Identification Food Nutrition and Weight Prediction using Image Processing

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***Abstract*— Obesity is a global issue with rising prevalence each year, driven partly by excess nutrient and calorie intake. Identifying nutrient content in food is vital to prevent obesity. This research employs image processing, specifically the YOLO (You Only Look Once) algorithm, to classify and identify fruits and vegetables quickly and accurately. YOLO is advantageous for its speed and ability to classify multiple objects simultaneously. The goal is to develop a system that recognizes, classifies, and predicts the weight of fruits and vegetables, providing nutritional and calorie information. Tests showed that the system accurately detects produce under various lighting conditions—achieving 100% accuracy with additional ring light (600–650 lux) and 99.2% without extra lighting. Beyond object detection, the system predicts weight with an average error of 5.6% when illuminated. This technology has the potential to aid users in monitoring nutritional intake by providing reliable identification and calorie data, contributing to obesity prevention efforts.**

Keywords: Detection, Intensity, Obesity, YOLO

I. INTRODUCTION

OBESITY is a health disorder that results from abnormal or excessive fat accumulation in the body. An obese person will be susceptible to dangerous diseases such as stroke, diabetes, heart disease and other diseases. The increase in obesity rates is generally related to the habit of a person who consumes a larger number of calories compared to the number of calories burned. In 2016, more than 1.9 billion adults aged 18 and over were overweight and 13% of them were obese [1]. According to the WHO (World Health Organization), obesity is a global problem and a serious threat to the world's public health. To reduce the increase in obesity, WHO recommends that each individual maintain a healthy lifestyle by exercising regularly for at least 150 minutes per week and limiting the number of daily calorie intake. To lose weight in a healthy way, as well as maintain weight for those who have a normal weight, the nutritional intake from food must be monitored. For this reason, everyone needs to estimate and measure the amount of nutrient intake from the food consumed.

Research on food image classification using Local Binary Pattern (LBP) and Hue Saturation Value (HSV) methods. LBP and HSV are used to perform color extraction, and then the features of each image are classified using the Naïve Bayes Classifier. From the tests, the accuracy results were 65% with the HSV method and 60% with the LBP method. Another research study was conducted to create a system that can identify nutrients from fruits and vegetables by image processing using the K-Nearest Neighbor (KNN) method. This study has an average accuracy level of 96.2% [2].

Some of the limitations of this study are that it can only identify fruits and vegetables singly, and there is no weight prediction feature of fruits and vegetables. Hence, the output in the form of nutrients displayed is not by the actual weight of fruits and vegetables that have been classified. Previous research related to weight prediction has been carried out by Jeerapa et al in 2017. This study applies linear regression analysis to predict egg weight in grams. The prediction was accurate at 87.58% [3], [4], [5].

The development of the previous research is a change in the object detection method and the addition of a weight prediction feature to the system. In the previous study, the object detection method used was the KNN algorithm, while in this study, the YOLO method will be used. YOLO is a faster method of object detection than other object detection methods. In this study, a new function will also be created in the system in the form of weight prediction so that the nutrients to be displayed will be adjusted to the actual weight of the detected object.

Nutrition is food substances that are essential for organisms to carry out the growth and development process properly according to their functions. Balanced Nutrition will be good for the body, but a lack or excess of nutrients will affect growth. Balanced Nutrition consists of 30% protein, 30% fat and 40% carbohydrates. Nutrition functions to maintain metabolic balance and organ function and repair damaged cells. The nutrition indicators used in this final project are based on the nutritional adequacy rate (AKG) recommended for the Indonesian people. AKG is determined by the Minister of Health of the Republic of Indonesia. AKG includes adequate energy, protein, fat, carbohydrates, fibre, water, vitamins and minerals [6], [7].

To get an overview related to the nutrients that each food has. One technique that can be done is to use image classification. Image classification is a process that aims to provide image identification in the form of labelling. Labelling is based on a set of predefined classes. Image classification techniques can use machine learning algorithms. The process of categorizing images or classes is carried out using computer training so that the patterns in the image can be categorized and associated with categories or classes that have been defined beforehand. After the image category process, modelling is carried out [8].

For a fundamental process, determining the relationship between the dependent variable and the independent variable is important. This can be done using a scatterplot to assess the strength of the relationship. The next stage after modelling is machine learning with a large amount of data. One of the things that can be learned is Deep learning [9].

