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Automatic Mass Waste Sorting System Using Inductive Proximity Sensor, Water Level Sensor and Image Processing using MobileNet Algorithm

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***Abstract*— The global municipal solid waste is predicted to increase by threefold in 2050. Indonesia's most wastes are unsorted and only end up in landfill and the waste management is less than ideal. An automatic mass waste sorting system is proposed to answer such problems. The automatic mass waste sorting system is designed to be able to identify and separate metal, plastic and organic waste using electrical sensors and image processing. The electrical sensors was able to identify waste types with 65% accuracy and the image processing system was able to identify waste types with 86.67% accuracy. The result doesn't offer much advantage compared to other research on waste management system, however it is hoped that this research may inspire other researches on mass waste sorting systems.**

***Index Terms*— inductive proximity sensor; metal waste; MobileNet; organic waste; plastic waste; trash sorting; water level sensor.**

I. INTRODUCTION

The global municipal solid waste is predicted to increase by threefold from 2.01 billion tons per year in 2050 [1]. Recycling can be one of the steps to prevent such prediction. To encourage recycling, a waste must be sorted first based on the type, such as separating plastic wastes from metal and glass [2]. However, most wastes in Indonesia are unsorted and only end up in a landfill [3]. It is also stated that the waste management in Indonesia is still not ideal; with waste reduction rate and recycling rate are only in 11% [4]. Another problem was 80% of waste management was still done by human, who are landfill workers [5]. These jobs are at risk of several diseases such as tuberculosis, bronchitis, asthma, pneumonia, dysentery, and malnutrition [6]. Therefore, an automatic waste sorting system is needed to answer such problems.

Several researches are already done in the context of waste sorting management using a technology. On the research using electrical sensors, an example of one of the research is a prototype of smart trash bin using LDR and proximity sensors [7]. The proposed system was able to differentiate plastic and paper waste. However, the disadvantage comes with the low detection distance. