Faculty of Computing & Informatics

Group Assignment Report

Vegetable Recognition and Market Price Prediction Web Application by Using CNN Machine Learning and Flask

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Abstract:

This paper analyzes how vegetable prices can be predicted for agricultural science by using classification methods. The price of vegetables has to be predicted to ensure that the smoothness of some industries such as supermarkets and vegetable processing factories could be carried out. Hence, a good predictor must be developed by applying machine learning (ML) in recognizing the features of the types of vegetables. To carry out the prediction of vegetable price on image recognition, 17 types of vegetables are used in this paper. In this study, Convolutional Neural Network (CNN) is used for the recognition of the type of vegetable and also for the prediction of the price of the vegetables. Next, a web app with all these functions is built using Flask and Heroku. The machine learning model is measured by using the accuracy classification score and normalized confusion matrix. The model has given a result of 91.05% accuracy on the test set which is considered a viable result. This study emphasizes the use of machine learning models in developing a web app to recognize the image and predict the price of vegetables.

Keywords: deep learning; flask; vegetables recognition; agriculture; market price; CNN

1.0 Introduction

Nowadays, the development and implementation of image recognition and computation vision in the agriculture industry play significant roles and are widely used. With the application of the development model in IOT, it ensures sustainability in agriculture development with the transformation from traditional agriculture to smart agriculture. Besides can ensure the quality of the horticultural product. There are various image recognition approaches applied in order for monitoring and preserving the crop of the horticultural product. Patricio et al. [1] proposed a comprehensive review with the goal of identifying the application of computer vision in precision agriculture for the growth of the top five grains produced globally: rice, wheat, soybeans, barley, and maize. Besides, the uprising food crisis problem can be upcoming with an image processing approach. Koirala et al. [7] proposed a study focused on fruit recognition and localization through a deep learning model application that could predict the yield estimation with the tree crop load estimation. Food security can be ensured with the image recognition approach. Da Silva Cotrim et al.[8] proposed an approach in developing a computational vision hybrid system that is composed of convolutional neural networks and supports vector machine image recognition for colour change on bread during thermal processing. However, there was still a need for a manual workforce in some of the agricultural-related farming activities such as vegetable picking, sorting for standardized vegetables, and sales tasks. This would cause low efficiency in the work progress. Thereby, the research on applying innovative approaches such as automatic recognition and classification of the horticultural product would be an essential technical approach to solving the manual workforce-related problem. Zhang et al. [9] proposed research on picking manipulators that used a collected array of tactile information for the robots to recognize the fruits and vegetable hardness in order for it to stably grasp the products (fruits and vegetables) without causing damage due to huge pressure during picking. The accuracy rate on the grabbing recognition experiment achieved 90%.

Neural Network is a machine learning development used for image processing. Convolutional Neural Network (CNN) which is one of the neural network approaches is the most commonly used algorithm and obtains high accuracy. There are significant progress has been done in agriculture with Convolutional Neural Network (CNN) approach. Li Ma et al.[10] proposed a study using Convolutional Neural Network in strawberry disease recognition. In this report, Convolutional Neural Network (CNN) approach is applied to recognition on the type of the vegetable. A web app is built to recognize the type of vegetable and a price range of the vegetable is shown. This is because of fluctuating vegetable price inconsistency. Thereby, the intention of the purpose of our assignment is to build a web app for consumers to recognize unknown vegetable types and can access the real-time price range to easily identify and purchase the type of vegetable at a reasonable price. In conclusion, the group assignment report presents an easy-to-use web application that helps the user to identify the type of a vegetable and its current market price.

2.0 Review of Related Work

2.1 Articles Searching

2.1.1 Generating Search Technology

This search method included creating search terms and selecting relevant digital libraries. This review relied on Google Scholar, as well as IEEE Xplore, ResearchGate, and others. Google Scholar is the first pick of every researcher while conducting research because it is the largest database that comprises research articles from all sources. Google Scholar is a free online resource that allows you to do broad searches for scholarly literature. It also allows you to search for similar works, citations, authors, and publications. The IEEE Xplore digital collection is a valuable resource for discovering scientific and technical material. It offers online access to over five million full-text papers from some of the world's most recognized periodicals. IEEE Xplore contains more than 260 journals, 4 million conference papers, and 6000 books. Every month, around 25,000 new papers are posted to IEEE Xplore.

Google Scholar provides articles on a wide range of topics, including computer science, biology, and chemistry. While conducting research on a relevant issue, some keywords connected to the topic are identified by searching for comparable phrases in the thesaurus. The articles chosen in this research must not be older than 2018. Hence, the articles found on google scholar are filtered first before they are referred. The search strings in table 1 are used to find some relevant articles.

Table 1: Search String

Database	Advanced Search String
Google Scholar	(("image processing") AND ("machine learning" OR "neural network") AND ("vegetable images" OR "vegetable imaging") AND ("price")) Year: Since 2018
Google Scholar	((“machine learning”) AND (“agricultural price prediction”)) Year: Since 2018
Google Scholar	((“web application development” OR “web application”) AND (“heroku”)) Year: Since 2018

The inclusion criteria are the papers based on the search strings provided in table 1, access to full-text articles and paper published since the year 2018.

2.1.2 Selection Process

Timeliness of publication is a basic criterion in the evaluation process. It is of primary importance. A journal must be published according to its stated frequency to be considered for initial inclusion in the google scholar database. As the review restricted that the timeliness for the articles must not be older than 2018, the articles which are published before the year 2018 are eliminated. Next, only articles and conference papers are selected concerning document type, meaning review articles, book chapters, letters, and short surveys are excluded. English is the universal language of science at this time in history. This is why this review focuses on articles that publish the full text in English. Non-English publications are excluded to avoid translation difficulties. The studies which are not related to machine learning are also excluded.

2.2 Review of Article

2.2.1 Image Recognition

Identification of fruits and vegetables is becoming increasingly important and is implemented in many areas. Based on Femling et al. [6], implementing machine learning or computer vision in agriculture can improve the process of identification of the types of vegetables and fruits. By eliminating the human element, it might speed up the product identification process and reduce the amount of mistakes. It would be beneficial if image recognition was implemented at supermarkets or shopping centers. The computer vision-based algorithm which was equipped with machine learning techniques was reviewed by V. [7] and found that computer vision technology is a reliable source for visual perception in any scheme. The vegetables' images were predicted from different aspects including size, colour, and shape. Computers may use a variety of algorithms and strategies to recognize object patterns and forecast outcomes with accuracy. Bhargava and Bansal [8] analyzed the use of computer vision and image processing techniques in the agri-food industry. They found that the most qualities in predicting agriculture are colour, size, texture, and shape. A neural network-based algorithm with a good architecture can predict any image that is kept in the drive or computer. The challenges in the detection of vegetables and fruits were concluded by Zhang et al.[9] as technology may reduce the efficiency of the process as the image may be not clear in certain areas.

2.2.2 Price Detection

Machine learning has been applied in many sectors but unfortunately it is rare to be applied in the agricultural sector, especially for vegetables. The application of machine learning in agriculture is mainly focused on smart farming which considered the climate, soil, fertilizer, and disease prediction. The price of agriculture is highly dependent on the production of agriculture. The higher the productivity, the lower the price. Climate factors and customers' demands for vegetables will totally affect the price. Chen et al. [10] stated that Neural Network (NN), Support Vector Regression (SVR), Genetic Algorithm (GA), Wavelet Analysis (WA) and Grey System (GS) can be used to estimate the price of agricultural products. Besides, Yu et al. [11] developed a forecasting model based on the genetic algorithm and the back propagation neural network algorithm to estimate the price of agricultural products, and the prediction impact was greatly enhanced. The back propagation neural network is the most active neural network and it is a model of multiple layers feedforward network which is trained by the error propagation algorithm. However, Bayona-Oré et al. [12] claimed that Neural Network is the most common model used in price prediction among all the models.

2.2.3 Web Application Development

An easy-to-use web application that is used to identify the vegetable images and predict the price range of vegetables is deployed. This web application will only work for certain types of vegetables. Our web application is deployed on the Heroku cloud application platform and the program code is maintained in Pycharm. Python language is used in this vegetable recognition project. Deep neural network (DNN) methods are computed by the computational engine, which is housed on the backend server, for image processing models. For the purpose of seeing predictions of the photos of their input vegetables, the user will access the front-end User Interface [13].