Deep learning is a new phase of machine learning that teaches computers to detect patterns in very large amounts of data [10], [11]. Deep learning is a new type of machine learning that has gained much traction thanks to its promising results. Artificial Neural Network (ANN) is inspired by the structure of biological neurons in the brain to create the structure and function of deep learning. Deep learning can receive raw data and then use a Deep Neural Network (DNN) to train representations automatically. To simulate neurons with mathematical expressions, ANN has several nodes and three layers, namely the input, hidden, and output layers, as shown in Figure 1. The more hidden layers in deep learning, the more ANN structures will be converted into DNN structures to better learn from thousands or even millions of parameters [10].

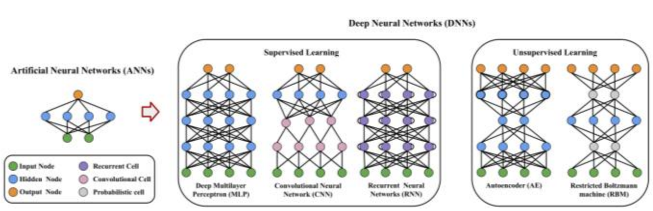

Figure 1. Visualization ANN and DNN [10], [12].

A Convolutional Neural Network (CNN) is a type of neural network that is purpose-built for two-dimensional inputs such as photos and videos. From an image, CNNs can extract connections and information across its layers and represent the corresponding characteristics within the image. CNNs are the best and most effective Deep Neural Networks (DNNs) for recognizing images. CNN has a reputation for separating 1000 categories from a million images in the Images Net Challenge [13], [14], [15], [16].

Redmon et al. proposed the YOLO algorithm in 2016. The YOLO algorithm identifies and localizes an object. A single neural network uses this system to predict the bounding box and class probability of a single evaluation image. In real-time object detection, this method can detect objects at speeds of up to 45 frames per second, which makes YOLO faster than other object detection systems. YOLO can predict objects using region-based techniques and learn to generalize object representations [17], [18].

YOLO is a version of CNN whose architecture mimics the neural connectivity patterns of the human brain. This approach is designed to improve other deep learning algorithms, such as AlexNet, SSD and R-FCN, that have problems with processing time. The YOLO method divides the input image into a grid consisting of cells S x S, with bounding box B and the resulting confidence value for each cell. The principle of YOLO is to use different sizes and windows to change the entire image to a specific size and then classify the area that corresponds to this window so that it can perform an overall detection on the image [19], [20].

Based on the problem, a system will be developed that can identify the nutrition of several fruits and vegetables using the You Only Look Once (YOLO) method. YOLO is a method that can detect multiple objects in real time. In this study, a system was also developed that can predict the weight of fruits and vegetables to find out how much nutritional content of fruits and vegetables has been classified.

II. METHOD

A. Data Acquisition

The data acquisition process is to take photos of fruits and vegetables to be trained. The data will later be used as a dataset for the training process. The dataset in the form of photos of fruits and vegetables was obtained by taking pictures of fruits and vegetables using a mobile phone camera by adjusting the distance of the camera to the surface of the object by 30 cm, as shown in Figure 2. The data obtained from the shooting process is as many as 500 images from 12 types of fruits and vegetables that will be detected. In addition to the images taken manually, the shooting was also done by searching for images through google image as many as 33 images. The total images used for the training process were 533 images.

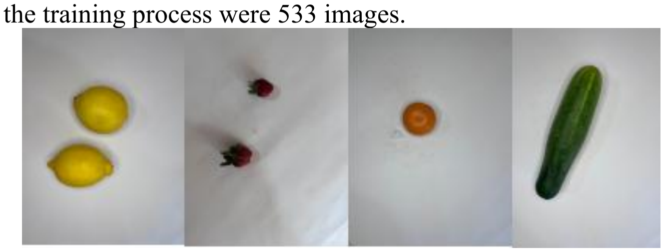
Figure 2. Example of a fruit or vegetable dataset

The dataset that has been prepared will be annotated or labeled to name the image or image object according to the format supported by CreateML during the training process. The annotation or labeling process is carried out using a web-based application, namely roboflow. In the process of annotating with roboflow, there are several stages that must be done.

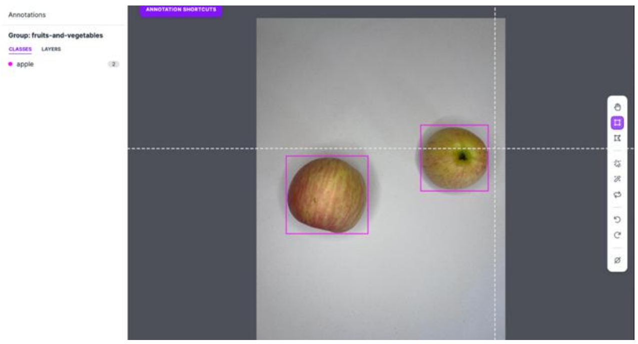

Figure 3. Images that have been annotated after uploading in roboflow

Figure 3 was shown the first is to create a new project in the workspace, and then upload the images that have been collected on the roboflow system. Once the image is uploaded, it will be marked unannotated which means it has not been annotated. When the image is clicked, it will enter the annotation or labeling process.

