Analysis Quality of Corn Based on IoT, SSD Mobilenet Models and Histogram

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***Abstract*—Corn is one of the main comestibles in our society. In these last few years, the production of comestible in Indonesia has decreased, including corn. For this reason, besides increasing the production of corn, it is necessary to research corn quality so that corn has a competitive advantage. The research aims to monitor the corn's growth and classify the corn's quality. The research was divided into two aspects: the aspect of good corn growth, with the internet of things (IoT) monitoring, and the classification of the corn quality based on the RGB intensity pattern of digital and TensorFlow using SSD Mobilenet models. On the corn growth, the research observed temperature, humidity, and plant distance based on two kinds of corn plant diseases (blight leaf and rotten knob), using a microcontroller (Arduino Uno), DHT11 sensor, VL53L0X sensor, and ESP8266 for accessing data to a website. The quality of corn was classified into three groups, namely rotten, moldy, and normal. The classification was carried out using Python programming on Raspberry Pi with open-source library TensorFlow using SSD Mobilenet models (as the primary option for classifying the quality of corn) and Delphi 7 on a computer (as an additional option). The number of samples used was 180 sample corn seeds tested ten times for each type of quality. The results showed that the recognition of normal corn quality was nine times correct, moldy corn quality was seven times correct, and rotten corn quality was six times correct with an accuracy rate of 73.3%.**

***Keywords*—Arduino Uno, DHT11, VL53L0X, ESP8266, SSD Mobilenet Models, RGB.**

I. Introduction

Indonesia is an agricultural country since most Indonesian rely on the agricultural sector to live. However, in recent years, the threat toward agricultural materials has significantly increased that it lowers productivity. One of the agricultural materials with threatened productivity is corn (*Zea mays L.*). In 2016, the total consumption of corn was 23.84 million tons, while the corn production was 23.58 million tons [1]. The data showed that Indonesia experienced a corn deficit of 0.26 million tons, which was also experienced in the previous year.

In addition to increasing the productivity of corn, improvement on the corn product quality must also be considered so that corn commodities have a competitive advantage. However, in fact, the corn quality remains an issue. This study examined the corn quality during its growth using internet of things (IoT)-based communication and identified the corn quality using computer vision. Therefore, it can facilitate farmers monitoring of corn during the growing season and after harvest.

There are two common problems encountered during corns' growing season. The first problem is leaf blight on corn plants, characterized by wet spots on old leaves that can infect young leaves. The cause of this plant disease is *H. turcicum* fungus which has infected corn plants. This fungus can grow in humid areas and survive up to one year. Therefore, leaf blight is frequently infecting corn plants during the rainy season and those grown in very humid areas. Since the medium for fungus to spread is the wind, it usually infects the leaves and then the corn stalks [2]. The second problem is cob rot which symptoms include rotting corn cobs that lead to crop failure. The infected corn plants by *Fusarium moniliforme* fungus and too close distance between corn plants cause this disease. The fungus on cob rot proliferates in areas with high humidity if the previously planted soil variety has also been exposed to cob rot [3].

A survey with corn farmers as the respondents has been previously conducted. The survey revealed that most farmers used high-yielding variety corn seeds to keep the corn plants healthy. In testing the occurrence of cob rot, this study used low-yielding variety seeds planted in cornfields located in normal, rain, and residential areas. Alternatives were made by monitoring air temperature, air humidity, and plant distance between corn using a microcontroller (Arduino), DHT11 sensor, and IoT-based VL53L0X sensor. IoT is a concept aiming to expand the benefits of continuously connected internet connectivity. The concept of IoT itself is simple. It has three main components: physical goods with IoT modules, device connected to the internet, and cloud data to store the database. The Arduino module and sensors served as physical items in the corn growth monitoring tool. The ESP8266 module connected the module to the internet, and the cloud data served as database storage using 000webhost. The corn growth monitoring will appear on the website in real-time [4]. Employing IoT communication can facilitate the corn farmers not to monitor corn fields directly as it can be done at home or other places.

Digital image processing is an alternative used in testing the quality of corn without damaging the sample (object). Using this technology, corn quality can be determined quickly and inexpensively with a reliable level of accuracy. The use of image processing technology to identify the physical quality of corn can provide up to 95% accuracy [5].

A convolutional neural network (CNN) is a machine learning method developed from multi-layer perceptron (MLP) to process two-dimensional data. CNN is a type of deep learning algorithm that can accept input in the form of images, determine what aspects or objects in an image can be used by

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TABLE I
DEFINITION OF CORN DISEASE

Disease	Definition	Reason
Leaf blight	Wet spots on old leaves and cause corn plant leave to dry out	Very high humidity
Cob rot	Infected maize plants with early symptoms of cob rot maize and maize seeds in maize are spaced.	Planting too close

machines to recognize images, and distinguish one image from another [6]. The modeling system used was the single-shot detector (SSD) Mobilenet model, which is one of the CNN architectures. The training process on this neural network is the stage where the neural network is trained to obtain high accuracy from the classification conducted. This stage consists of a feed-forward process and a backpropagation process [7].