2.3 Analysis of Article

2.3.1 Image Recognition

Based on Femling et al. [6], the article’s main topic is Fruit and Vegetable Identification Using Machine Learning for Retail Applications. This study aimed to improve the self-service systems' ability to identify fruits and vegetables in the retail environment. Convolutional Neural Networks (CNN) was employed to carry out the task of image recognition. Architectures like Inception and MobileNet were also in use. 1.2 million images from hundreds of different categories were used as the training data for Google's open-source Inception v3 architecture. The GoogleLeNet module was created with strict memory and computational constraints in mind. MobileNet was built using depthwise split convolutions to reduce processing and model size. The traditional convolution method of combining and filtering was divided into two layers by the depthwise separated convolutions approach: one for combining and one for filtering. This method significantly reduced calculation size. A fresh set of photos can be made to increase the results' accuracy. Avoid gathering datasets that contained pictures of veggies that had been cut down because the pictures did not represent what they look appear in the working environment and the network might not able to recognize them. The propagation time which is the start and end of the classification can also be calculated in our own project. The weight of the fruits or vegetables must be taken into account in this research to better distinguish between them, which is a gap in the findings. The researchers drew the conclusion that the text size and item size were constrained by the small display on their Graphical User Interface. A larger display will lengthen the processing time, though. The investigation showed that there was a high likelihood of unneeded things being captured since photos were captured by cameras. The accuracy obtained for both Inception and MobileNet models were quite the same which is 76%. The surprising finding is that the researchers used Inception and MobileNet architectures in their project which makes it different from others.

The article’s main topic is Fruits and vegetables quality evaluation using computer vision [8]. The project carried out was purposely to give an analogous survey of computer vision and image processing skills in the food industry and analysis of the different distribution of image details in the pictures, and study fruits and vegetables on different aspects including color, shape, size, texture and the diseases present. The research questions were is there any relationship between computer vision and image processing skills, What aspects can be studied for vegetables and fruits in image recognition using machine learning. This paper used KNN, Support Vector Machine (SVM), and Artificial Neural Network (ANN) to do with image processing. KNN focused on sample similitude as evaluated by the distance metric. It first chooses K neighbors, then counts the number of data points in each category based on Euclidian distance, and finally chooses a new location where fresh points can be tallied. An advanced classification technique called SVM makes use of both linear and nonlinear regression. Data that is non-linear is classified. It non-linearly converts data to a high-dimensional space using kernel functions. For

2-class problems, SVM determines the linear optimal hyperplane so that the separation between support vectors is kept to a minimum. ANN are simply computer algorithms that mimic how the human brain processes information and are biologically inspired. A classifier powered by an artificial neural network achieves an accuracy of 96.47 percent. Future image processing performance improvements would need to take into account issues including the uneven distribution of light on an arch surface, surface assessment, the time-consuming capture and processing of spectral pictures, and fault discrimination. The gap that can be found in this research is different weight values were used and the weight value should be tuned in the future. Fruits and vegetables can be analyzed for quality using the most cutting-edge 3D technology. To sum up, acquisition, segmentation, feature extraction, and classification made up computer-based quality inspection. The article revealed that the accuracy achieved by ANN is the highest which is 96.47 percent, followed by SVM with an accuracy of 95.94 percent and KNN with an accuracy of 92.93 percent. To remove any geographical bias from the system, several angles might be used to capture the photos of fruits and vegetables.

2.3.2 Price Prediction

The article’s main topic is Price Prediction of Agricultural Products Based on Wavelet Analysis-LSTM [10]. This work was aimed to help farmers with equitable production and marketing skills through accurate price estimation. The research question was “Is there any possibility that the machine learning approach can help in equitable production of vegetables?”. The Wavelet Analysis (WA) was applied to minimize the noise of the data while the Long Short Term Memory (LSTM) model was used to predict the normalized data. WA-LSTM was believed to provide a better output than a traditional LSTM model. In the future, a time series model can be used in predicting the prices of vegetables since the price is changed periodically. The gap that we identified is the model should predict the current data instead of the historical data and the database should be up-to-date. The article concluded that by using WA and LSTM, the accuracy of the models can be improved. The analysis revealed that WA-LSTM can forecast the price of cabbages more accurately with the MAE value of 0.03408 as compared to BP, SVM and LSTM. The surprising finding is the output forecasted by the WA-LSTM was the best since BP was most commonly used in predicting price.

The main topic of the article written by Yu et al. [11] is Research on an agricultural product price forecasting model based on an improved BP neural network. It aimed to study the BP neural network agricultural product price prediction. Hence, the research question was “Can a BP neural network model successfully predict the price of agricultural products. The back propagation neural network model, K nearest neighbors, Support Vector Machine (SVM), and Random Forest (RF) were used in this research. The neural network model needed to be trained continuously to make the modeling works well and be suitable for large-scale datasets. The gap identified is to consider the weight value of the vegetables as the unit is important. It had been concluded that BP neural network had a tenacious ability in many algorithms and it was more flexible compared to other models. The analysis revealed that BP neural network is more prone to overfitting and a genetic algorithm can be implemented to solve this problem.

The theme of the study by Bayona-Oré et al. [12] is Machine Learning for Price Prediction of Agricultural Products. The purpose of this study was to investigate the research on forecasting agricultural commodity pricing using machine learning algorithms. The aim of this study was to examine the evolution of the use of these algorithms, identify the most often used algorithms in agricultural price prediction, and identify the research paradigms and performance criteria that are utilized. This review was primarily intended to compare the findings of other scholars in recent years. The researchers compared the outcomes by taking the efficiency and precision of the models into account. A combination of several hybrid models can be used in the future to find out which is the best model for predicting the price. The article concluded that it is hard to have complete and accurate data on time. The agricultural products evaluated in price prediction research were selected by the availability of the necessary data across time. The article revealed that no single tool is best suited to grade the performance of different machine learning models. The surprise finding is most of the data collected were from China and India.

Table 2: A synthesis matrix organized by the key studies for image processing

Author & Year	Purpose/ Objective/ Aim/ Goal	Method/ Technique/ Model	Sample Dataset/ Database	Finding/ Performance/ Result	Identify any uniqueness of articles	Identify any similarities between all these articles	Offer your own critics
Femling et al. (2018)	To improve the self-service systems' ability to identify fruits and vegetables in the retail environment.	Convolutional Neural Networks with two architectures, Inception and MobileNet	There are 10 classes in the study. About 400 images per class have been extracted from ImageNet and 30 images per class are manually taken by researchers using the camera.	Inception: Average propagation time: 3.3 sec MobileNet Average propagation time: 0.43 sec The accuracy for both architectures is quite the same which is 76% for the top 1 class. The top 1 accuracy is calculated by performing a division of the sum of diagonals	Datasets were collected from the ImageNet and manually collected by researchers.	Neural Network models were used.	The researchers can include some different types of vegetables in their work.

				with the number of test. performed			
Bhargava, A., & Bansal, A. (2018)	To give an analogous survey of computer vision and image processing skills in the food industry and analysis of the different distribution of image details in the pictures and study the vegetables and fruits from different aspects	K nearest neighbor (KNN), Support Vector Machine (SVM), Artificial Neural Network (ANN)	Researchers did not mention where the dataset is from	KNN = 92.93%, SVM = 95.94%, ANN = 96.47%	The researchers were able to analysis different distribution and image features of the agriculture.	Both predicted the vegetables and fruits based on different aspects including size, shape, color and so on.	The researchers did not mention clearly where the dataset originated, making us face difficulty when referring.

Table 3: A synthesis matrix organized by the key studies for price detection in agriculture

Author & Year	Purpose/ Objective/ Aim/ Goal	Method/ Technique/ Model	Sample Dataset/ Database	Finding/ Performance/ Result	Identify any uniqueness of articles	Identify any similarities between all	Offer your own critics

						these articles	
Chen et al., (2019)	To help farmers with equitable production and marketing skills through accurately price estimation	Wavelet Analysis- Long Short Term Memory (WA-LSTM), BP neural network, Support Vector Machine	3502 datasets from the Fuzhou basket official website	WA-LSTM is the best model with the MAE value of 0.03408 and MSE value of 0.00023 with epochs = 50	The training dataset consisted of 95% from the whole data and the testing dataset was from the last 5% where usually the ratio of the train to test dataset is 70:30.	Both used historical dataset to carry on the price prediction.	The price is predicted based on the historical dataset instead of the current data. Researchers only studied on an only type of vegetable which is cabbage.
Yu et al. (2018)	To study the BP neural network agricultural product price prediction	BP neural network (Optimized and Unoptimized), K nearest neighbors, Support Vector Machine (SVM) and	Train datasets consist of 611 records while test datasets consist of 262 items in the ratio of 70:30	Mean square error (MSE) of optimized BP neural network is 0.043 while the MSE of unoptimized BP neural network is 4.3587 when the test data is fitted.	The data was collected by using a web crawler instead of obtaining ready data from the website.	The researchers used neural network as one of the models.	BP neural networks are prone to be overfitted. Cross selection and mutation selection are applied to optimize the weight and thresholds of BP neural network.

