Journal of Theoretical and Applied Information Technology
15th November 2022. Vol.100. No 21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

TOMATO PLANT OBSERVATION AND DISEASE DETECTION USING MACHINE LEARNING AND IOT

JOHANNES FARRELL LANDUTAMA[1], GALUH PUTRA WARMAN[2], BENFANO SOEWITO[3]

Computer Science Department, BINUS Graduate Program – Master of Computer Science,

Bina Nusantara University, Jakarta, Indonesia, 11480

E-mail: [1]johannes.landutama@binus.ac.id, [2]galuh.warman@binus.ac.id, [3]bsoewito@binus.edu

ABSTRACT

The development of technology in the agriculture sector has shown promise in the last few years. Crop management, disease detection, and irrigation management are examples of activities that can be implemented with modern technological approaches using artificial intelligence and IoT. Modern disease detection in agriculture uses machine learning to classify the health condition of plants by processing input images of leaves or branches into pre-trained machine learning models. Studies for plant disease detection have been done by other researchers using high computing capability devices; in contrast, there is still little research on implementing such machine learning models for mobile or small IoT-based devices. This study explores and proposes a model of machine learning algorithm namely CNN MobileNet and SVM, to run on small IoT-based devices. After some experiments, it was found that MobileNet can be used for this particular purpose. Furthermore, this research also shows a new contribution regarding the implementation of machine learning for disease detection into an IoT microcontroller commonly used for irrigation and soil moisture observation. The proposed model in this study has been tested in real-world experiments for Tomato plant disease detection with an approximate accuracy of 91.45%.

Keywords: *Disease Detection, Machine Learning, IoT, MobileNet, Arduino*

1. INTRODUCTION

The rapid development of science and technology has given rise to various new fields of knowledge that are useful for everyday human life. Science and technology are two interrelated things. In everyday life, technology is defined as an "Appliance of Science" and often has an exclusive meaning as a modern device that makes it easier for us to do activities [1]. The development of this technology has also given rise to various kinds of devices that can be connected to the internet, forming an ecosystem called the Internet of Things (IoT). IoT devices are generally made of small computers or Microcontroller Units (MCU) that are designed to receive and send certain signals. One IoT implementation that has attracted the author's attention is its use in agriculture.

A common implementation of modern IoT in agriculture is to develop a sustainability management system with real-time data acquisition using an automated Arduino-based microcontroller and capacitive soil moisture sensor [2]. Microcontroller unit is a hardware with an integrated circuit to execute instructions that allow users to program within this circuit. Arduino, as one of many microcontrollers that exist on the market has a variety of modules that can access peripheral input & output; not only that, the board and components can also communicate between the microcontroller and the computer via serial communication. The Arduino microcontroller can be used for various agriculture and biomedical needs due to its low power consumption, battery lives, compactness, and portability; It consists of circuits, sensors, electrodes, amplifier, sampler, and filter to acquire signals and send the output in usable format [3].

In addition to using microcontrollers, the implementation of Artificial Intelligence (AI) and Machine Learning (ML) in agriculture is also commonly found in the current era. Artificial intelligence is a field of computer science study focusing on machines with human-like intelligence that have cognitive abilities, learning, adaptability, and decision-making capabilities [4]. According to the Literature Review results conducted by Eli-Chukwu [5], recent implementation of AI and ML in agriculture sector are generally used for crop management, pest management, disease management, agricultural product monitoring, irrigation management, and yield improvement; with Artificial Neural Network (ANN), Support Vector Machine (SVM), and Fuzzy Logic being the most common methods in use. With the open-source library developed by the Arduino community, the implementation of AI on small devices such as microcontrollers for IoT purposes is exciting to explore. The author is interested in conducting research that combines the two things above, namely the Internet of Things and Artificial Intelligence for Tomato plant observations in agriculture.

Tomato (Solanum Lycopersicum L.), in a book is referred to as one of the crops with the highest production rate in the world, second only to potatoes; following that statement, the world tomato production and consumption have continued to grow in the last 25 years with production levels reaching 170.75 million tons on 5.02 million hectares of land located in more than 150 countries [6].