This paper aims to describe what affects corn's quality in terms of corn plant growth and the physical aspect of corn harvest. In terms of corn plant growth, research was carried out by monitoring the growth based on two types of corn diseases, namely leaf blight and cob rot which were communicated by IoT. From the physical aspect of corn harvest, digital image processing research was conducted using the SSD Mobilenet model to classify corn quality and analyze the differences in the RGB color index as an additional option in classifying corn quality. Table I shows the definition of each corn disease, the physical characteristics of corn disease, and the causes of corn disease [8].

II. METHODOLOGY

A. Corn Plant Growth

The research monitored the growth of corn concerning leaf blight and cob rot. The focus included monitoring air temperature, air humidity, and plant distance where the data would appear on the device's LCD and could be accessed on the website as IoT-based communication. LEDs and buzzers were used to notify the conditions of planting and growing corn in fields as well as accessing websites.

The workflow of the corn growth monitoring tool is described in Fig. 1. Based on Fig. 1, the programming is done using the Arduino programming application. DHT11 sensor is used to read the air temperature and humidity; meanwhile, the VL53L0X sensor with IoT-based communication is used to read the plant distance. In this research, IoT communication was used to facilitate corn farmers remotely monitoring the condition of cornfields, namely the corn growth. This monitoring could be accessed on a website designed without any control related to corn growth conditions. Data in the form of air humidity, air temperature, and plant distance were data appearing on the website. In the work system of the corn growth monitoring tool with IoT communication, the web page was designed on the 000webhost site with the main tools in the form of *index.php* and *log.php*. The ESP8266 module was used to connect the Arduino module to the internet network using the

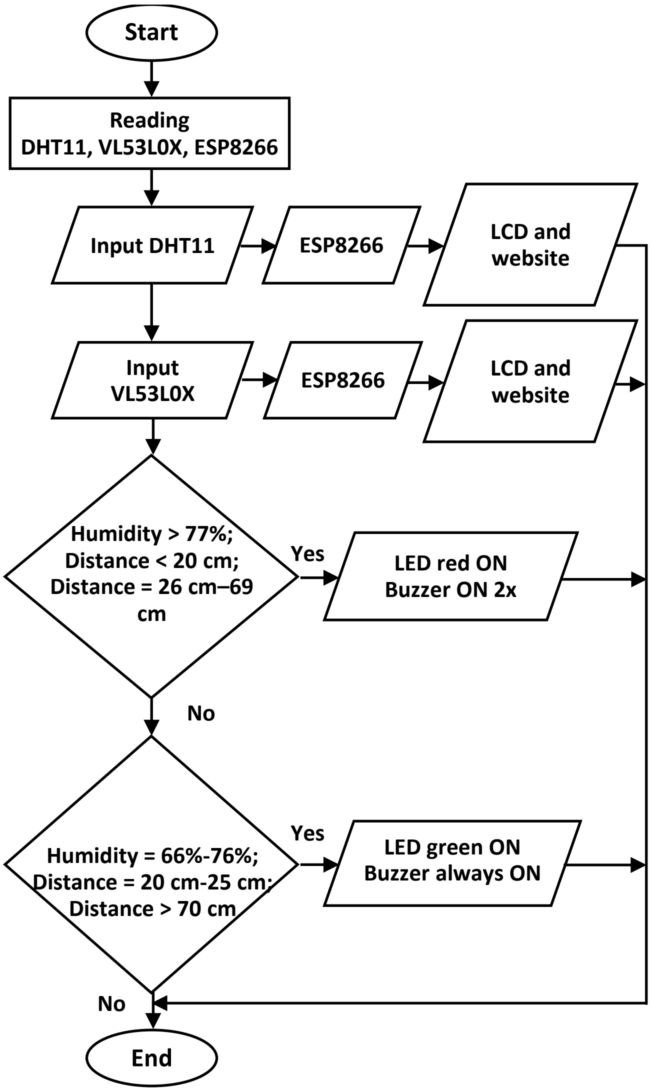

Fig. 1 Flowchart of corn growth monitoring tool.

[9]. Besides the display on the website, the output of this monitoring tool was the display on the LCD, LED, and buzzer.

The yellow LED turned on when the Arduino was connected to the internet. The red LED was on when the air temperature and humidity were not suitable, and the green one was on when the air temperature and humidity were suitable. The buzzer was used explicitly for the output of the plant distance. The buzzer turned on twice if the distance between corns was suitable; if it was not, the buzzer was always on.

B. Identification of Corn Quality with Digital Image Processing

The research methodology on corn quality is described in Fig. 2.

1) Corn Samples: The samples used consisted of three types of corn quality, namely normal seeds, moldy seeds, and rotten seeds, with the number of samples used being sixty seeds for each corn quality. The training data was 80%, and the test data was 20% of the total sample. The testing of the new data used three types of corn quality, as many as 30 cobs.