		Random Forest (RF)					
Bayona-Oré et al. (2021)	To investigate the research on forecasting agricultural commodity pricing using machine learning algorithms.	No machine learning models were used in this research. RMSE, MAPE and MAE were used to evaluate the performance of the models.	-	The predictive models that work best are Neural Network.	-	The datasets used were collected from China.	The researchers make a summary of the results obtained by others.

3.0 Depth and Analysis of Review of Related Work

3.1 Image Processing

From the two articles above, different types of neural network models are used to perform image processing in the agricultural field. We can see that both Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) can be used for image processing. ANN is more helpful for solving complex problems while CNN is more suitable for solving computer vision-related problems and is more accurate in classifying the images. The types of agricultural products used by most researchers are limited. Thus, more types of agricultural products should be included in the research to make the dataset more diverse. We plan to allow users to upload the vegetables' images to our website application that they wish to check for the prices. Once the submit button is clicked, the images along with the prices will be shown.

3.2 Price Detection

From the articles gathered above, we can conclude that most of the datasets are from China due to their biggest popularity. Although Neural Network was commonly used in price detection problems, Wavelet Analysis- Long Short Term Memory gives a better result in predicting the price. The time series analysis model can be implemented in this case as the price of agricultural products changes periodically. Besides, training the machine learning model with the current data was the best measure instead of using historical data. Create a website that can check for the current price of the agricultural products along with the images shown. The price will be kept updated day-to-day.

4.0 Motivation

In recent years, issues of the food crisis have been gaining more concern from the public, not just domestically but also globally. Various factors, such as climate change, extreme weather, economic instability, and wars, have greatly affected the food supply globally. The fluctuation in food prices has also been influenced by these factors. Weather patterns such as rainfall are changing, and there are more climate shocks like cyclones, floods, and droughts that all affect harvests. Additionally, crop pests like locusts, which ruin and damage harvests, are more prevalent now as a result of climate change.

Due to the soaring and fluctuating food prices, consumers are often confused by the food price spikes. Due to the rising inflation rate, it is more likely that a family would like to reduce their expenditure on food in order to lower their cost of living and save money for the future. In some extreme cases, some even choose to skip meals in order to reduce their financial burden. According to the New Straits Times[14], various responses were shared across New Straits Times social media platforms when asked how people were coping with the rising cost of living (#NSTalkToUs). They have received responses as follows. "I am eating only two meals a day now." I still need to feed my baby, no matter how difficult life is now.” "The rising cost of living has severely affected our livelihood. I'm surviving on only one miserable meal a day that costs RM5 per person. " This issue has to be addressed seriously. Even though adults can skip meals to spend less, but not the kids, they need sufficient nutrients for their growth. Furthermore, adults' inability to cope with the soaring food prices may lead to crimes and suicides. This issue is not just impacting the physical well-being of the people but also the mental health of the public, people are stressed and frustrated to earn more income and save on their cost of living.

The desired situation is that people are able to purchase vegetables at reasonable and appropriate prices. According to former Second Finance Minister Datuk Johari Abdul Ghani(2016)[15], Malaysians spend 31.2 percent of their disposable income on food and food away from home. Avoiding purchasing overpriced vegetables could help to ease the financial burden of the people. This project can be furthered by adding other items instead of just vegetables.

5.0 Objective

The objective of this work is to build a web application that is able to recognize the types of vegetables based on the image uploaded and give a price range for that vegetables. This objective is mapped with a problem statement which states that the fluctuating food prices are confusing the customers, the customers are having difficulties in identifying the market that sells the vegetables and fruits with a reasonable and appropriate price range, and the team seeks to resolve this issue by developing an application that will provide a price range based on the type of vegetables detected.

6.0 Methodology

6.1 An Overview Of The Methodology In This Study

In this study, a Convolutional Neural Network (CNN) machine learning model will be built to predict the vegetable types through image processing. A dataset of images will be gathered by the team for the model training purpose. After finishing training, the CNN model will be integrated into the development of a web application called "Vegetable Price Prediction App" built in Python. This web application is going to be designed as a vegetable predictor and a vegetable price teller at the same time. It allows the user to upload a picture of the vegetable to recognize the vegetable type and retrieve its current market price in Malaysia.

6.2 The Choice Of The Machine Learning Model

The Convolutional Neural Network (CNN) model is just like the brain of a human. A human brain is a group of neurons that works together to operate the visual impulse received by the retina of the human eyes. Different groups of neurons would be given different jobs, from basic works to detailed works. For example, the human brain will firstly analyze the basic patterns such as the figures and the lines of the vision, then more complex tasks like analyzing the details of the objects or the gestures of the human. CNN has a common way of operating the image to produce artificial intelligence that emulates the human brain system. The CNN model has various hidden layers: the upper part layer known as the convolutional layer, the middle layers known as the nonlinear layer and pooling layer, and the deepest layer known as the fully connected layer. Each layer will have a different level of image processing. [16]

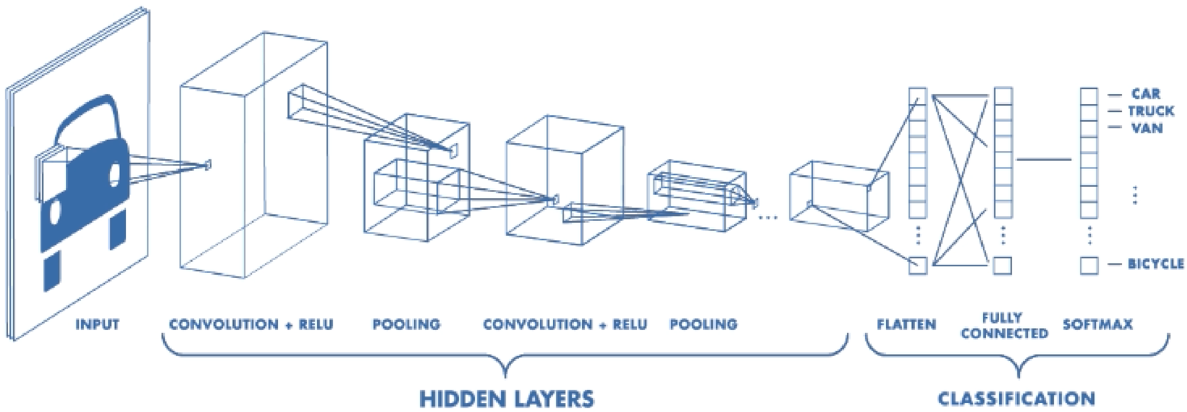

Figure 1: An example of hidden layers in CNN

The CNN will operate the image in 2 dimensions(height × width) in the hidden layers. Each image input into the model would be processed as a grid-like topology and the grid boxes are represented by the pixels of the image. These boxes are just like multiple neurons in a human brain. Each of them is from a different region of receptive fields. These receptive fields are presented in matrix form. They are considered as the parameters that could be studied by the model. Thus, in the convolutional layer, these matrices, also known as kernels, will be applied in the process of multiplication with other matrices from different fields of reception, or different feature selection. The switching of kernels through all parts of the grid of an image is called the activation map [17]. It will eventually show a full picture of the image in 2D. The output volume is measurable by using the formula below:

$$w_o = \frac{w-s+2p}{S} + 1$$

Where the w is the width of kernels, s is the spatial size of the kernel, p is the number of padding, and S is the size of sliding by the kernel. After the convolution, there is another layer called the non-linear layer. It usually has three different types including Sigmoid, ReLu, and Tanh. The outputs gained from the previous layer will proceed with another operation in the pooling layer. In this layer, some of the outputs will be overridden by the summarized analysis of their neighbor's outputs. This reduces the size and weight of the load of computations. Moving to the next layer, the fully connected layer. The output in this layer will be completed with a complete connection with its input as the neurons in this layer are all linked without any exception. [18]

Choosing the CNN algorithm was due to its accuracy in dealing with the image recognition issues. Multiple layers of the CNN model provide the image processing in different scales resulting in a more comprehensive image grid analysis. Therefore, a more accurate prediction ability is the detection of the image, and the object in the image. In addition, based on [19], it is able to automatically predict the critical features without the need for a human monitor. The model has the ability to observe most likely all parts of an image and identify the special characteristics of it. By looking super deeply down into the structures of the image, CNN learns to recognize them. Thereby, finding the most related features used by the CNN model in recognition of specific kinds of images has become an easy job for the developers. It is essential to know the features of the prediction in most cases in machine learning as they affect the forecast process performed by CNN. This became the reason that CNN was chosen in most cases of image recognition. This is also the reason why CNN is chosen for this work.