However, tomato plants can also be attacked by various kinds of diseases that can cause the quality of crop yields to decrease. Bacteria, viruses, and fungi commonly cause diseases in tomato plants. [7] Like any other crops, the occurrence of this disease is generally caused by local environment, cultivation, and management factors, making the types of diseases and pests different from one region to the other. These diseases can cause losses and damage ranging from 5 - 40% of tomato plant's yield and make 50% of fields severely infected. In addition, several diseases that are common to be found include Early Blight, Late Blight, Leaf Fungus, Spider Mites, Target Leaf Curl Virus, and Mosaic Virus. This disease should be detected early enough to minimize losses that arise in crop yields. One of the detection efforts that can be done to solve this problem is utilizing advance AI technology for examinations of plants.

2. RELATED WORKS

2.1 Identifying and classifying plant disease using resilient LF-CNN

[8] Research on disease detection using AI and machine learning has been carried out in recent years using resilient loss function in Convolutional Neural Network (CNN). The result shows an accuracy of 98% is met by the proposed resilient LF-CNN methods and shown promising compared to other CNN methods namely AlexNet, VGG16, Resnet-50, and GoogleNet when using leaves as an observation media. Nevertheless, the experiment was carried out by Gokulnath in Windows 10 PC with high processing capabilities supported by Nvidia Geforce GTX 950M; and shows no discussion of implementation possibilities for small microcontroller devices.

2.2 Attention embedded residual CNN for disease detection in tomato leaves

[9] Another study observing diseases on tomato plant leaves was conducted using Residual CNN Model architecture. The research process was carried out by Karthik using Nvidia Tesla P100 computer and obtained the following results: Residual CNN Model Architecture has an accuracy rate of 0.95 and is better than the Baseline CNN Model architecture with an accuracy rate of 0.84. Karthik [9] mentioned that the model used in their research is accurate and efficient enough to detect the type of infestation in tomato leaves; unfortunately, the research shows the whole process on high processing unit capabilities (Nvidia Tesla P100) and shows no discussion of implementation possibilities other than the used system.

2.3 Internet of Things (IoT) For Smart City, Agriculture, and Healthcare

[10] This study exposed some possibilities of IoT implementation in many sectors that could still be improved, including the agriculture sector. [11] A smart irrigation system was created earlier and proposed to solve difficulties faced in protecting crops from unconditional rain. Arduino Uno is used with soil moisture sensor, temperature sensor, rain sensor, and relays that manage water pumps. The results prove that water and energy savings are achieved with the proposed smart irrigation system. Overall flows have also shown three main functionalities: temperature check, soil moisture check, and rainfall availability check; however, they did not consider the health condition aspect of the crops. Since the water requirement differs between healthy and infected plants, improvement is needed to understand the water level of plants related to their health condition.

2.4 Research Gap

Following the three recent research that has been mentioned, there are two major issues that were not covered enough. The first one is related to the machine learning method used for disease detection published by Gokulnath in 2021 [8] and Karthik in 2020 [9]. It shows that machine learning has already been helpful in detecting disease in plants and could become handy when it can be used directly in the fields; nevertheless, both research still has no experiment and discussion to implement those machine learning in a small device that can be planted in the field or used by hand in the field. The second one is related to the issue that not every aspect is currently taken into account when implementing small IoT tools for agriculture; hence, further research needs to be done to get these small IoT tools improved a little by little.

The author sees these two issues as a research gap in one another and would like to explore the idea to fill this research gap by combining the implementation of machine learning for disease detection and soil moisture humidity for observation into a small compact microcontroller device that can be used directly and accessible through IoT ecosystem.

The aim of this research is to answer the following research question: What kind of machine learning approach can be implemented for disease detection in a small microcontroller device that is typically used for soil moisture observation?

