$$

$$Average\ Prediction\ Class\ (VGG19) = \frac{The\ Sum\ of\ correct\ forecast\ values}{Total\ number\ of\ images\ tested} = \frac{1555.84}{1600} = 97.24 \quad (6)$$

The Sum of correct forecast values comprises a total of 1600 predictions obtained as test results from the CNN model's classification of lime images. For comparison, the features and the capability of VGG19 with AlexNet, GoogLeNet, and ResNet50 can be summarized as follows: VGG19 is the model with the most significant size at 535 MB, while AlexNet, ResNet50, and GoogLeNet are much smaller sizes at 227 MB, 96 MB, and 27 MB, respectively. VGG19 has the highest parameters at 144 M, while AlexNet, ResNet50, and GoogLeNet have much lower parameters at 61 M, 25.6 M, and 7 M, respectively. This model has 19 layers, less than ResNet50 and GoogLeNet, which have 50 and 22 layers, respectively, while AlexNet has the least number of layers, only 8. Moreover it has a much higher training time than AlexNet, ResNet50, and GoogLeNet.

However, when comparing the features and the capability of all 4 models to classify limes according to the quality classes as mentioned above, it is found that VGG19 is a large model with higher size and parameters. It can classify the limes with little difference in color and defect size with greater accuracy than AlexNet, ResNet50, and GoogLeNet, which are smaller models with lower sizes and parameters, as shown in Tables 4 and 5. Therefore, VGG19 is the most appropriate model for designing the limes classification system according to the quality classes in this research.

3.6 *Phase 3.2: The appropriate mathematical models*

The present investigation commences with the acquisition of empirical data concerning key attributes associated with limes. These attributes encompass measurements such as skin brightness values, skin color values, fruit density values, and skin defect size values, in addition to data pertaining to the categorization of lime quality classes. Subsequently, the acquired data undergoes analysis, with the primary objective of

Table 4: The results of training and testing VGG19, AlexNet, GoogLeNet and ResNet50

Convolution Neural Network Model	Training 6,400 Lime images (80%)	Testing 1,600 Lime images (20%)		
	Validation Accuracy	Accuracy Quality Class	Prediction Quality Class	Average Prediction Class
VGG19	93.60%	94.62%	86/1,600	97.24%
AlexNet	89.39%	92.04%	126/1,600	94.19%
ResNet50	92.61%	88.18%	189/1,600	94.76%
GoogLeNet	90.58%	92.93%	113/1,600	95.43%

Table 5: Compare the features and the capability of VGG19, ResNet50, AlexNet, and GoogLeNet

Convolution Neural Network Model	Size (MB)	Parameters (M)	Layers	Training Time (Hour)
VGG19	535	144.0	19	59.80
ResNet50	96	25.6	50	4.10
AlexNet	227	61.0	8	3.01
GoogLeNet	27	7.0	22	11.47

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Const(1)	162.667	23.1164	7.04	0.000			
Const(2)	244.350	33.2178	7.36	0.000			
Const(3)	266.315	35.7845	7.44	0.000			
Brightness	-1.19716	0.154706	-7.74	0.000	0.30	0.22	0.41
Green	1.89918	0.289714	6.56	0.000	6.68	3.79	11.79
Yellow	0.368804	0.153965	2.40	0.017	1.45	1.07	1.96
Firmness	-1.03881	0.151904	-6.84	0.000	0.35	0.26	0.48
Skin Defects	-0.655922	0.0876244	-7.49	0.000	0.52	0.44	0.62

Figure 13: Results Logistic of Regression from the Minitab

Measures of Association:

(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	Value
Concordant	539566	99.9	Somers' D	1.00
Discordant	418	0.1	Goodman-Kruskal Gamma	1.00
Ties	16	0.0	Kendall's Tau-a	0.75
Total	540000	100.0		

Figure 14: Measures of Association from the Minitab

elucidating the relationships between the independent variables, representing the characteristic attributes of limes, and the dependent variable, denoting the lime quality classes. This analytical process is executed utilizing the Minitab program. The outcomes of this empirical inquiry unveil that, in accordance with the statistical significance levels outlined within the framework of this research, all independent variables exhibit p-values that fall below the specified threshold, as visually depicted in Figure 13.