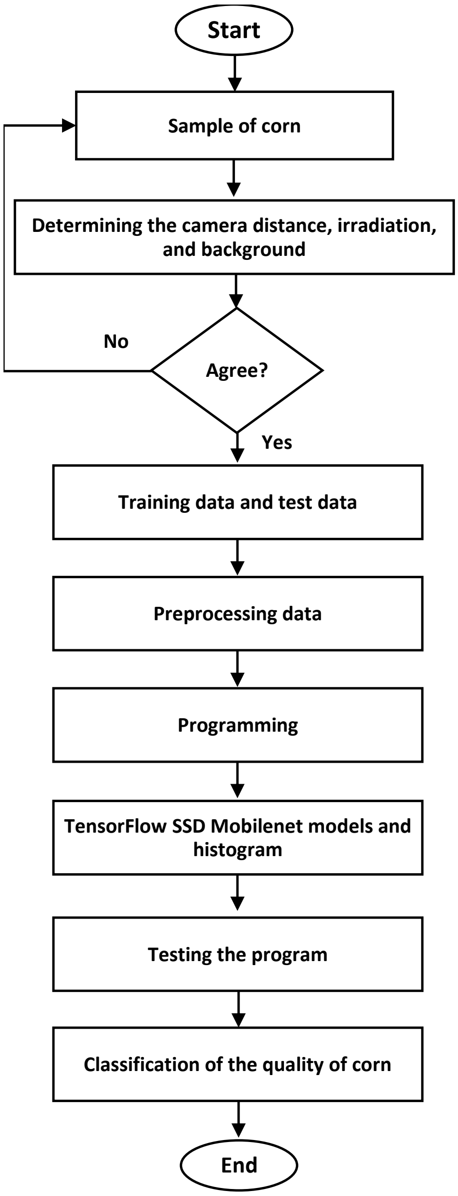

Fig. 2 Flowchart of research methodology of maize digital image processing.

2) Camera Distance, Illumination, Background: The camera distance, illumination, and background were determined, which later resulted in training and test data processed by Python Raspberry Pi programming with the TensorFlow open-source library using SSD Mobilenet models. Subsequently, the accuracy/similarity of the data was observed in which final testing used corn cob. The training and test data obtained would enter the data preprocessing stage according to each predetermined quality of corn kernels.

3) Training and Test Data: The process of collecting training and test data is as a training process in the form of sampling the quality of three corn kernel types, namely normal, moldy, and rotten corn seeds, and extracting the main features of each type of corn kernel quality.

4) Preprocessing Data: Data preprocessing is an important stage in data collection. The data used in the data retrieval process is not always in good condition for processing. There are obstacles such as unsuitable data formats for the system, outliers, missing values, etc. Preprocessing data is one of the steps that eliminate these problems. Data preprocessing stages included image labeling, XML data conversion to CSV, CSV conversion to TF Record, and map labeling.

TABLE II
DHT11 SENSOR READ DATA IN NORMAL AREA

Days after Planting	Average Air Temperature (°C)	Average Air Humidity (%)	Average Distance 1 (cm)	Average Distance 2 (cm)
1-10 days	27.39	70.56	25.36	75.87
11-20 days	26.46	74.34	25.05	75.90
21-30 days	28.28	66.43	25.66	75.40
31-40 days	28.08	67.27	24.02	74.84
41-50 days	29.70	62.93	24.05	74.83
51-60 days	28.45	62.83	23.30	73.66
61-70 days	29.21	65.73	23.40	72.07
71-80 days	29.13	62.47	21.10	72.30
81-90 days	28.47	64.73	21.62	72.45
91-100 days	26.75	64.20	21.40	72.05

5) Digital Image Processing Programming: There are two types of digital image processing programming applications. The first type was Python programming on Raspberry Pi with TensorFlow using the SSD Mobilenet model to display corn quality in real-time. The second type was Delphi 7 programming used to display the histogram analysis on each corn quality, which was an additional option for corn quality recognition.

In programming Python on Raspberry Pi, TensorFlow was used. TensorFlow is an open-source library for building and training neural networks, enabling pattern detection and correlation, which are similar to learning and reasoning used by humans. TensorFlow is intended for research, coding, and machine learning development. This library can be used in various programming languages such as Python, Java, and C++ [10].

The programming design on the TensorFlow used deep learning algorithms and the SSD Mobilenet model. The SSD Mobilenet was used for image processing in classifying corn quality. The SSD Mobilenet is one of the CNN architectures. What distinguishes SSD Mobilenet from CNN is the use of a convolution layer according to the filter thickness matching the input image thickness [11].

Fig. 3 shows the stages of corn quality classification using Python programming with TensorFlow using the SSD model. The training data was 80% of the total sample and the test data was 20% of the total sample. These datasets were labeled with corn quality classification.

After the data preprocessing stage, the SSD Mobilenet training was conducted. In this stage, the image was processed with the SSD model consisting of a convolution process, activation function, and pooling. The convolution process was carried out six times with a convolution layer of 3 x 3, while the pooling size used was 2 x 2. Pooling was carried out two times, after the first three convolution processes and the second three convolution processes. It was done so that the input size was not drastically reduced in every process conducted. Meanwhile, the activation function was intended to faster the training process.