To meet the answer and findings of the research question, the author will explore other machine learning architectures that can be implemented in a microcontroller device. The two approaches that come to mind and will be studied in this research are MobileNet CNN and SVM. One machine learning algorithm with better result will be installed on a microcontroller for disease detection of tomato plants using leaves as an observation medium, followed by utilizing additional soil moisture sensor to understand the humidity and irrigated level of the plants.

3. METHODS

One way to identify diseased tomato plants is to use image classification to classify leaf images of the plants, as mentioned in chapter one. Dhruv and Naskar [12] state that one of the main objectives of image classification is to differentiate images into categories based on content and perception of the object. Classification is included in the category of supervised learning. A supervised learning model is formed on data with a predetermined target or label class to predict new unlabeled problems; in contrast, the unsupervised learning model is a method for identifying patterns from data that does not have a label or class by grouping them into clusters [13].

To achieve the solution of running image classification in a small microcontroller device; the research process will be conducted with steps as follows:

- ***Understanding Image Classification on SVM & CNN MobileNet***
  A literature review is conducted to understand how both algorithms classify images compared to one another. The results of this process are explained the sub-chapter 3.1 and sub-chapter 3.2.
- ***Understanding Variety of Microcontroller and Sensor***
  A literature review is conducted to understand the type of microcontroller and sensor that will be used in this study. The results of this process are explained the sub-chapter 3.3.
- ***Training Model***
  Training is performed for both machine learning algorithms to find which performs better and decided to be implemented on the microcontroller. This process is explained the sub-chapter 3.4.
- ***Assembling and Wiring Proposed Device***
  Microcontroller and sensor must be assembled before implementing the device on real-world plants. This process is explained the sub-chapter 3.5.
- ***Setting Up IoT Ecosystem for Observation***
  Final assembled device will be connected to the IoT ecosystem to make observation process easier by making it accessible through mobile devices. This process is explained the sub-chapter 3.6.

According to Nandhini and Bhavani [14], the main method of image classification consists of extracting important features of color, edge, and shape. Generally, images will be transformed into black and white color (grayscale) to maximize computation performance when training the neural network model [15]. Wang and Lee [16] stated that another objective of grayscale transformation is to reduce the complexity that arises from different contributions of each color channel (red, green, blue) in the image. However, grayscale images are not always the best option for classifying images; He et al. [17] obtained better classification results when using color images compared to grayscale images. In the dataset used in this study, there are diseases that cause the color of the leaves to change, as shown in Figure 1 and Figure 2. For this consideration, the color image dataset will be used for model training.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Figure 1: Healthy Leaf

Figure 2: Infected Leaf

3.1 SVM Image Classification

Support Vector Machine (SVM) is one of many classification methods that can be used to analyze data and recognize patterns in images. SVM forms a classification by drawing a hyperplane line on existing dimensions to separate different data groups with a margin called “support vector”.

Each pixel in the image has 8 bits color value information for each RGB (Red, Green, Blue) channel. This means that each channel has a value of 2^8 or equivalent to 256. SVM will process this value to form a hyperplane line for each classification class that has been determined. In RGB images, processing will be carried out for a total of three-color dimensions; while in grayscale images, the processing will use one-color dimension.

3.2 CNN MobileNet Image Classification

Song et al. [18] state that the Convolutional Neural Network (CNN) is a type of deep learning network that have many advantages over a shallow structure model; its capabilities include convolution, image representation, and weight sharing-spatial subsampling. The structure of the CNN usually consists of an input layer, convolution layer, activation function, pooling layer, fully connected layer, and an output layer [19]. The results in recent years have shown that CNN models with large data samples achieve high accuracy in image recognition [20]. According to Phiphiphatphaisit and Surinta [21], MobileNet architecture uses a discrete convolution approach to maximize CNN generation with a smaller model size, reduced computation time, and increased prediction speed. Ghoury, Sungur, and Durdu [22] state that MobileNet is a smaller lightweight deep CNN with faster performance. Hence, the use of MobileNet in this research is considered suitable for image classification implementation in microcontroller devices.