In addition, Minitab also provided results on the analysis of the level of relationship between the variable (x) and the predicted value (Y). The research by Minitab indicates that the importance of Somer's D and Goodman-k, both registering at 1 and Kendall's Tau-a, measuring 0.75, as shown in Figure 14, is favorable. Implies that the independent and dependent variables in the research are related in the same direction. The correlation coefficients of the research variables demonstrate a high degree of correlation. The equation derived from the analysis can effectively explain the relationship between the independent and dependent variables.

In the assessment of the Goodness-of-fit Test, both the Pearson value and the Deviance value yielded a result of 1. Additionally, the Degrees of Freedom value was found to be 5, and the P-value equated to 0, as visually depicted in Figure 15. These outcomes signify that the mathematical models generated from the Ordinal Logistic Regression equation, derived through correlation analysis of the variables processed using the Minitab program, are suitably applicable to the dataset under investigation. Furthermore, these models demonstrate the capacity to elucidate the association between the independent and dependent variables within the context of this study.

For this reason, the Coef (Coefficient) value obtained from the correlation analysis of the variables processed by the Minitab program can be used to write a mathematical model in the form of Ordinal Logistic

Test of All Slopes Equal to Zero

DF	G	P-Value
5	3213.043	0.000

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	370.834	3592	1.000
Deviance	114.064	3592	1.000

Figure 15: Measures of Association from the Minitab.

Regression equations to classify the quality of lime. The three equations are as following:

$Logit[P(Y \geq 1)] = 97.07 - 1.19(x_1) + 1.89(x_2) + 0.36(x_3) - 1.03(x_4) + 0.65(x_5)$

$Logit[P(Y \geq 2)] = 178.57 - 1.19(x_1) + 1.89(x_2) + 0.36(x_3) - 1.03(x_4) + 0.65(x_5)$

$Logit[P(Y \geq 3)] = 200.72 - 1.19(x_1) + 1.89(x_2) + 0.36(x_3) - 1.03(x_4) + 0.65(x_5)$

When Y is the limes quality classes.
x_1 is the skin brightness.
x_2 is the green value.
x_3 is the yellow value.
x_4 is the density.
x_5 is the skin defect size.

When testing for lime quality classes of the above mathematical models, it is found that these models can show the relationship between the lime characteristics and the lime quality classes. Therefore, the mathematical models in the form of Ordinal Logistic Regression equations can be applied to design the limes classification system in this research.

3.7 *Phase 4: Designing the Limes Classification System and Creating the Graphical User Interface on the Computer Screen*

Designing a lime classification system involves selecting the VGG19 test results, the most accurate model for classifying limes by quality. Characteristic values for each quality class, calculated using mathematical models like Ordinal Logistic Regression equations, are then used to code conditions for lime classification based on Thai Agricultural Standard No. TAS 27-2017. This research uses the MATLAB program version R2022a, which uses the Deep Network Designer tool and Design App tool in the program to design the system to display the image and the lime quality class, including the probability rate that such lime is in this class. It also includes characteristic values and storage periods for the consumption or sale of this lime, and it shows the day/month/year that this system is used. All these results are displayed through the Graphical User Interface on the computer screen of the user, as shown in Figure 16. In this regard, the classified lime must have a probability greater than or equal to 85% for an accurate lime image classification result.

3.8 *Phase 5: Test the lime classification system*

After developing a lime classification system using MATLAB, the accuracy of this system was empirically evaluated. A Convolutional Neural Network (CNN) was employed to classify previously untrained lime images. Subsequently, the outcomes of the testing phase are collected and analyzed to derive a comprehensive summary of the research findings.

4 Results and Discussion

The research findings present several key observations of significance. The utilization of Convolutional Neural Network (CNN) models, specifically VGG19, ResNet50, AlexNet, and GoogLeNet, in the study, has demonstrated the capacity to discriminate between Ripe Lime, Raw Lime, and Rotten Lime based upon variations in color and brightness, achieving remarkably high levels of accuracy. Notably, VGG19, AlexNet, and GoogLeNet exhibited the capability to correctly classify all instances of Ripe Lime, while ResNet50, although displaying a slightly elevated error rate of only 0.25% in classifying Ripe Lime, still maintained a commendable level of accuracy. This evidence suggests that these models can be applied in classifying the ripeness of fruits characterized by distinct color and brightness attributes, such as mangoes, papayas, and blueberries, aligning with the findings of Behera *et al.* [7].