In the SSD Mobilenet generated model, the SSD generated model was stored to load the data considered. Subsequently, the SSD model could be used at any time with the new data to evaluate the accuracy/similarity percentage of the model. Mobilenet's complete SSD architecture for corn quality classification added a full connection network layer to the training architecture.

After the Mobilenet SSD model was generated, the next step was to test the model by testing/evaluating the trained model. The test used thirty corn cobs with various qualities of corn. This study used the same training parameters, namely the maximum epoch value of 100 and the mini-batch size of 6. The setting of the convolution2d layer used the length and width of filter2 and maxpooling2d layer in the size of 2 x 2. The experimental data was a set of corn images. This data was the input for the model generated by SSD Mobilenet to predict the accuracy level in the image that was close to the similarity of the corn image.

The last stage was image evaluation conducted by comparing the accuracy/similarity of the dataset with new data (video), which output displayed the level of accuracy/similarity in the form of a percentage which was the comparison of accuracy value with the additional concentration of layer numbers on the Mobilenet SSD architecture. This addition did not change the value of predefined parameters such as epoch value and learning rate. The accuracy value was obtained from the sum of the accuracy values of each convolutional layer. In this research, six convolutional layers were used, so that after the sixth layer was the accuracy values average of each layer. The training and test data were corn kernels, while the final testing data was corn cobs.

The Delphi 7 programming aims to analyze the histogram on corn quality. In this stage, the RGB index analysis on corn quality images displayed a diagram describing the frequency distribution of the pixel intensity values in an image.

Histogram feature extraction in this study was an additional option for corn quality recognition. It was carried out by extracting the average (mean) and deviation values (standard deviation) of each RGB index value, so three mean values and three standard deviation values for each image were obtained [12]. These values were obtained from the Delphi 7 toolbox. The higher the color index, the brighter the image is; the smaller the color index value, the darker the image is [13].

The mean value indicates the average intensity value of each RGB index; meanwhile, the standard deviation value indicates the maximum deviation from the average intensity value of each RGB color index. The following is the calculation of the standard deviation.

$$\mu = \frac{\Sigma X}{N} \quad (1)$$

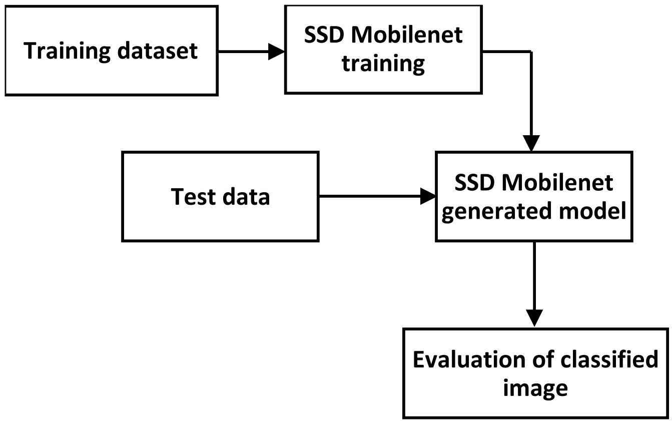

Fig. 3 Flowchart of corn quality detection using TensorFlow with SSD Mobilenet model.

$$\sigma = \sqrt{\frac{\Sigma(X-\mu)^2}{N}}. \quad (2)$$

Where σ is the standard deviation, Σ is the addition operation symbol, μ is the average value of the calculated data, X is the value of each data, and N is the total number of data [14].

III. Results and Discussion

A. Corn Plant Growth Monitoring

The values were read by the DHT11 sensor and the VL53L0X sensor using Arduino programming. The data read by the sensor was then displayed on the LCD and the website using ESP8266 to connect the device to the internet network.

In the leaf blight data collection, there were two areas as the research object. The first was the normal area in Tilatang Kamang, Agam Regency, West Sumatra. The second was high rainfall area, namely Padang Panjang, West Sumatra. The research for the cob rot disease was carried out in the residential area, namely Tambuo, Tilatang Kamang, West Sumatra, with a close plant distance and in previous areas (normal and rain areas) with an appropriate plant distance.

The appropriate value of air temperature for growing corn is 21ºC until 34ºC, with the humidity between 60%-76%. Meanwhile, the appropriate air temperature value for fungus to grow is 18C - 27ºC with humidity above 77%. The corn should be planted within a distance of 75 cm x 25 cm.