For separate convolutions based on network depth, MobileNet uses a single filter for the input data, then a 1x1 convolution is used to combine this filter into output features. This separated convolution can be divided into two layers: the separating filtering layer, and the separating combine layer. These two layers reduce the model's size and computing power. MobileNet has a total of 28 layers, with each depthwise and pointwise layer followed by batch norm and ReLU except for the last fully connected layer, which functions to classify using the softmax layer.

3.3 Microcontroller and Sensor

Espressif ESP32-CAM and Arduino Mega 2560 R3 (with built-in ESP8266 WiFi Module) microcontrollers will be the main brains for data processing in this study. Since the ESP32-CAM has no USB port and a built-in serial driver interface, the Arduino Mega 2560 R3 microcontroller will be used as a bridge for programming the ESP32-CAM. The Arduino Mega 2560 R3 board will also be connected to a capacitive soil moisture sensor for measuring soil humidity levels. Capacitive moisture sensor has a more accurate measurement compared to other models because it is not affected by other variables such as fertilizer. The disadvantage of the capacitive moisture sensor is that it requires a charge-discharge time to measure changes in soil water capacity rate, which will not show the output value directly. According to the Food and Agriculture Organization of the United Nations (FAO) [23], tomato plants require a moisture content of 400 to 600 mm, depending on climatic conditions. To get the best growth results on tomato plants, it is also explained that the plant must be irrigated with a small mass of water on the soil with intense high frequency. This is because tomato plants should not have moist or wet conditions too often on their leaves.

3.4 Model Training

The MobileNet and SVM model will be trained using "New Plant Diseases Dataset"[1] by Bhattarai in 2018 [24]. Based on the observations, the following information was obtained from the dataset:

- Dataset is divided into three main folders with their respective uses as follows:

[1] https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

- ***Train***
  Dataset used for model training purposes. The total images that can be used in this folder are 18,345.
- ***Valid***
  Dataset used for model validation purposes. The total images that can be used in this folder are 4,585.
- ***Test***
  Dataset used for prediction testing purposes.

  - The entire dataset has a training and validation ratio of 80:20.

Following the observation, the two architectural designs for both SVM and MobileNet have been prepared, as seen in Figure 3. Before putting the dataset for model training, the author ran some pre-processing through basic image augmentation with factors seen in Table 1.

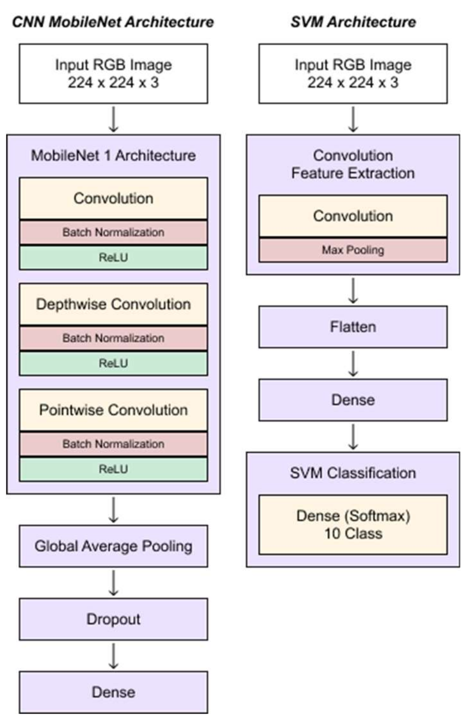

Figure 3: Proposed Architecture for Experiment

Table 1: Dataset Augmentation

CNN Augmentation	SVM Augmentation
Rescale 1/255	Rescale 1/255
Fill Mode "nearest"	Shear Range 0.2
Width Shift Range 0.2	Zoom Range 0.2
Height Shift Range 0.2	
Zoom Range 0.2	
Shear range 0.2	

The training process is carried out in the Google Collabs environment using the GPU Hardware Accelerated option; furthermore, the output model is hosted on GitHub Pages for fetching purposes from the ESP32-CAM camera web server. The MobileNet architecture used in this model is obtained from the Tensorflow and Keras libraries.