After all the images are annotated, they will be split into three parts, namely the training set, validation set, and testing set with percentages of 70%, 20%, and 10%. The output of the labeling or annotation process is an image file and a file in JSON format that contains information about the class, location, width and height of the bounding box. This format is the format supported by CreateML in carrying out the training process.

B. Design system

At this stage, the system flowchart can be seen in Figure 4. There are two parts in the flow diagram, namely the training system and the testing system. The first part of the system is to take image data.

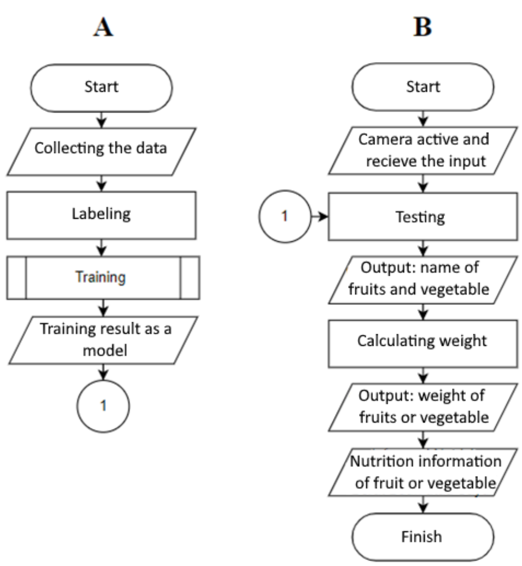

Figure 4. Flowchart training (A) and testing (B)

The tool used for the training process is CreateML. CreateML is a framework provided by Apple to make it easier for developers to create machine learning models. CreateML is used for the training process for several reasons such as ease of use, has training controls such as pause and resume, and has a model preview feature that can speed up and make it easier to test on a trained model. To conduct training using CreateML, it is necessary to install the XCode Integrated Development Environment (IDE), as shown in Figure 5. Once Xcode is successfully installed, open CreateML and create a new document. There will be many training data options in CreateML, which will be chosen to perform the object detection system.

TABLE I
REGRESSION EQUATION FOR FRUIT AND VEGETABLE

No	Fruit and Vegetable	Regression Equation
1	Apple	y = 91.89 + (1319 * x)
2	Grapes	y = 8.555 + (17.86 * x)
3	Mango	y = 61.82 + (2633 * x)
4	Lemon	y = 32.91 + (1927 * x)
5	Pear	y = 48.39 + (1915 * x)
6	Carrot	y = 29.65 + (1619 * x)
7	Potato	y = 7.829 + (2457 * x)
8	Tomato	y = 41.58 + (794.7 * x)
9	Cucumber	y = -63.70 + (2775 * x)
10	Orange	y = -11.19 + (2495 * x)
11	Banana	y = 68.74 - (9.574 * x)
12	Strawberry	y = -3.348 + (1532 * x)

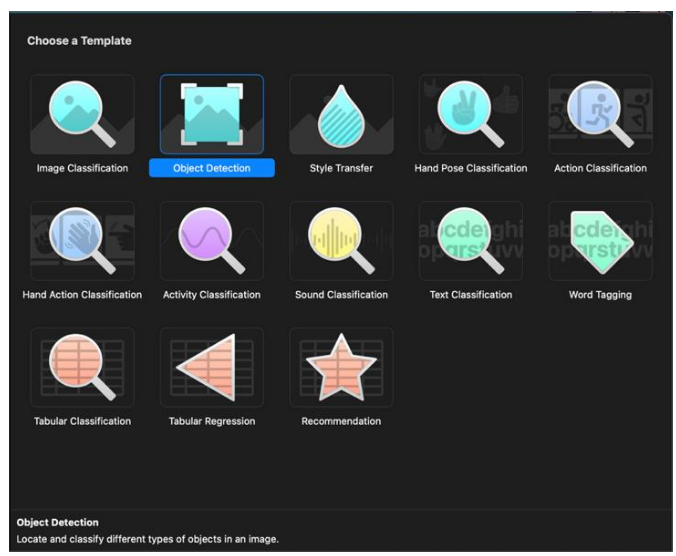

Figure 5. Menu view in CreateML

Next is to enter the image or dataset that has been prepared previously in CreateML. After the data training, data validation and testing data are successfully inputted, CreateML can run the training. Once the training is complete, the output of the training is a model with the .mlmodel file extension. The model file can later be used on Ios-based systems or applications.