1) Normal Area: Table II describes research data taken in normal areas. Based on Table II, the average temperature of cornfields in normal areas during the research conducted from March to June 2021 is in the range of 26.46ºC to 29.7ºC. The highest average temperature was 29.7ºC. It occurred on the fifth ten days when plants were 41-50 days old. The lowest average temperature was 26.46ºC. It occurred on the second ten days when the plants were 11-20 days old. This temperature range is the optimal temperature for corn to grow. The average humidity during the research ranged from 62.47% - 74.34%. Due to frequent rains, the highest average humidity occurred on the second ten days when the plants were 11-20 days old. The lowest average humidity occurred on the eighth ten days, when

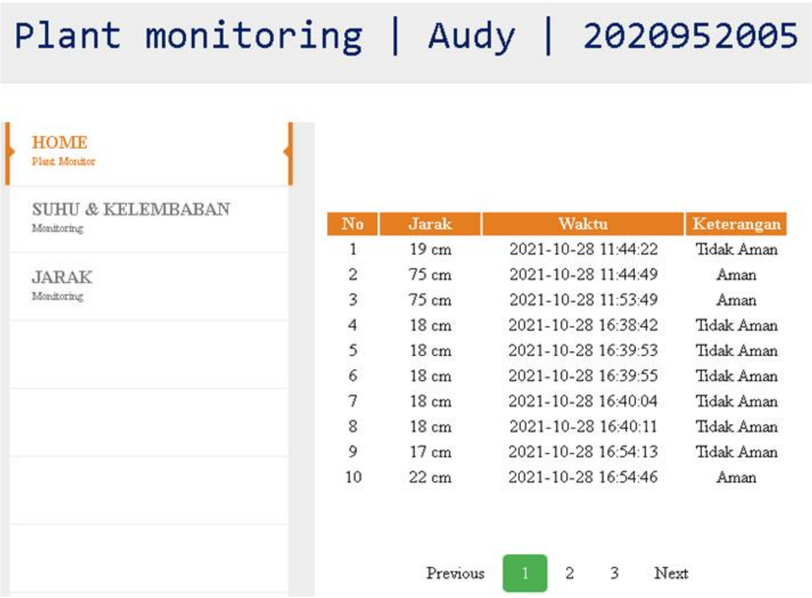

Fig. 4 Display of corn growth monitoring data.

TABLE III
DHT11 SENSOR READ DATA IN THE RAINY SEASON

Days after Planting	Average Air Temperature (ºC)	Average Air Humidity (%)	Average Distance 1 (cm)	Average Distance 2 (cm)
1-10 days	24.21	83.34	25.04	75.86
11-20 days	21.23	95.22	25.12	75.67
21-30 days	25.09	87.45	25.87	75.21
31-40 days	26.67	83.31	25.02	75.09
41-50 days	26.54	87.21	24.17	75.63
51-60 days	25.42	89.78	24.90	74.06
61-70 days	24.19	90.20	23.66	74.98
71-80 days	24.20	94.67	23.10	73.20
81-90 days	24.51	88.80	22.62	71.09
91-100 days	21.89	91.20	22.89	71.56

the dry season started. The rain rarely falls and the humidity decreases during this season. In this average air humidity, the fungus is unlikely to grow.

The corn was planted within a distance of 75 cm x 25 cm. Corn monitoring was conducted for 100 days and the data were averaged every ten days. The distance between corn plants changed along with the growth of corn stalks. Based on Table II, for 100 days, the corn plants are at an appropriate distance of 21 cm-25 cm and 70 cm-75 cm. The observations conducted in normal areas using low-yielding corn seed showed that corn plants did not get leaf blight and cob rot.

2) Rain Area: Table III describes research data taken during the rainy season. Based on Table III, the average temperature in the rainy season, during the research conducted from March to June 2021, is in the range of 21.23ºC to 26.67ºC. The highest average temperature was 26.67ºC. It occurred in the fourth ten days, when plants were 41-50 days old. The lowest average temperature was 21.23ºC. It occurred on the fourth ten days when the plants were 11-20 days old. This temperature range is the optimal temperature for corn and fungus to grow.

The average humidity during the study ranged from 83.31% to 95.22%. Due to frequent rains, the highest average humidity occurred on the second ten days, when the plants were 11-20 days old. The lowest average humidity was 83.31%. It happened at the fourth ten days, when the plants were 31-40 days old. In this air humidity range, fungus quickly grows. On the 43rd day, yellow spots appeared on the corn leaves as an early stage of leaf blight disease. On the 60th day, the lower leaves of the corn plant turned yellow and yellow spots on the corn stalks were visible.

Corn is planted at 75 cm x 25 cm apart. Corn monitoring was conducted for 100 days and the data were averaged every ten days. The distance between corn plants changed along with the growth of corn stalks. During the 100-day observation, the corn plants were at an appropriate plant distance of 21 cm - 25 cm and 70 cm - 75 cm.

In the observations during the rainy season with low-yielding corn seeds, corn plants showed early signs of leaf blight in the form of yellow spots at the age of 1 month (43 days) and were not infected with cob rot (since the plant distance was set at 75 cm x 25 cm).