3.5 Device Wiring

One between MobileNet and SVM model with the better result will be chosen and fetched to run in the microcontroller unit. The first wiring circuit that needs to be compiled is the ESP32-CAM camera web server with Arduino as the programming bridge. The breadboard prototype of this circuit can be seen in Figure 4. Using this circuit, the ESP23-CAM can now be programmed to fetch our trained model.

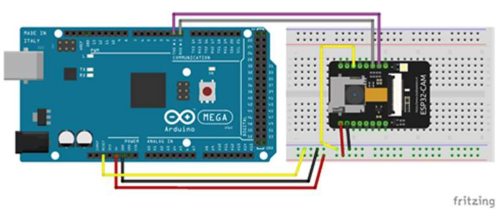

Figure 4: Wiring for Programming ESP32-CAM

After the programming process of ESP32-CAM is completed, all connected cables can be removed. The second circuit that must be assembled is the Arduino with a soil moisture sensor connected through the analog input pin. The wiring process can be done without the help of a breadboard and can be seen in Figure 5. For the final circuit, the previously programmed ESP32-CAM can be connected to the Arduino next to the soil moisture sensor. The ESP32-CAM will use 5V pin to power up the camera, and the soil moisture sensor will use 3V pin to power up the sensor. The final wiring can be seen in Figure 6.

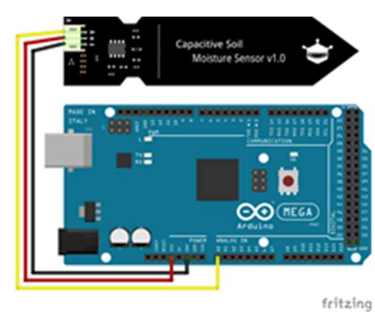

Figure 5: Wiring for Soil Moisture Sensor

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

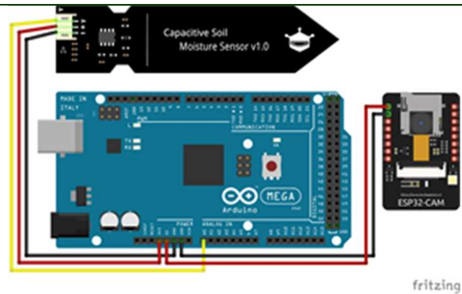

Figure 6: Final Wiring Combined

3.6 IoT Ecosystem and Observation

The observation data will be processed through Blynk IoT ecosystem. Blynk Cloud will be used as a cloud provider to store data from processed analog sensors, as seen in Figure 7. The installed analog sensor will read the value of the capacitive change in the soil caused by water. This value will be processed by the program on the Arduino board and sent to the IoT Blynk Cloud through API.

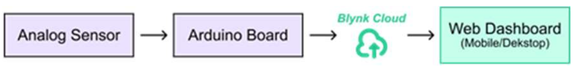

Figure 7: Soil Moisture and Blynk Cloud Workflow

For health condition observation, the workflow will also include a broadcasted camera web server that must be accessed on a browser, as seen in Figure 8. The stream from the camera can be viewed directly in a web browser by accessing the IP address of the ESP32-CAM from a smartphone in the same network. Users need to point the camera at the observed leaf and press the "Start Classification" button shown on the browser. Web browser will then request a still image captured from the buffer of ESP32-CAM for classification purposes. Classification will then be processed using the ML model that has been trained.