Furthermore, when evaluating the outcomes of classifying the four lime categories within the research Extra Class, Class I, Class II, Ripe Lime, and Rotten Lime, an observation emerges regarding the impact of model size on performance. The larger models exhibited a superior ability to classify limes, surpassing their smaller counterparts accurately. For instance, VGG19 excelled with a classification accuracy rate

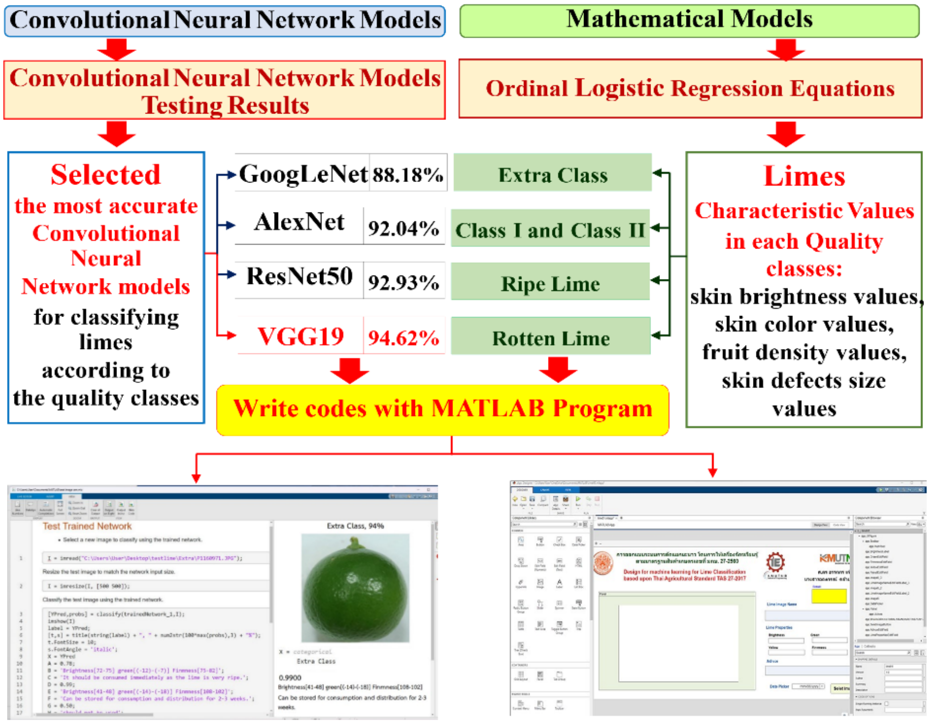


Figure 16: Designing the limes classification system and Creating the Graphical User Interface on the computer screen.

of 94.62%, outperforming the smaller models, namely GoogLeNet, AlexNet, and ResNet50. However, it is essential to acknowledge that adopting larger models entails a trade-off, necessitating extended training durations. VGG19 necessitated 59.8 hours for training, whereas AlexNet, ResNet50, and GoogLeNet demanded significantly shorter training periods of 19.82, 14.59, and 5.21 h, respectively, as corroborated by the research of Ngugi *et al.* [19]. Consequently, the selection of VGG19 as the model of choice for designing the lime classification system is justified, given its accuracy in lime classification.

The integration of lime characteristics, encompassing fruit density, skin color, and skin defects, which are empirically measured in this investigation, to determine lime quality is achieved by applying the Ordinal Logistic Regression Equation. Facilitates the establishment of a coherent link between lime attribute classes by employing the Minitab program. The research demonstrates that these lime characteristics can effectively ascertain the appropriate quality group to which a lime belongs. Consequently, utilizing the Ordinal Logistic Regression equation in conjunction with the CNN model, as expounded in this study, substantially enhances the precision of lime quality classification.

During this research, Convolutional Neural Network (CNN) models, known for their precision in agricultural crop classification, were employed, complemented by Ordinal Logistic Regression equations, which efficiently elucidate the relationship between lime attributes and their corresponding quality classes. The user interface for accessing this information is made available through an intuitive Graphical User Interface displayed on the user's computer screen, as depicted in Figure 17.