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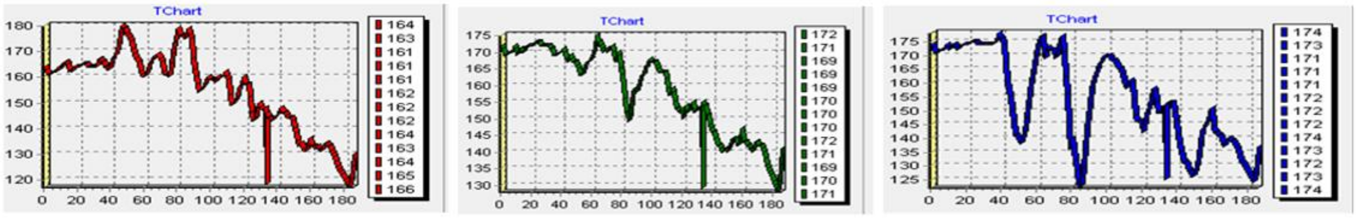
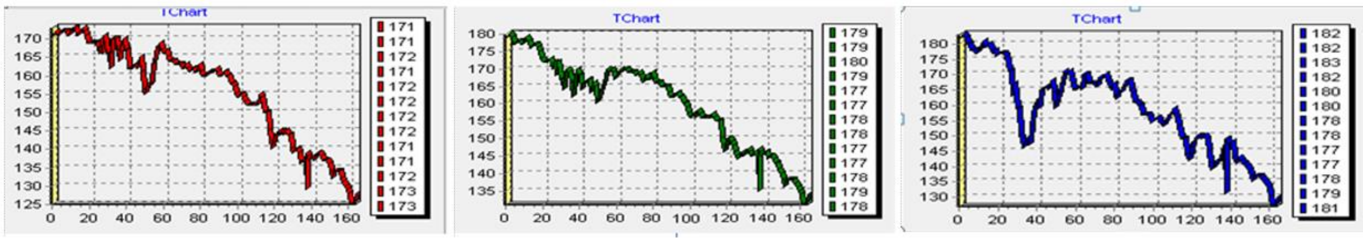
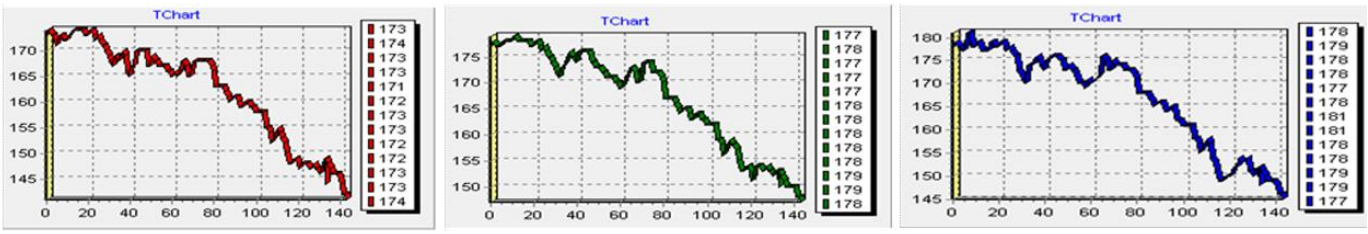


(a)



(b)



(c)

Fig. 5 Histogram testing on, (a) normal corn, (b) moldy corn, (c) rotten corn.

TABLE IV
VL53L0X SENSOR READ DATA ON RESIDENTIAL AREA

Days after Planting	Average Distance 1 (cm)	Average Distance 2 (cm)
1-10 days	10.30	40.56
11-20 days	10.25	40.73
21-30 days	10.78	41.25
31-40 days	10.50	41.98
41-50 days	11.47	42.07
51-60 days	11.80	42.74
61-70 days	11.23	43.06
71-80 days	12.67	43.71
81-90 days	13.54	44.65
91-100 days	13.98	44.98