6.3 Procedure of The Vegetable Price Prediction App Development

The proposed procedure that is going to be applied in this study is based on the Waterfall methodology where everything will be done on a forward path. [20] After the planning and analysis problem and requirements of the project, two sets of data will be collected: vegetables image and vegetables' current market price. Once the data collection is done, the design of the database, the design of the app functions, and the design of the user interface will be conducted. Next, the process of building the CNN model that recognizes the image of vegetables will be started. The model trained is then applied to the final step, which is the web application implementation process.

6.4 Details of The Planned Events

After collecting the dataset of images, the machine learning model building process needs to be carried out. It begins with the image file paths created for train, test, and validation purposes in which the train dataset has labels noted on their file names. The succeeding process is to resize all the images of the dataset into 224 ×224 pixels and the kernel size will be set to 3 × 3. Thus, the input will have a size of 224 × 224 × 3. The pre-trained model is using Mobilenet2 with 58 layers and is combined with a pooling layer of average size. Following the pre-trained layers, the next layers are the fully connected layer 1 and 2 with the setting of 128 ReLu for layer 1 and Softmax for layer 2a as shown in figure 2. Finally, the model will be tested for its accuracy.

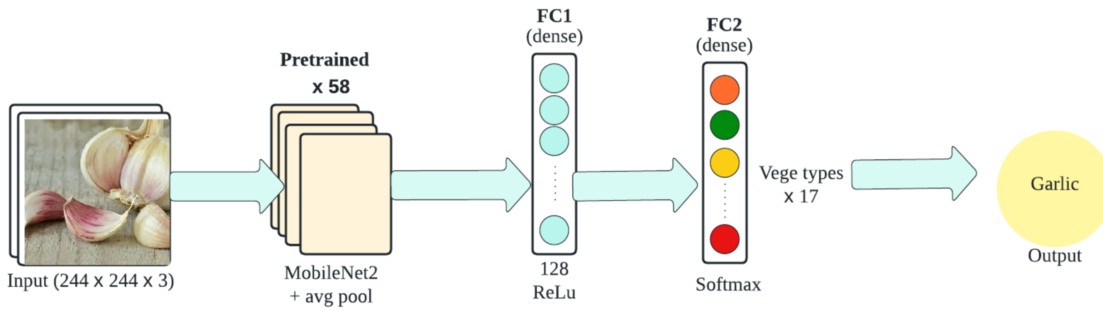

Figure 2: CNN model used in this work

6.5 Citation of Machine Learning Models

6.5.1 Face mask detection using YOLOv3 and faster R-CNN models

A CNN model was a high potential image processing algorithm that was not only able to recognize the image but also capable of detecting the object in an image. This concept was applied by the [21] in detecting the mask on the human face to identify the people who are not following the disease prevention steps. To accomplish the task, two types of CNN models have been trained and tested in this study which was the YOLOv3 and the faster R-CNN models. It was found that both of the algorithms worked in accomplishing the task of mask detection. Both of the methods were suitable to be deployed in mobile systems. However, the deployment should apply the faster R-CNN if it has high-end GPUs.

6.5.2 Banana ripeness stage identification: a deep learning approach

There has been an issue that came across by the developer[22] which was found to be solvable with the help of CNN machine learning. The issue was the difficulty in identifying the ripeness level of a banana. It was not easy to differentiate the banana maturity into four separate stages by using a biological vision system. However, the developer in this work has proposed a simple CNN model and compared it with the VGGNet16 and ResNet50. Eventually, the CNN outperformed the other models with an accuracy of 96.14%.

6.5.3 A Review of Convolutional Neural Network Applied to Fruit Image Processing

In recent years, the agricultural sectors have been putting most of their focus on the application of Deep Learning method in solving some of the problems. In this work, the developers have proposed a study that introduces the basic tools of developing a CNN model to work in fruit image processing.[23]

6.5.4 Mellowness Detection of Dragon Fruit Using Deep Learning Strategy

As the agricultural sectors continue to grow and become the main economic income of most countries, the technology used to improve the quality of products was emphasized. In the proposed work, the mellowness of the dragon fruit was detected by using the CNN deep learning strategy. The images of dragon fruits from different stages were collected and fitted into the RESNET 152 CNN model for training purposes. The model was tested repeatedly with epoch numbers from 10 to 500. The final result has shown that the RESNET 152outperformed the VGG 16 /19.[24]

6.5.5 Noise Immunity and Robustness Study of Image Recognition Using a Convolutional Neural Network

In this study, the developers found that there was some noise and immunity that affects the accuracy of the CNN model. Thus, some methods have been proposed to overcome the issue.[25]

7.0 Experiment Setup

7.1 Database Preparation

In this project, a website application that allows users to upload certain vegetables' images is created. When the vegetables' images are uploaded, the information which includes the vegetables' names and price range will be displayed.

There are a total of 17 vegetables included in this project which are holland sweet potato, yellow holland onion, India red onion, green chilli, red chilli kulai, garlic, coriander, okra, green bean, long beans, luffa, China round cabbage, choy sum, long eggplant, cucumber, tomato and scallions. The types of vegetables are referred to the FAMA website.[26] FAMA website shows the latest price range of vegetables in certain distinct in Malaysia every two days. The minimum, maximum and average prices of vegetables are collected in an excel file. The prices for each vegetable are calculated per kilogram.

The images of those vegetables are then collected for image processing purposes. Different angles of vegetables' images are taken. At least 100 images are collected for each type of vegetable to ensure that our datasets are large enough to be trained. In the training phase, a large dataset can produce more samples for training and can reduce the impact of overfitting, Similar images are then eliminated to remove the redundancy.

7.2 An overall flowchart

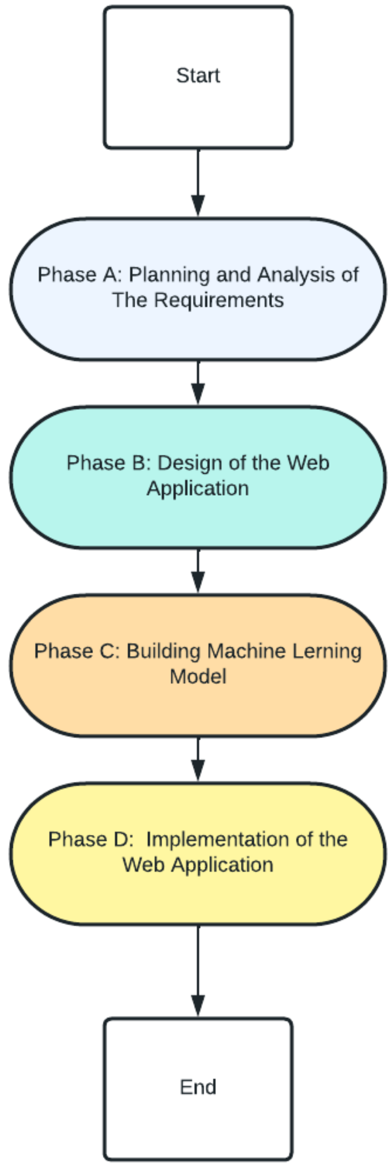

Figure 3: An overall flowchart of vegetables price prediction app development process

Figure 3 shows an overall flow chart of the development process of the vegetables price prediction. It consists of a total of four main phases. The workflow of the phases was actually based on the typical Waterfall System Development Life Cycle (SLDC) methodology. The phases proceeded periodically, in which the start of a new phase was only allowed after the accomplishment of its previous phase. For example, the phase B: design of the web application was continued only when the phase A: planning and analysis of the requirements were completed and approved by the development team.