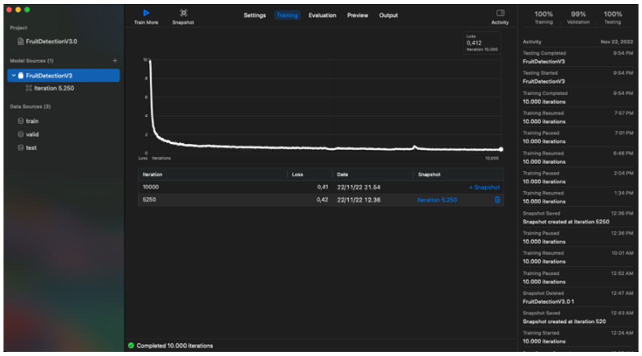

Figure 6. Graph of losses during training in CreateML

After the essay is trained with CreateML, the model of the training results will be used in the iOS application codebase, as shown in Figure 6. The iOS application is created using the swift programming language and can be run on the iOS operating system with at least iOS 12.0 version. After completing the training with CreateML, the model of the training results will be used in the iOS application codebase. iOS apps are built using the swift programming language and apps can run on iOS operating systems with at least iOS 12.0 versions.

To predict weight using linear regression, a linear regression equation of each fruit or vegetable that has been trained is required. The dependent variable of the regression is the weight of the fruit or vegetable and the independent variable is the extent of the bounding box. The data of the regression equation of fruits or vegetables can be seen from the Table 1.

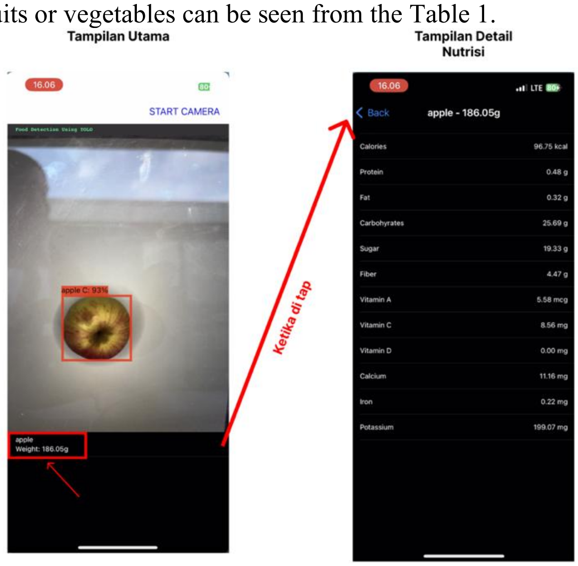

Figure 7 . Nutrition display

Nutrient identification can be done after the system can detect fruit or vegetable objects that have been trained beforehand. The parameters needed by the system to obtain nutritional data are the names of fruits and vegetables along with the weight prediction value. After obtaining these parameters, the system will look for nutrient data that has been defined in the system.

Fruit and vegetable nutrition data is obtained from the fatsecret platform, which is a verified nutrition information provider, as shown in Figure 7. Fatsecret is the largest provider of food and nutrition data verified through APIs for health programs, mobile applications, web services and integrated fitness devices [19]. Once the nutritional information is obtained, the system will display the nutritional data of the detected fruits and vegetables.

III. RESULT AND DISCUSSION

At this stage, testing will be carried out using the model obtained from the training results. The test will be carried out 10 times in the object detection test and 5 times in the weight prediction test. The system that has been created will be installed on iOS devices, namely iPhone 13 iOS version 16.1. Testing will be carried out using the system installed on the iPhone 13. The test was carried out indoors with a light intensity of 80 – 650 lux. In testing the model obtained, the training results will show that fruit and vegetable objects can be detected properly, incorrectly detected or undetected. The way to determine the accuracy of each experiment is to use the confusion matrix with the following calculations:

$$\text{Accuration} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

A. *Object detection test with additional light intensity on a white background*

Confusion Matrix can be seen in Table II.