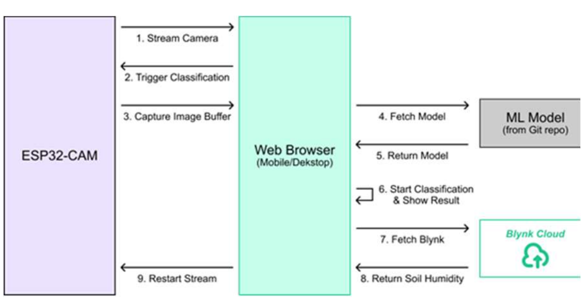

Figure 8: Health Condition Observation Workflow

4. RESULTS AND DISCUSSION

The training process was conducted using both train and validation dataset folders. At the end of the training process, the result shows that the CNN MobileNet model outperforms the SVM model by a big difference. An accuracy of 90.40% is met by the CNN MobileNet and is better than the SVM with an accuracy of 9.96%. Results for each epoch run on the training process can be seen through the graphs in Figure 9 and Figure 10.

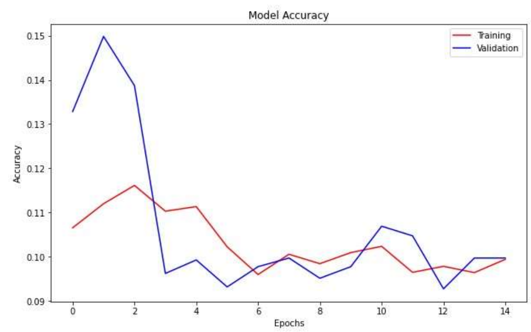

Figure 9: SVM Training Validation

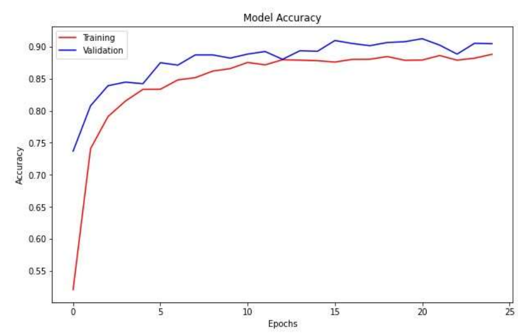

Figure 10: CNN MobileNet Training Validation

SVM training process shows no improvement in results with more given epochs; hence the graph above only shows a total of 15 epochs for the SVM. In the other case, the MobileNet model shows a better accuracy after the first 15 epochs; thus, a total of 25 epochs was set to get the optimum accuracy and to see if the graph is stagnant between 0.87 and 0.90 accuracy score.

4.1 Real World Experiment Result

From the results obtained in the model training, it is decided that the CNN MobileNet model will be the chosen algorithm installed on the ESP32-CAM microcontroller. The machine learning model was installed into the ESP32-CAM using the first circuit configuration shown in Figure 4. Classification process was done by pointing the camera to the observed leave, as seen in Figure 11.

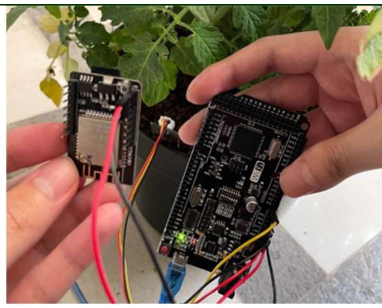

Figure 11: Pointing Assembled System to Leaves

The first experiment was done on young tomato plants (3 months) and showed the output class obtained were dominated by Early Blight and Late Blight. This inaccurate result presumably occurred due to the different leaf shapes of the observed young tomato plants compared to the leaf shape of mature tomato plants from the dataset used in the model training. Furthermore, the second experiment was taken with mature tomato plants (6 months) as objects of observation to test if the classification results will obtain more varied results. Sample results on mature tomato plants can be seen in Figure 12.

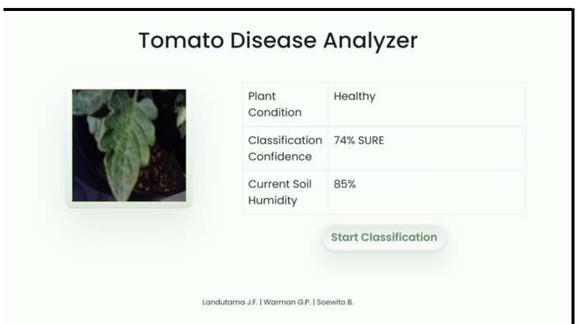

Figure 12: Sample Classification Result

Six samples are taken from the experiment with results that can be seen in Table 2. The following table includes probability scores (confidence scores) of each neuron class in the last layer of CNN MobileNet. At the same time, the soil humidity percentage was also obtained from the calibrated soil moisture sensor and fetched through Blynk API.