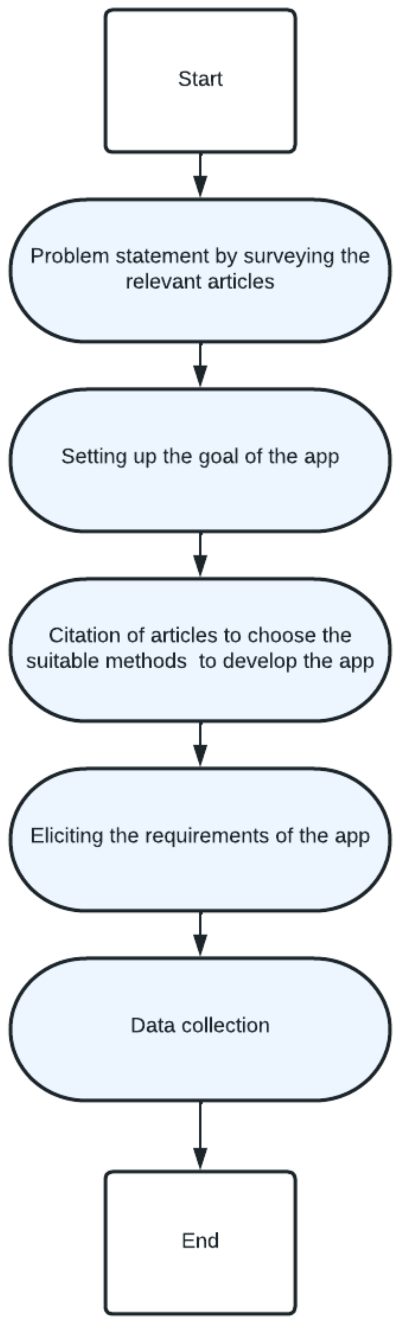

Figure 4: Phase A flowchart for planning and analysis of the requirements

The first phase of the project was phase A: planning and analysis of the requirements. Based on the flowchart shown in the figure 4, a phase representing the planning and analysis procedures was depicted. It was the base of the whole vegetables price prediction app development process which was started with the step of problem statement by surveying the relevant articles. In which, the development team has been investigating the recent economic situation and the demands of the society to find out the problem faced by the society. The goals of the project were configured by the team and their acceptance was tested by the team.

After deciding on the goals of the project, the theories and methods utilized in the previous studies related to the project goals were cited by the team. By combining all the knowledge in the previous findings, the developer had some clues of the ways to carry out the app development process. Subsequently, the requirements of the web application were elicited. The requirements included the functional features and non-functional features of the web application. For instance, the functional features were the functions to upload images to the app, recognize the vegetable type by using the vegetable's image uploaded, and retrieve the current market prices of the recognized vegetables. On the other hand, the non-functional features were the harmonic user interface of the web app and the accuracy of the vegetable recognition. Lastly, when the requirements elicitation was done, phase B ended up with the process of data collection of vegetable images and vegetables' current market price in Malaysia.

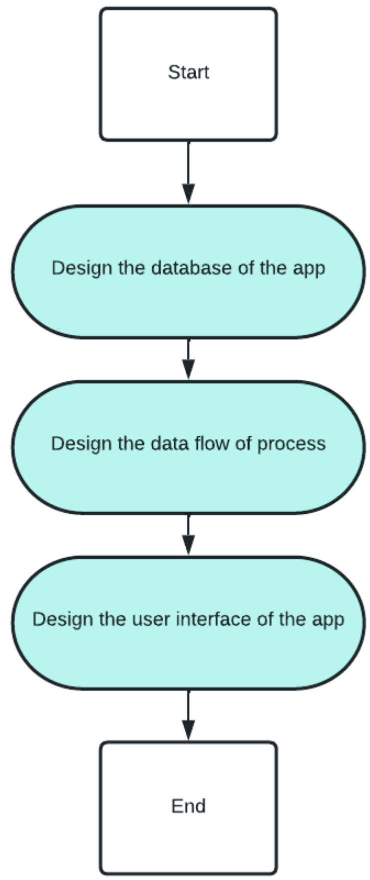

Figure 5: Phase B flowchart for design of the web application

Followed by the phase of planning and analysis of requirements, the next phase is phase B: design of the web application. As depicted in figure 5, phase B started with the design of the background database of the application. Since the web application does not need a huge amount of data, the database only contains two parts of data. Firstly, the vegetable market price dataset, which was stored in the Github repository, would be retrieved when the application needed to get the price of a vegetable. Secondly, the images of vegetables uploaded by the user, which were stored in a cloud database server, known as Firebase, would be retrieved to display the image in the user interface once the user submitted the image. Both of the datasets would be constantly updated.

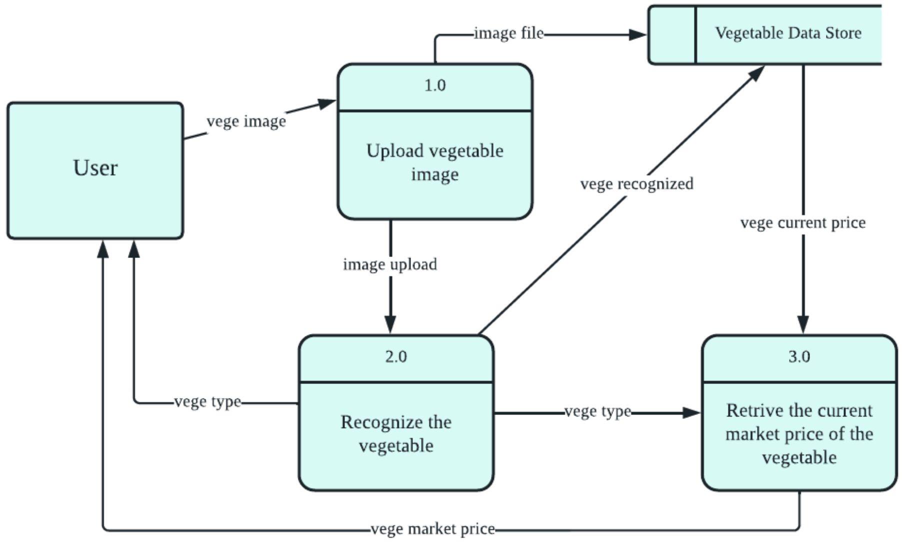

Figure 6: Level 1 DFD of the vegetable price prediction application

Next, the data flow of the application was also designed by the team. A data flow diagram (DFD) has been drawn in this phase to illustrate the flow of data in the application as shown in figure 6. In which, there was only one entity that interacted with the system. Data flow design helped the developers to discover the potential problems of the application, and explore ways to improve the application performance.

Figure 7: User interface of the vegetable price prediction app in mobile phone.

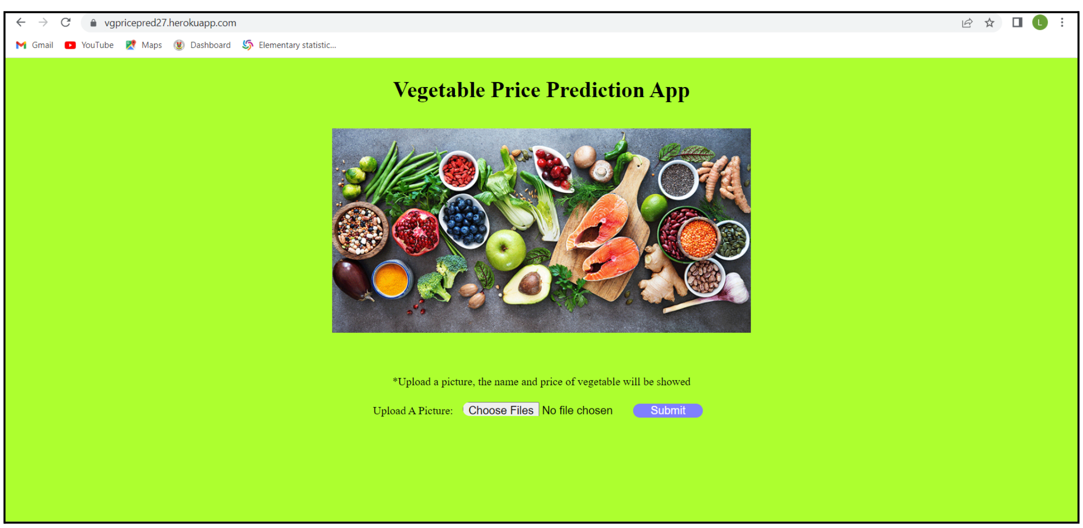

Figure 8: User interface of the vegetable price prediction web app in desktop.