TABLE II
CONFUSION MATRIX WITH 100% ADDITIONAL LIGHT INTENSITY

Prediction /Actual	Apple	Grape	Mango	Lemon	Pear	Carrot	Potato	Tomato	Cucumber	Orange	Banana	Strawberry
Apple	10	0	0	0	0	0	0	0	0	0	0	0
Grape	0	10	0	0	0	0	0	0	0	0	0	0
Mango	0	0	10	0	0	0	0	0	0	0	0	0
Lemon	0	0	0	10	0	0	0	0	0	0	0	0
Pear	0	0	0	0	10	0	0	0	0	0	0	0
Carrot	0	0	0	0	0	10	0	0	0	0	0	0
Potato	0	0	0	0	0	0	10	0	0	0	0	0
Tomato	0	0	0	0	0	0	0	10	0	0	0	0
Cucumber	0	0	0	0	0	0	0	0	10	0	0	0
Orange	0	0	0	0	0	0	0	0	0	10	0	0
Banana	0	0	0	0	0	0	0	0	0	0	10	0
Strawberry	0	0	0	0	0	0	0	0	0	0	0	10

At this stage, the test is carried out with the expected output in the form of a bounding box along with the names of fruits and vegetables. The test was carried out by setting the height of the camera, which is 30 cm. Light assistance from ring lights of 100% (600-650 lux), 50% (350-400 lux), and 10% (60-80 lux) is also used so that the results of object detection by the application or system have higher accuracy. In this test, fruits and vegetables will alternately be placed on a white background right under the camera 10 times.

Accuracy calculation based on confusion matrix by testing at the additional light intensity of the ring light of 100% (600-650 lux), apples, grapes, manga, lemons, pears, carrots, potatoes, tomatoes, cucumbers, oranges, bananas, and strawberries got 10 times true positive in 10 trials, as seen in Table 2.

Accuracy calculation based on confusion matrix by testing at the additional light intensity of the ring light of 100% (600-650 lux), apples, grapes, manga, lemons, pears, carrots, potatoes, tomatoes, cucumbers, oranges, bananas, and strawberries got 10 times true positive in 10 trials. Accuracy calculations show that the application or system can detect fruits and vegetables at an additional light intensity of 100% (600-650 lux) well without any errors in detecting by producing an accuracy of 100% on each fruit and vegetable object and with a total accuracy of 100%, as seen in Table III.

TABLE III
CALCULATION ACCURACY WITH 100% ADDITIONAL LIGHT INTENSITY

Fruits/Vegetables	TP	TN	FP	FN	Accuracy
Apple	10	110	0	0	100%
Grape	10	110	0	0	100%
Mango	10	110	0	0	100%
Lemon	10	110	0	0	100%
Pear	10	110	0	0	100%
Carrot	10	110	0	0	100%
Potato	10	110	0	0	100%
Tomato	10	110	0	0	100%
Cucumber	10	110	0	0	100%
Orange	10	110	0	0	100%
Banana	10	110	0	0	100%
Strawberry	10	110	0	0	100%
Total Accuracy					100%

Accuracy calculation based on the confusion matrix by testing at the additional light intensity of the ring light by 50% (350-400 lux), apples, grapes, manga, lemons, pears, carrots, potatoes, tomatoes, cucumbers, oranges, bananas, and strawberries got 10 times true positive in 10 trials. Accuracy calculations show that the application or system can detect fruits and vegetables at an additional light intensity of 50% (350-400 lux) well without any errors in detecting by producing an accuracy of 100% on each fruit and vegetable object and with a total accuracy of 100%, as seen in Table 4.

TABLE 4
CONFUSION MATRIX WITH 50% ADDITIONAL LIGHT INTENSITY

Prediction /Actual	Apple	Grape	Mango	Lemon	Pear	Carrot	Potato	Tomato	Cucumber	Orange	Banana	Strawberry
Apple	10	0	0	0	0	0	0	0	0	0	0	0
Grape	0	10	0	0	0	0	0	0	0	0	0	0
Mango	0	0	10	0	0	0	0	0	0	0	0	0
Lemon	0	0	0	10	0	0	0	0	0	0	0	0
Pear	0	0	0	0	10	0	0	0	0	0	0	0
Carrot	0	0	0	0	0	10	0	0	0	0	0	0
Potato	0	0	0	0	0	0	10	0	0	0	0	0
Tomato	0	0	0	0	0	0	0	10	0	0	0	0
Cucumber	0	0	0	0	0	0	0	0	10	0	0	0
Orange	0	0	0	0	0	0	0	0	0	10	0	0
Banana	0	0	0	0	0	0	0	0	0	0	10	0
Strawberry	0	0	0	0	0	0	0	0	0	0	0	10

Calculation of accuracy based on confusion matrix with additional light intensity from Ring Light 10% (60-80 lux) objects of apples, grapes, manga, lemons, pears, carrots, potatoes, tomatoes, oranges, bananas, strawberries get 10 times true positive in 10 trials. Meanwhile, cucumbers got 9 times true positive. Accuracy calculations show that the application or system can detect fruits and vegetables at an additional light intensity of 10% (60-80 lux) well without any fatal errors in detection by producing 100% accuracy on apples, grapes, lemons, pears, carrots, potatoes, tomatoes, oranges, bananas and strawberries, while mangoes and cucumbers are 99% and with a total accuracy of 99.9%, as seen in Table 5.