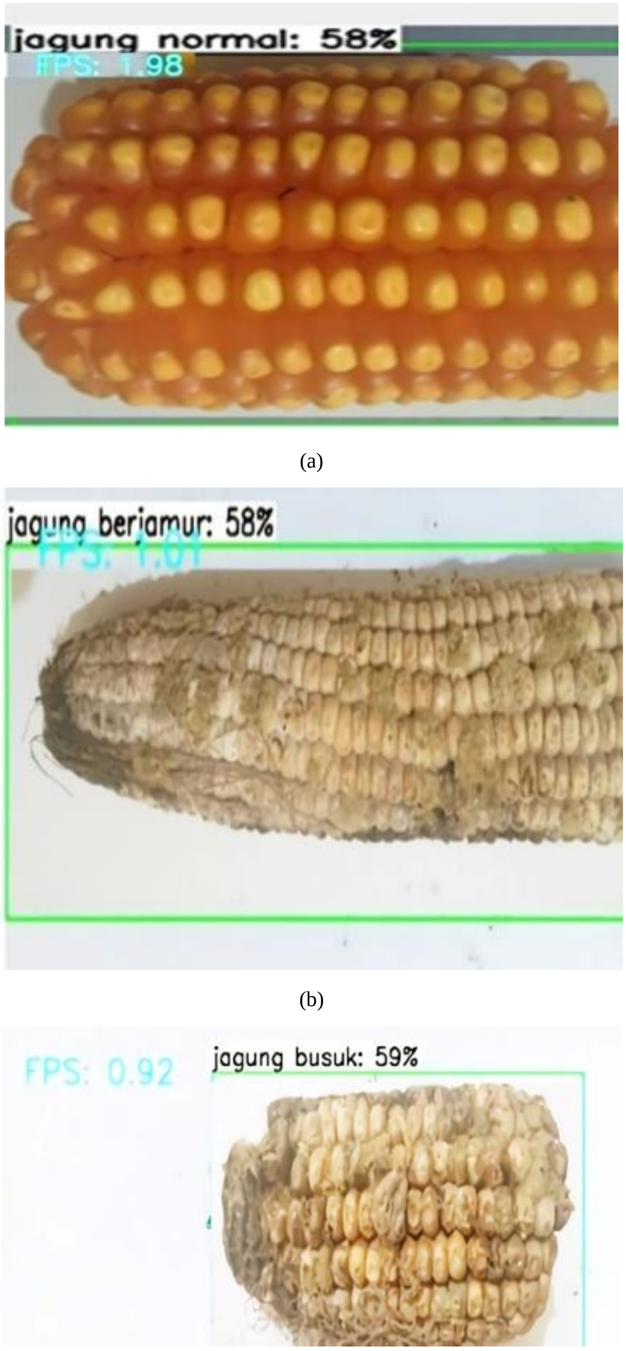
3) Residential Area: Table IV presents research data on residential areas for monitoring the distance between corns. In the observations of cob rot disease in the residential area, the low-yielding variety seeds were planted close together. Meanwhile, the seeds were planted in the normal and rain areas at appropriate distances. Based on Table IV, the corn planting in the residential area is at 40 cm x 10 cm. The results obtained showed that corns were infected with cob rot and had spaced kernels.

Based on the observation of corn planting in normal and rain areas, the main factor causing corn plants to get infected with leaf blight is the humidity. Even though the temperature is suitable for fungus to grow, the corn plant will not get leaf blight if the humidity is not. In the research conducted, cob rot disease could be avoided by planting the corns 75 cm x 25 cm apart. In normal and rain areas, corn plants were not infected with cob rot as the plant distance was 75 cm x 25 cm. On the other hand, cob rot infection occurred when planting corn in the residential area with a plant distance of 40 cm x 10 cm.

4) Data Display on Websites with IoT-Based Communication: in this research, the IoT was utilized to monitor the corn growth with parameters of air humidity, air temperature, and plant distance which data can be accessed on a website designed without control. The research did not show the results of the IoT corn quality classification.

The concept of IoT used in this research has three main components, namely physical goods with IoT modules, connection devices to the internet, and cloud data to store the databases. In the corn growth monitoring tool, the Arduino module and sensors were the physical items, the ESP8266 module connected the module to the internet, and 000webhost was used as the cloud data to store the database.

The data obtained and analyzed was in the form of LCD notifications, LEDs, and buzzers on the device. Data and information (safe and unsafe) were displayed on the website according to the conditions of observing corn growth from March to June 2021. The programming for the website data display was conducted on the Arduino module and tools available at 000webhost, using ESP8266 as an intermediary



(a)

(b)

(c)

Fig. 6 Results of the process of recognizing the quality, (a) normal corn, (b) moldy corn, (c) rotten corn.

between the Arduino module and the internet network. Fig. 4 is a display of corn growth monitoring data on the website.

Fig. 4 is the data access display through the designed website. The website was designed in the 000webhost site, with several tools function as module access to the internet network. The tools used were *log.php* and *index.php*.

The *log.php* is a tool that functions to enter data that has been read by modules such as sensors, enter data in the form of information (safe and unsafe) that has been programmed on the tool, and add time and hour data to the website. Meanwhile, tool *index.php* is a tool that aims to design website pages such as color, number of menus, data display, font size, etc.

TABLE V
MEAN VALUE AND STANDARD DEVIATION OF EACH TEST

Histogram Feature Extraction		**Normal (pixels)**	**Mold (pixels)**	**Rotten (pixels)**
Average	Red	36,558	31,902	27,749
	Green	35,939	31,961	28,012
	Blue	33,244	29,866	27,078
Standard deviation	Red	11,560	10,088	87,751
	Green	11,364	10,106	88,582
	Blue	10,512	94,446	85,629

TABLE VI
CORN COB READING QUALITY ACCURACY VALUE

Image	**Number of Images**	**Detected as**			**Level of Accuracy (%)**	**Error (%)**
		N	***M***	***R***		
Normal	10	9	1	0	90	10
Mold	10	0	7	3	70	30
Rotten	10	0	4	6	60	40
Total	30	**Average percentage**			73.3	26.67

B. Identifying Corn Quality with Digital Image Processing

1) Histogram Test Data: At this stage, the RGB image of corn was read using RGB values to obtain the image segmentation values for each color of the RGB value index. There are two axes: the horizontal axis is the pixel intensity, while the vertical axis is the value of R, G, B. Histogram testing was conducted using the Delphi 7 programming, shown in Fig. 5.