The last step of phase B is the user interface design. There were several principles of designing the user interface that was followed in this step. Based on the figure 8, the interface of the web application offered simple and informative dialog which were easy to understand for the user. Also, the web application provided clearly marked exits of the items such as the image file uploader and the button to submit. [27]

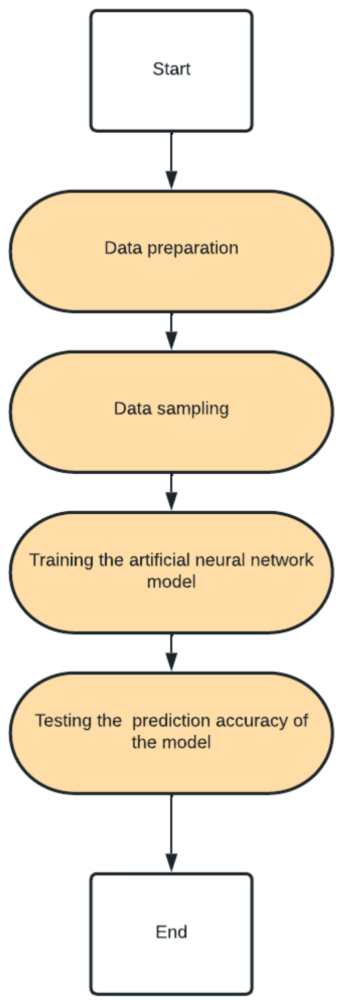

Figure 9: Phase C flowchart for building machine learning model

The succeeding phase is the step of building a machine learning model, phase C. By referring to the figure 9, the phase was started with some data preparation work. The dataset needed to be used in the vegetable image processing has been generated at this step. Once it was done, the project continued with a data sampling process. An 80% of the images were divided from the total of 1576 images for the use of model training, while 20% of the images were used for model testing. After the data sampling, an artificial neural network model was trained by fitting in the images of the vegetables to make it learn the pattern of the image classification. When the model training was done, the ability to properly classify the vegetable images to their labels was tested. Finally, the model trained was saved and ready to be applied to the web application.

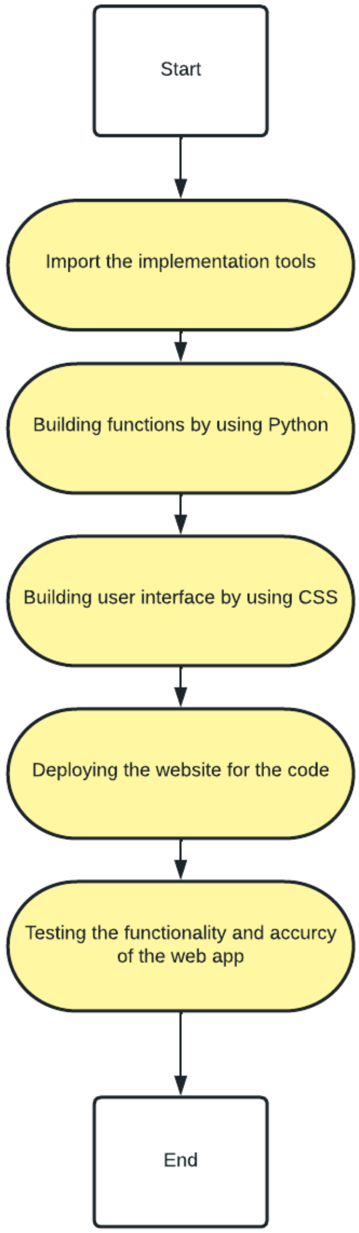

Figure 10: Phase D flowchart for implementation of the web application

The last phase of the web application development was phase D: implementation of the web application. Phase D was where the real game began. At this stage, a lot of coding has been done by the developers to build the web application and a lot of issues with the application floated into appearance.

Figure 11: Diagram of the tools imported into the application implementation

Initially, the tools needed to create the application were identified and imported as shown in figure 11. The first tool included was the Flask which has been widely used in developing web applications along with the Python language. The next tool is the Numpy library which was used to resize the dimension of images uploaded into the application. Following Numpy, TensorFlow and Keras were also used for the purpose of image processing. Moreover, a library called Pandas was imported to handle the operation of data frames included in the project such as reading in the CSV file. Finally, a tool called Pyrebase was imported. It worked as a Python wrapper for the Firebase platform. It was used to manage the cloud storage for the images uploaded to the application by the user.

After importing the relevant tools. The functions of the application were built by the developers by using Python language. The functions included the *submit()*, a function that allows the user to upload the vegetable's image, the *processed_img()*, which was used to resize the image uploaded by the user, and the *get_price_range()*, which returns a market price range of the vegetables in Malaysia. Subsequently, the user interface was built by the developers using the CSS language.

After the coding of the application was done, the files of the application were deployed to the website. The files were first uploaded to a Github account's repository. Thereafter, an account of the platform called Heroku was connected to the Github repository, and the application files were deployed to Heroku. Then, the deployment of the web application was done. Finally, the testing of the functionality and the accuracy of the vegetables price prediction application was carried out by the team to ensure there was no error.

8.0 Result

CNN model was found to be the most suitable model in the image recognition cases. Thus, in this work, it was trained with MobileNet2 algorithm along with other layers such as the pooling, Softmax, ReLu, etc. The model was validated and tested after the training has been done.

8.1 CNN Model Performance on Vegetable Images

The training and validation of the model have been conducted for 5 epochs, with a batch size of 32 and with the application of the Adam optimizer. The reason for choosing this epoch was due to the concern on the issues of underfitting and overfitting. Thus, to narrow down the chance of facing such troubles, an optimal number of epochs was chosen, that is the 5. The accuracy of training and validation was illustrated in figure 12. Based on the figure 12, it was found that the best model training was on the 5th epoch, with an accuracy of 99.37 %, while the best model validation was on the 5th epoch, with an accuracy of 91.05%.

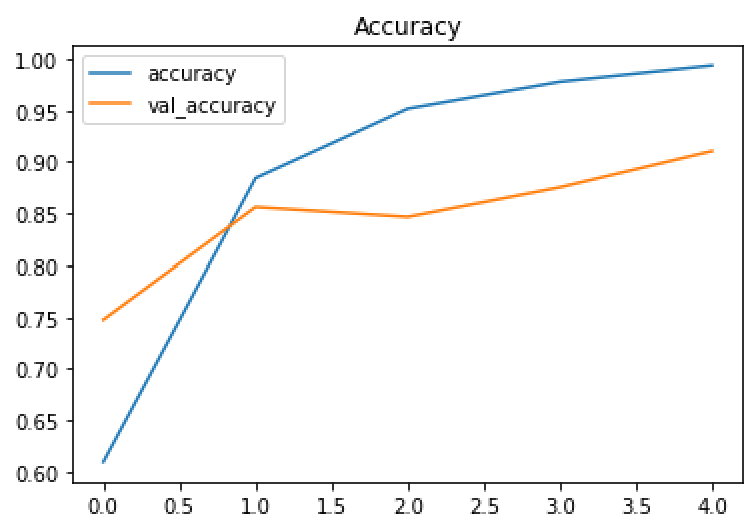

Figure 12: AUC of the training and validation of the CNN model

After training and validation, the process was followed by the testing of the image recognition function of the model. There were 33 images used for testing the model. The accuracy of the model on the testing set was 91.05% based on the figure 13. The value was obtained from the confusion matrix shown in figure 14. In the normalized confusion matrix, the accuracy in recognizing each type of vegetable was shown. Based on the result, the model was able to recognize most of the vegetable types 100 % accurately. For example, the CCN model has managed to accurately recognize the coriander, Holland sweet potato, red onion, round cabbage, tomato, and yellow Holland onion. However, there were also some types of vegetables that the CNN model failed to recognize well. The CNN model only managed to achieve 74% accuracy in identifying green chili, luffa, and scallions.

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Accuracy on the test set: 91.05%
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Figure 13: Screenshot of testing accuracy calculated from the confusion matrix