TABLE 5
ACCURATE CALCULATION WITH 50% ADDITIONAL LIGHT INTENSITY

Fruits/Vegetables	**TP**	**TN**	**FP**	**FN**	**Accuracy**
Apple	10	110	0	0	100%
Grape	10	110	0	0	100%
Mango	10	110	0	0	100%
Lemon	10	110	0	0	100%
Pear	10	110	0	0	100%
Carrot	10	110	0	0	100%
Potato	10	110	0	0	100%
Tomato	10	110	0	0	100%
Cucumber	10	110	0	0	100%
Orange	10	110	0	0	100%
Banana	10	110	0	0	100%
Strawberry	10	110	0	0	100%
			Total Accuracy		100%

Accuracy calculation based on the confusion matrix by testing at the additional light intensity of the ring light by 10% (350-400 lux), apples, grapes, manga, lemons, pears, carrots, potatoes, tomatoes, oranges, bananas, and strawberries got 10 times true positive in 10 trials, except cucumbers. Accuracy calculations show that the application or system can detect fruits and vegetables at an additional light intensity of 10% (350-400 lux) with errors in detecting by producing an accuracy of 50% on each fruit and vegetable object and with a total accuracy of 50%, as seen in Table 6.

TABLE 6
ACCURATE CALCULATION WITH 10% ADDITIONAL LIGHT INTENSITY

Prediction /Actual	Apple	Grape	Mango	Lemon	Pear	Carrot	Potato	Tomato	Cucumber	Orange	Banana	Strawberry
Apple	10	0	0	0	0	0	0	0	0	0	0	0
Grape	0	10	0	0	0	0	0	0	0	0	0	0
Mango	0	0	10	0	0	0	0	0	0	0	0	0
Lemon	0	0	0	10	0	0	0	0	0	0	0	0
Pear	0	0	0	0	10	0	0	0	0	0	0	0
Carrot	0	0	0	0	0	10	0	0	0	0	0	0
Potato	0	0	0	0	0	0	10	0	0	0	0	0
Tomato	0	0	0	0	0	0	0	10	0	0	0	0
Cucumber	0	0	1	0	0	0	0	0	10	0	0	0
Orange	0	0	0	0	0	0	0	0	0	10	0	0
Banana	0	0	0	0	0	0	0	0	0	0	10	0
Strawberry	0	0	0	0	0	0	0	0	0	0	0	10

B. *Object Detection Testing Without Additional Light Intensity on White Background*

At this stage, the test is carried out with the expected output in the form of a bounding box along with the names of fruits and vegetables. The test was carried out by setting the height of the camera, which is 30 cm. No light assistance from ring lights is used and the light intensity from the room ranges from 10–25 lux. In this test, fruits and vegetables will be placed alternately on a white background right under the camera 10 times, as seen in Table 7.

Accuracy calculation based on confusion matrix with unassisted conditions of light intensity from ring light with light intensity ranging from 10-25 lux., apples, grapes, lemons, carrots, potatoes, tomatoes, bananas, and strawberries got 10 times true positive in 10 trials. Meanwhile, mangoes, cucumbers, and oranges got 9 true positives, and pears got 8 true positives.

TABLE 7
CONFUSION MATRIX WITHOUT ADDITIONAL LIGHT INTENSITY

Prediction /Actual	Apple	Grape	Mango	Lemon	Pear	Carrot	Potato	Tomato	Cucumber	Orange	Banana	Strawberry
Apple	10	0	0	0	0	0	0	0	0	0	0	0
Grape	0	10	0	0	0	0	0	0	0	0	0	0
Mango	0	0	9	1	0	0	0	0	0	0	0	0
Lemon	0	0	0	10	0	0	0	0	0	0	0	0
Pear	0	0	0	0	8	0	1	0	0	0	1	0
Carrot	0	0	0	0	0	10	0	0	0	0	0	0
Potato	0	0	0	0	0	0	10	0	0	0	0	0
Tomato	0	0	0	0	0	0	0	10	0	0	0	0
Cucumber	0	0	0	0	0	0	0	0	10	0	0	0
Orange	0	0	0	1	0	0	0	0	0	9	0	0
Banana	0	0	0	0	0	0	0	0	0	0	10	0
Strawberry	0	0	0	0	0	0	0	0	0	0	0	10

As seen in Table 8, the accuracy calculations show that the application or system can detect fruits and vegetables without the help of light intensity from the ring light well without any fatal errors in detecting by producing an accuracy of 99.4% on apples, grapes, carrots, tomatoes and strawberries, 99% for mangoes, potatoes, cucumbers, oranges, and bananas while lemons and pears are 98% and with a total accuracy of 99.4%.