Table 2: Observation Result

No	Condition/Infected	Confidence (%)	Humidity (%)
1.	Healthy	74	85
2.	Healthy	53	85
3.	Mosaic Virus	57	86
4.	Early Blight	90	86
5.	Target Spot	47	67
6.	Late Blight	98	78

4.2 Discussion

Following the result obtained above; more experiments were conducted, and it was found that the lighting conditions of the camera affect the classification results. The first optimization to overcome this problem is to adjust the ESP32-CAM camera sensor to get a better image from a limited light source. QVGA resolution with the frame size of 320x240 which was the default value of the ESP32-CAM was changed to XGA resolution with the frame size of 1024x768. The second optimization approach is to modify the image dataset using brightness augmentation to simulate certain lighting conditions for new model training. Datasets were divided into two sets; each set was given a change in value of 60% brighter and 60% darker than normal conditions. The new augmentation factor for model training can be seen in Table 3.

Table 3: Dataset Augmentation

Darker Dataset	Brighter Dataset
Rescale 1/255	Rescale 1/255
Fill Mode "nearest"	Fill Mode "nearest"
Width Shift Range 0.2	Width Shift Range 0.2
Height Shift Range 0.2	Height Shift Range 0.2
Zoom Range 0.2	Zoom Range 0.2
Shear Range 0.2	Shear Range 0.2
Brightness Range 0.4 - 1.0	Brightness Range 1.0 - 1.6

There is slightly increased accuracy when performing the new model training using both datasets. However, experiments with real plant objects did not significantly differ and still showed poor classification results in rooms with limited light conditions. Hopefully, this problem can still be investigated in further research with more varied datasets. The accuracy results obtained for each data set can be seen in Table 4.

Table 4: Optimization Accuracy

Dataset	Accuracy (%)
Original Dataset	90.40
Brighter Dataset	90.58
Darker Dataset	91.45

5. CONCLUSION

To answer the research question in sub-chapter 2.4 regarding what kind of machine learning approach can be implemented for disease detection in small microcontroller devices, it is found that MobileNet can be used for this particular purpose. Furthermore, this research's new finding is also an improvement from the previous research conducted by Elhattab in 2022 [10]; which adds disease detection as an extra aspect of observation in implementing IoT microcontrollers for agricultural usage. Hence, the main contribution of this work is the integration of machine learning for disease detection into existing IoT microcontrollers, which have already been used for irrigation and soil moisture observation.

This research shows that functional requirements for agricultural observation and disease detection can be done using artificial intelligence and IoT. The use of tomato plants as an observation object in this research helps us show that the process can be fulfilled using Arduino Mega 2560, ESP32-CAM microcontroller, and soil moisture sensor. The proposed system for tomato plant disease detection also functioned properly using the MobileNet CNN approach that runs with the Tensorflow in a camera web server.

The advantage of MobileNet can also be seen with high accuracy obtained in a small model size installed on the ESP32-CAM. Despite getting a relatively high accuracy score in testing and validation on the computer; unfortunately, real-world usage still depends on good lighting conditions to get maximum classification results.

Experiments with plant subjects showed poor classification results in rooms with limited lighting conditions. Assessment and efforts have been made to optimize the performance, including changing the resolution of the camera sensor and retraining the model using a dataset with brightness augmentation. A slight improvement exists in accuracy when performing training and validation for the new model on a computer but shows no significant changes in real-world testing. This lead to an open issue where further investigation and experiment is needed with more supportive datasets; several other algorithm options can also be explored to obtain a model with better feature extraction in certain lighting condition, especially to classify plant diseases using leaves as an observation medium.

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