As an illustration, consider the processing results for an Extra Class lime showcased through the Graphical User Interface. These results showcase a lime image with a 100% probability of being in the Extra Class. The skin brightness value ranges from 42 to 57, the green value ranges from –30 to –19, the yellow value ranges from 18 to 31, and the fruit density value ranges from 103 to 130. Notably, there

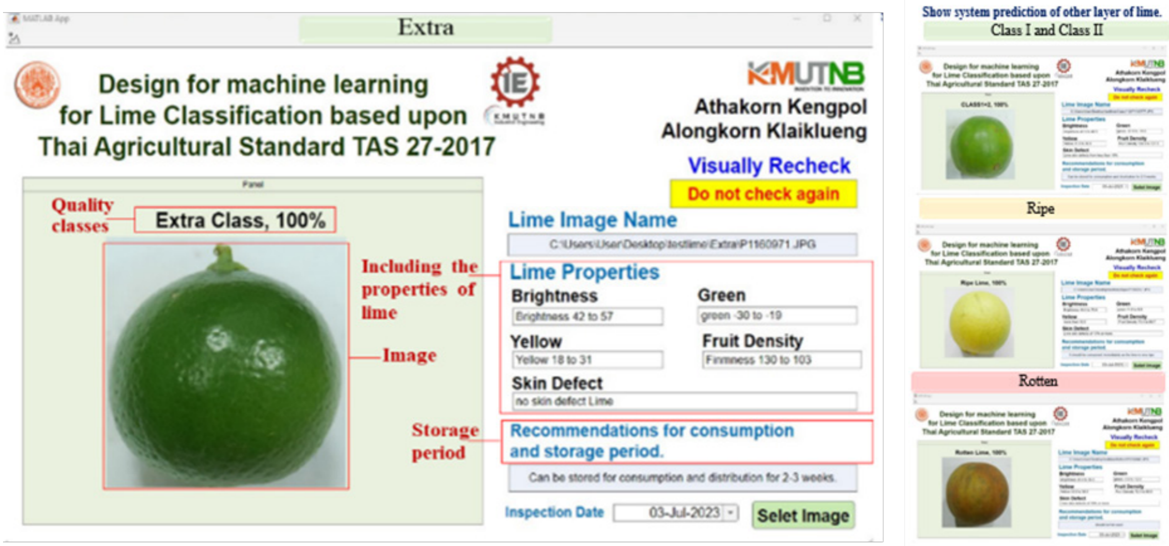


Figure 17: The limes classification result of Extra Class and other classes.

are no skin defects, and these limes can be stored for consumption and sale for 3 weeks [20]. However, it is worth noting that limes in this class exhibit higher green values and fruit density values compared to other classes.

5 Conclusions

This study aimed to enhance the existing lime classification system, which relies on the capacity of machines to differentiate lime quality based on skin color variations through color sensors, as presented by Rodkasem *et al.* [21]. However, the previous system fell short in accurately classifying limes with diverse colors and skin defects as stipulated by the Thai Agricultural Standards, specifically No. TAS 27-2017. Consequently, this investigation sought to advance the limes classification system by integrating Machine Learning techniques, enabling automated recognition of limes based upon their external skin characteristics, encompassing instances where limes exhibit yellow patches and skin imperfections by the TAS 27-2017 standards, which is unavailable in the literature.

Validation testing of this system demonstrated its competence in classifying limes into Extra classes, Class 1, Class II, Ripe Limes, and Rotten Limes, with a classification accuracy rate consistently exceeding 90%. Nevertheless, it is imperative to note that the limes classification system developed within this research remains in the prototype stage and is yet to be fully automated. As such, the findings of this study represent experimental outcomes and algorithmic designs. Moreover, the research findings bear significance beyond the domain of limes, as they can be extrapolated for application in the quality classification of various fruits and agricultural products. Such an extension can considerably facilitate the classification of superior-quality products in accordance with desired standards, thereby streamlining the processes for producers and consumers.

This research confines its focus exclusively to the classification of lime quality based solely on external skin attributes. Alternative determinants such as juice content and lime size are not considered. Therefore, future research should consider broadening the scope of classification criteria to encompass a broader spectrum of qualities and standards, thereby facilitating the categorization of limes that meet a more comprehensive range of measures, catering to the diverse needs of producers and consumers.

Additionally, the quality classification method developed in this research can be applied in the food industry. This application aids in improving efficiency and reducing errors during the selection of high-quality agricultural raw materials that meet safety standards for consumption, such as lemons, oranges, papayas, etc., for using in the industrial sector. This approach is beneficial for both domestic consumption and export and contributes to building trade confidence for manufacturers of such products.

Author Contributions

A.K.: conceptualization, investigation, data curation, reviewing, writing, and editing; A.K.: research design, data analysis, methodology, writing an original draft. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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