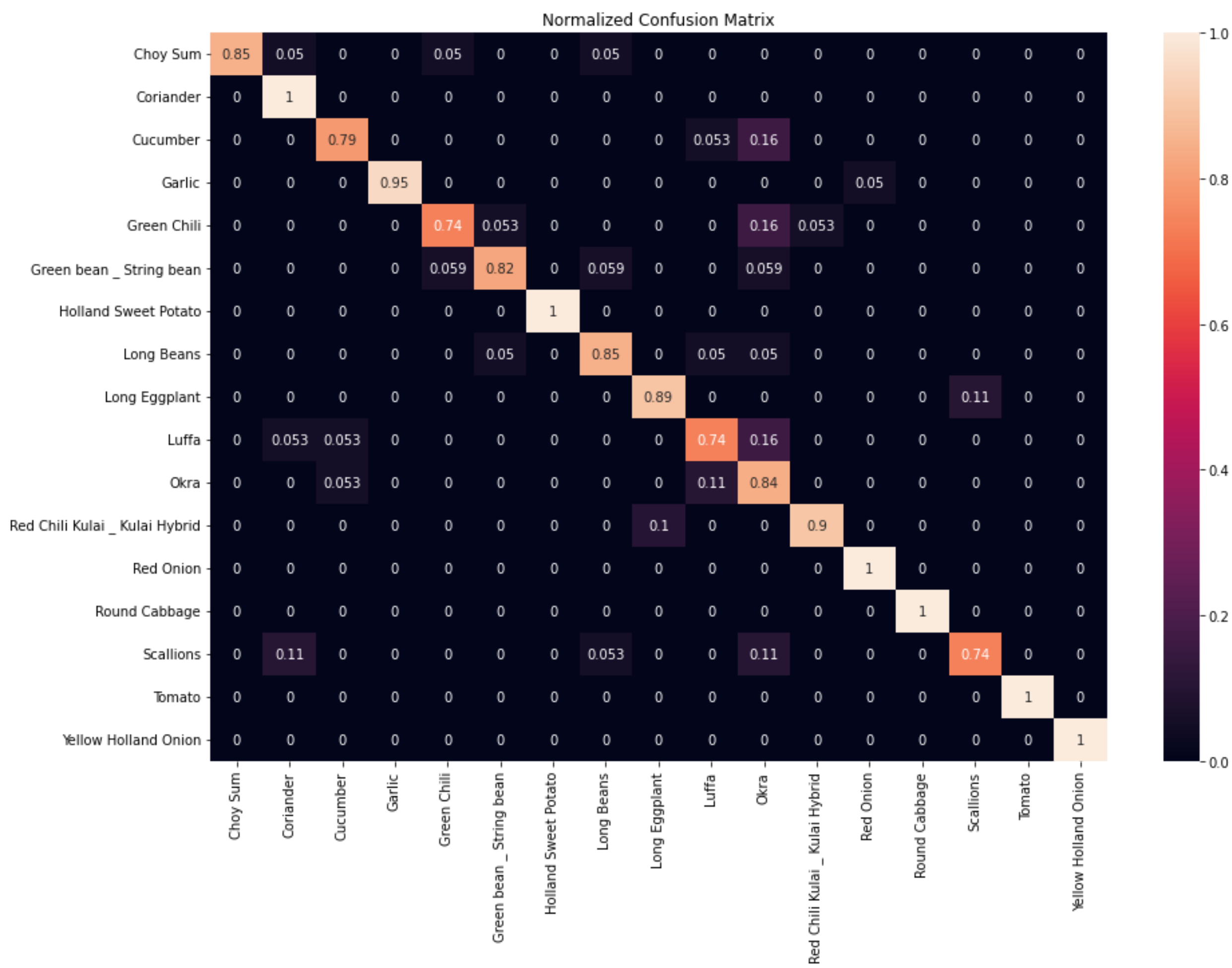

Figure 14: Normalized confusion matrix of the CNN model

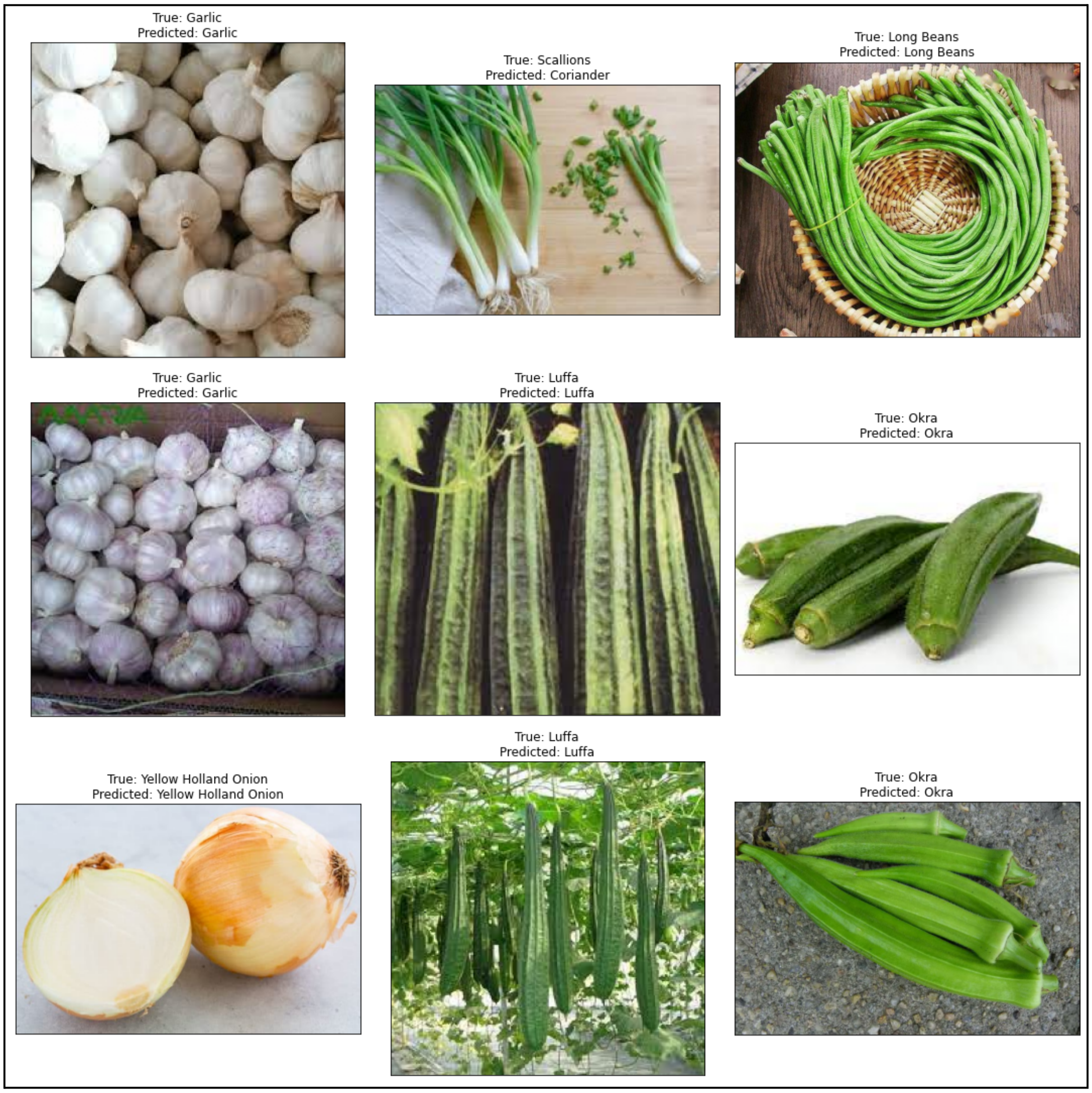

Figure 15: Part of the results of the image recognition on the test data

The result shows that the model has some problems in detecting the Luffa, Green Chili, and the Scallions. The reasons for getting such outcomes were most probably due to the small amount of the dataset applied in model training. Besides, It may also be due to the patterns of the images applied were not natural as most of them were online images with planned backgrounds. It caused the CNN model to fail to receive enough kinds of patterns of the Luffa, Green Chili, and the Scallions images. Thus, the CNN model was unable to perform well in detecting these three types of vegetables. To conclude, it was found that the real world nature image and the size of the training set are important in training a quality image recognition model.

8.2 Comparison of The Results With Other Studies

Table 4: Comparison of the results of this work with the other studies

Image Processing Study	Model	Accuracy
Femling et al. (2018)	CNN with Inception & MobileNet	76%
Bhargava, A., & Bansal, A. (2018)	KNN	92.93%
	SVM	95.94%
	ANN	96.47%
This Study	CNN with MobileNet2	91.05%

Table 4 shows the comparison of the results in this work with the other studies. Based on the table, it was found that the CNN with MobileNet2 in this work was having a lower accuracy compared to the KNN, SVM, and ANN with the accuracies of 92.93%, 95.94%, and 96.47% in the study of image processing skills in the food industry and analysis of the different distribution of image details in the pictures and study the vegetables and fruits from different aspects by [8]. However, there was another study that applied the same machine learning model with this project. They also used the CNN machine learning algorithm but with Inception and MobileNet in a study to improve the self-service systems' ability to identify fruits and vegetables in the retail environment. It was having a much lower accuracy compared to this study, which was only around 76%. Thus, it could be found that the CNN with MobileNet2 works better than the CNN with Inception and MobileNet but performs not as well as the KNN, SVM, and ANN for some reasons. [1]

8.3 Limitations of The Work

There were some weaknesses and limitations in this work that might have affected the results. For example, the size of the dataset was not big enough. The project team only managed to gather roughly 100 images for each type of vegetable. This was caused by the restrictions of the time. To collect larger amounts of images, longer time for research would be needed. Moreover, the hypertuning process was not included in the model training phase. To get the most suitable parameters for each algorithm, the hypertuning process would be required. These two limitations might be the reasons that affect the accuracy of image recognition by CNN model in this work.