TABLE 8
ACCURATE CALCULATIONS WITHOUT ADDITIONAL LIGHT INTENSITY

Fruits/Vegetables	TP	TN	FP	FN	Accuracy
Apple	10	110	0	0	100%
Grape	10	110	0	0	100%
Mango	9	110	0	1	99%
Lemon	10	110	2	0	98%
Pear	8	110	0	2	98%
Carrot	10	110	0	0	100%
Potato	10	110	1	0	99%
Tomato	10	110	0	0	100%
Cucumber	9	110	0	1	99%
Orange	9	110	0	1	99%
Banana	10	110	1	0	99%
Strawberry	10	110	0	0	100%
			Total Accuracy		99,4%

C. Object Detection Testing Without Additional Light Intensity and Without White Background

The test is carried out with output in form of bounding box along, names of fruits and vegetables. The test was carried out by setting the height of the camera, which is 30 cm and no light assistance from the ring light is used. The only light source is from lamps in rooms with light intensity between 10-25 lux.

TABLE 9
CONFUSION MATRIX WITH NO ADDITIONAL LIGHT INTENSITY AND NO WHITE BACKGROUND

Prediction /Actual	Apple	Grape	Mango	Lemon	Pear	Carrot	Potato	Tomato	Cucumber	Orange	Banana	Strawberry
Apple	10	0	0	0	0	0	0	0	0	0	0	0
Grape	0	10	0	0	0	0	0	0	0	0	0	0
Mango	0	0	10	0	0	0	0	0	0	0	0	0
Lemon	0	0	0	10	0	0	0	0	0	0	0	0
Pear	0	0	0	0	5	0	5	0	0	0	0	0
Carrot	0	0	0	0	0	10	0	0	0	0	0	0
Potato	0	0	0	0	0	0	10	0	0	0	0	0
Tomato	0	0	0	0	0	0	0	10	0	0	0	0
Cucumber	0	0	0	0	0	0	0	0	10	0	0	0
Orange	0	0	0	0	0	0	0	0	0	9	0	0
Banana	0	0	0	0	0	0	0	0	0	0	10	0
Strawberry	0	1	0	0	0	0	0	0	0	0	0	9

The calculation of accuracy based on the confusion matrix with the condition without the help of the light intensity of the ring light with the light intensity ranging from 10-25 lux and without a white background, apples, grapes, mangoes, lemons, carrots, potatoes, tomatoes, cucumbers, oranges, and bananas got 10 times true positive in 10 trials, as seen in Table 9.

TABLE 10
ACCURATE CALCULATIONS WITHOUT ADDITIONAL LIGHT INTENSITY AND WITHOUT WHITE BACKGROUND

Fruits/Vegetables	TP	TN	FP	FN	Accuracy
Apple	10	110	0	0	100%
Grape	10	110	1	0	99%
Mango	10	110	0	0	100%
Lemon	10	110	0	0	100%
Pear	5	110	0	5	96%
Carrot	10	110	0	0	100%
Potato	10	110	5	0	96%
Tomato	10	110	0	0	100%
Cucumber	10	110	0	0	100%
Orange	10	110	0	0	100%
Banana	10	110	0	0	100%
Strawberry	9	110	0	1	99%
			Total Accuracy		99,2%

While pears get 5 true positives, and strawberries get 9 true positives. Accuracy calculations show that the application or system can detect fruits and vegetables without additional light intensity from the ring light and without a white background well without any fatal errors in detecting by producing the accuracy on apples, mangoes, lemons, carrots, tomatoes, cucumbers, oranges, and bananas is 100%, grapes and strawberries are 99%, pears and potatoes are 96% and with a total accuracy of 99.2%, as seen in Table 10.

The percentage of potato errors occurs because of the similar geometry of lemons without additional lighting. This phenomenon will affect the percentage of accuracy in the calculation of potatoes.

D. Fruit and Vegetable Weight Prediction Testing

At the fruit and vegetable weight prediction testing stage, the system test results are in the form of bounding boxes and weight prediction values in grams. The test was carried out by setting the background on a white object, adjusting the height distance of the camera which is 30 cm and providing additional light intensity from the ring light measured using the lux meter application. The test experiment was carried out five times, with the light intensity of the ring light being 100% (600-650 lux) and 50% (350-400 lux).