The histogram analysis for the RGB color index was an additional option to recognize the corn quality. Each color image has various RGB color index values. The higher the color index, the brighter the image; the smaller the color index value, the darker the image will be. In this study, the three indices were separated and analyzed for the analysis parameters of corn quality classification. The graph of each corn quality suggests that the image has normal brightness and high contrast (the histogram is evenly distributed in one place, not clustered in one place).

2) Corn Quality Testing with TensorFlow Mobilenet Using SSD Model with Raspberry Pi 3: Python Raspberry Pi programming with TensorFlow using an SSD Mobilenet model was used to recognize the three categories of corn quality, namely normal, moldy, and rotten, in real-time. It consisted of several processes, namely gaining the training model, converting the model that has been made, running the inference with the model, and object detection according to the training and test data that has been uploaded and labeled.

Fig. 6 shows the results of identifying the quality of corn using Python programming on a Raspberry Pi with TensorFlow using Mobilenet SSD models in real-time. The new sample tested was corn cobs used to maximize corn kernels testing. It aims to improve corn quality detection efficiency by detecting a large number of corn seeds (not detecting the quality of corn per seed).

The corn quality testing with the TensorFlow using SSD Mobilenet model generated corn kernels quality reading. The result showed that the similarity percentages of normal, moldy, and rotten quality corn were 58%, 58%, and 59%, respectively. The accuracy value in the detection results was obtained from a class called *graph()*, functioned to compute the output value on the neural network representing the data flow in the form of a graph. The graph in question was a graph that had been previously trained in the form of checkpoints during the training process, which was then exported to graph inference. After the computation was completed, this class will call the data TensorFlow based on the name which returns data in the form of the name TensorFlow, namely “detection_scores:0”; the accuracy value was initialized to 0, so that the percentage of results returned ranged from 0% to 100%. The testing, namely the dataset examiner (training and testing), was carried out in real-time with corn kernels (per 1 corn kernel) as the testing object. At the same time, the final testing using new data in the form of corn cobs demonstrated that the testing remained successful in identifying the corn quality.

3) Mean and Standard Deviation: The histogram feature extraction taken in this study was the extraction of the average value (mean) and deviation value (standard deviation) of each RGB index value. The mean value shows the average intensity value of each RGB color index. In contrast, the standard deviation value indicates the maximum deviation from the average intensity value of each RGB color index. Table V demonstrates that most of the mean values are high, while the standard deviation value is low. The calculation of the accuracy value on corn quality readings is described as follows.

$$Accuracy\ rate = \frac{sum\ detected\ as\ correct\ data}{sum\ of\ testing\ data} \text{x } 100\ \% \quad (3)$$

$$Error\ = \frac{sum\ detected\ as\ failure\ data}{sum\ of\ testing\ data} \text{x } 100\ \% \quad (4)$$

$$Average\ percentage\ = \frac{sum\ for\ each\ data}{total\ each\ type\ of\ data} \quad (5)$$

In Table VI, N represents normal corn, M represents mold corn, and R represents rotten corn. The accuracy rate of the corn quality recognition is 73.3%. Each corn quality (normal, moldy, and rotten) was tested ten times using Python on Raspberry Pi. Normal corn was detected nine times, moldy corn was detected seven times, and rotted corn was detected six times. Using the Delphi 7 programming on a computer in RGB index reading, moldy corn and rotten corn exhibited almost the same green and blue index values and the same level of image resemblance; therefore, often remained undetected.

IV. Conclusion

The corn quality testing was conducted by monitoring corn plants with IoT communication and identifying corn with digital image processing. In the observation of corn plants for 100 days by monitoring air temperature, air humidity, and the planting distance in normal, rain, and residential areas. In normal areas with the appropriate air temperature for fungus to grow and humidity below 77%, corn plants were not infected with leaf blight. In rain areas where the air temperature and humidity are suitable for fungus to grow, the corn plants were infected with leaf blight on the 43rd day. Based on this result, high humidity affects corn plants to get infected with leaf blight, while air temperature does not. In addition, due to the plant distance of 75 cm x 25 cm, cob rot was not infected with the corn plants in both normal and rain areas. On the other hand, a plant distance of 40 cm x 10 cm in the residential area caused corn to get infected with cob rot. From this result, it can be concluded that cob rot disease can be avoided by planting corns at an appropriate distance. Corn growth monitoring data was displayed on the LCD with IoT-based communication via access to a website page designed on the 000webhost site in the form of air humidity, air temperature, plant distance, date, time, and description of cornfield conditions based on observations of corn plants.

On physical identification of corn quality with normal, moldy, rotten categories using digital image processing, identification of corn quality in real-time was conducted using the TensorFlow using SSD Mobilenet model with Python programming on Raspberry Pi and. RGB index analysis was carried out employing the histogram method (histogram feature extraction, namely the mean and standard deviation) in the Delphi 7 programming. The accuracy rate of 73.3% was obtained in ten trials in each category. In testing, errors often occurred in moldy corn and rotten corn because the green and blue RGB index values were almost the same and had the same level of image similarity.

Conflict of Interest

The author declares that there is no conflict of interest.

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