Although the image recognition was not perfect, the accuracy of the image recognition was satisfying as it has managed to outperform some other studies. Moreover, the work has brought an informative finding to us, that is the importance of using real world pictures to increase the accuracy of image recognition.

9.0 Discussion

This paper has presented an application that makes use of computer vision to automatize the identification process of vegetables. Neural network architecture has been evaluated as a classifier of 17 different types of vegetables. The highlights of this paper are summarized in this section.

The neural network needs to carry out feature extraction before it can perform image recognition or classification. Features are the portions of the data that are important to the network. The features are the clusters of pixels, such as edges and points, that make up an object that the network will examine for patterns in the specific situation of image recognition[28].

Figure 16: Screenshot of testing accuracy calculated from the confusion matrix

In this paper, the machine learning model was measured by using the accuracy classification score to determine the accuracy of the model in image recognition. In multilabel classification, this function computes subset accuracy[29]. The set of labels predicted for a sample must exactly match the corresponding set of labels in y_test as shown in the diagram above. The accuracy classification score is one of the methods of scikit-learn metrics, it is used to calculate either the fraction or count of correct prediction in Python. It mathematically denotes the ratio of the total number of true positives and true negatives out of all predictions[30]. From the figure 16 above, the accuracy of the test set is 91.05%. This shows that there's a high percentage the classifier will be able to predict the types of the vegetable in the image.

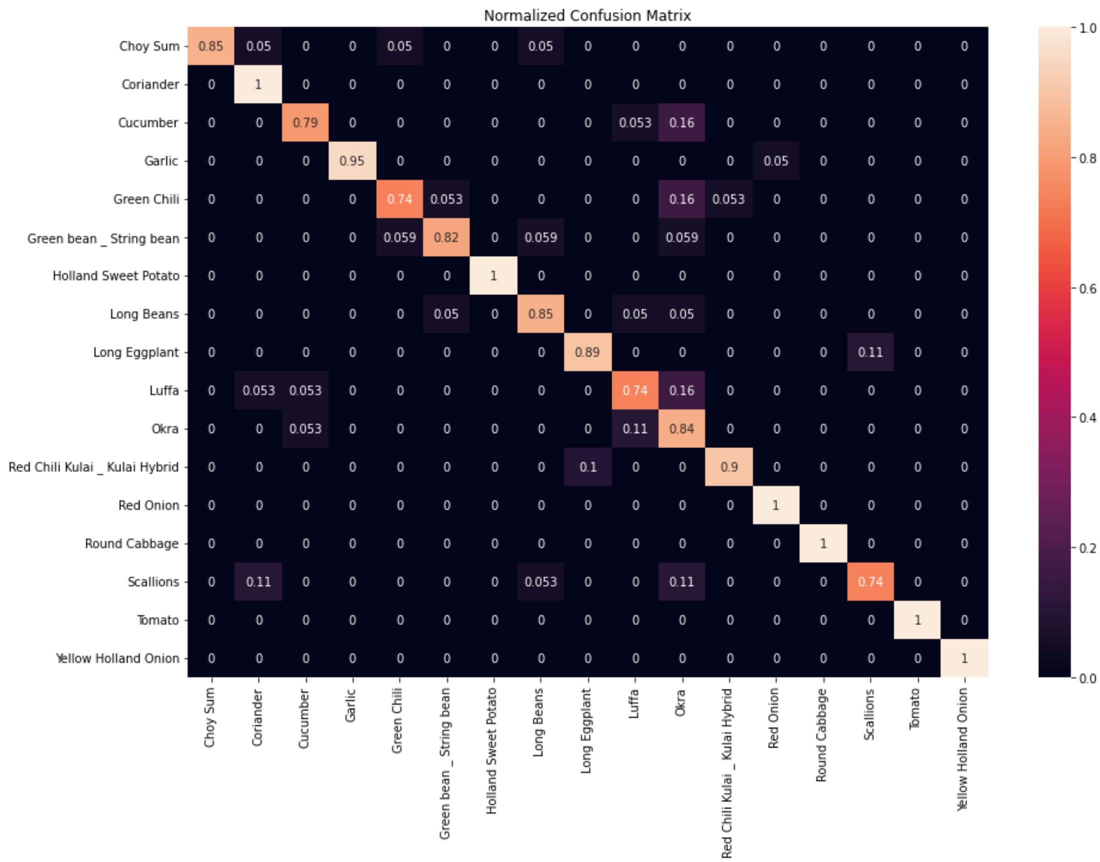

Figure 17: Normalized confusion matrix of the CNN model

The machine learning model can't be only evaluated using accuracy as it will be misleading, because in some critical scenarios, only 1% failure can also create a significant impact[31]. Thus, the model also was evaluated by using the normalized confusion matrix to determine each of the accuracy of the types of vegetable. Confusion matrix is a matrix that allows you to visualize the performance of the classification machine learning models[31]. The normalized confusion matrix is used instead of the confusion matrix in this paper because it is easier to visually interpret how the labels are being predicted. Next, the normalized confusion matrix is visualized as a heat map as shown in the figure 17 above.

By comparing the model performance when using the normalized confusion matrix, the coriander, holland sweet potato, red onion, round cabbage, tomato and yellow holland onion have 100% of accuracy. It means that these vegetables will be 100% identified as correct vegetables while the classification process is undergone. Besides, the accuracy of the other vegetables also shows a high percentage which is above 70%. Luffa, Green Chili, and the Scallions get a low accuracy among the other vegetables is most probably because of the small amount of the dataset applied in model training. This figure 17 shows the probability of predicting the correct vegetables for each type of vegetable.

The results built on existing evidence of a vegetable price can be predicted by using vegetable images. It is well known that the classification accuracy becomes important and difficult due to the complexity of video images and the distribution of objects in different application backgrounds[32]. Since there is a development trend of artificial intelligence and machine learning nowadays, there will be potential applications arising from the result such as plant disease detection application. In addition to posing a threat to global food security, plant diseases can have serious impacts on smallholder farmers whose livelihoods depend on robust crops. The system could detect the plant disease by recognizing the plant image. Thus, it is possible to carry on the further research on this potential application from the results of this paper.

Furthermore, this paper also contains some limitations throughout the process. Lack of data and lack of good data would probably become the limitation of this study that will affect the results of the image recognition[33]. Both a lack of strong features and a lack of good ground truth data can restrict the potential of the model and make it perform poorly. Besides, more different types of species of vegetables could be used in this study in order to provide a more comprehensive application for users. Due to the time constraints, these limitations should be solved and considered in the next future. Hence, the data of this research could be more varied and huge in order to produce viable results. Further research is needed to establish from the limitations that obtained in this paper.

In short, the application that is built in this study is to provide a platform for the users to predict the name and price of the vegetable according to the image. The application is applying image-processing techniques and image is probably an important source of data in agricultural science. One of the main applications that may be used in supermarkets is categorization, which can be used to automatically identify the types of vegetables that customers buy and to establish the right pricing for the produce[34. Various methods and image-processing approaches have been used in this paper in addressing vegetable classification such as data preprocessing, data augmentation, model training and class activation heatmap for image classification. The methods discussed in this study can discriminate between several vegetable types even though their color and texture are fairly similar. Real world nature image and the size of the training set are important in training a quality image recognition model. A crucial practical issue that is frequently neglected in the development of machine vision systems is image quality.

10.0 Conclusion

In this paper, the progress that has been made in the application of information in agriculture is reviewed. Generally, several computer vision and image-processing approaches adopted for the classification of vegetables have been explored in this paper. Most of these approaches involve three main steps: (1) background subtraction, (2) feature extraction, and (3) training and classification. The image processing techniques include image segmentation is performed using the Convolutional Neural Network (CNN). Also, the literature for image recognition based on machine learning and image-processing-based solutions that use color and texture features for automatic recognition of vegetables have been surveyed. At last, the images are classified and predicted by the name and price of the vegetables.

Besides, the overall accuracy on the test set is 91.05% which means that a high accuracy is obtained in this study in recognizing the image of vegetables. In this review, the model performance is obtaining a viable result. In the future, the work could be extended towards identifying different species of vegetables in a single image and also identifying more species of vegetables. The work could also be extended towards building a potential application such as plant disease detection application. Moreover, the knowledge that has been applied in this study such as machine learning, image processing approaches and image recognition can also help in different industries, since technology is increasingly advanced. In conclusion, the potential future directions for this study may include the implementation of such systems in real-life scenarios such as in supermarkets or vegetable processing factories. The improvement of the accuracy of classification and usage of different methods in classifications may also be considered.

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