TABLE 11
ERROR CALCULATION WITH 100% ADDITIONAL LIGHT INTENSITY

Fruits/Vegetables	Testing#1 Error (%)	Testing#2 Error (%)	Testing#3 Error (%)	Testing#4 Error (%)	Testing#5 Error (%)
Apple	0,58	9,75	1,25	1,26	5,86
Grape	15,89	8,92	12,47	4,70	2,59
Mango	0,91	2,05	2,24	0,13	8,23
Lemon	3,38	6,44	7,08	3,34	3,91
Pear	5,76	10,90	0,32	7,62	14,05
Carrot	7,21	5,13	0,74	3,60	3,21
Potato	23,57	9,14	0,08	6,69	2,03
Tomato	2,94	10,71	0,42	2,54	6,47
Cucumber	6,77	4,02	5,82	1,08	1,93
Orange	0,39	1,58	2,91	10,89	6,59
Banana	4,91	6,29	7,18	7,26	6,97
Strawberry	11,89	10,21	5,26	9,80	0,65

After obtaining the actual data and prediction data generated by the system, errors in each fruit and vegetable can be calculated in each experiment. The biggest error in this test was on the potato object. This happens because of the light factor that causes the area value of the bounding box to be larger. With the placement of fruits and vegetables, the error and prediction values can be reduced. The quality of regression data that produces regression equations also greatly affects the results of weight prediction calculations carried out by the system. The average error in the weight test with 100% additional light intensity conducted in five trials was 5.61%. After obtaining the actual data and prediction data generated by the application, errors in each fruit and vegetable can be calculated in each experiment. The biggest error is in wine. This can happen because of the light factor that causes the area value of the bounding box to be larger. With the placement of fruits and vegetables, the error and prediction values can be reduced. The quality of regression data that produces regression equations also greatly affects the results of weight prediction calculations carried out by the system.

TABLE 12
ERROR CALCULATION WITH 50% ADDITIONAL LIGHT INTENSITY

Fruits/Vegetables	Testing#1 Error (%)	Testing#2 Error (%)	Testing#3 Error (%)	Testing#4 Error (%)	Testing#5 Error (%)
Apple	0,42	2,53	0,86	2,84	0,46
Grape	12,47	4,70	2,36	7,95	27,73
Mango	4,21	5,58	9,53	0,32	0,24
Lemon	6,63	14,59	3,28	2,35	8,20
Pear	20,01	14,30	5,86	3,45	0,39
Carrot	8,73	6,96	7,05	15,09	6,60
Potato	4,05	0,79	6,70	1,86	4,39
Tomato	3,60	9,49	4,74	6,62	2,21
Cucumber	4,55	15,43	9,64	5,39	5,58
Orange	1,59	1,17	1,34	3,05	8,85
Banana	1,64	7,23	4,65	2,75	2,82
Strawberry	4,21	1,37	11,71	5,71	14,25

The average error in the weight test with 50% additional light intensity conducted in five trials was 6.06%. By reducing the intensity of light, the average error produced by the system is greater because the accuracy of the system in determining the bounding box of the object is also reduced.

IV. CONCLUSION

Based on the testing process that has been carried out, the application or system for detecting and predicting the weight of fruits and vegetables using iOS-based YOLO V2 has obtained good results. The system is able to classify fruits and vegetables using the camera from an iOS device. The system is also able to display weight prediction values and also nutritional information from fruits and vegetables. The accuracy of an object detection system with supporting lighting can be up to 100% and an accuracy of 99.4% if the exposure is reduced by 10%. When lighting only uses room light without the help of light from a ring light, the system can still be able to get an accuracy value of 99.2%. The system is also able to detect several fruits and vegetables at once in real time. In addition to detecting apples, grapes, mangoes, lemons, pears, carrots, potatoes, tomatoes, cucumbers, oranges, bananas, strawberries, the system can also predict the weight value of each fruit and vegetable. The average error value of five experiments conducted on 12 types of fruits and vegetables was 5.6% with an additional light intensity from the ring light of 100%. With an additional ring light of 50%, the error rate in the prediction increased to 6.06% due to the increasingly inaccurate placement and calculation of bounding boxes in the system. To improve the accuracy of the detection system, what must be done is to multiply the dataset or iteration during the learning process. The quality of the dataset also needs to be considered, the images of each fruit are taken from different backgrounds, points of view, and heights as much as possible so that the dataset is more varied. To reduce the error value in weight prediction, it is necessary to take more data on area and weight with more fruit variety.

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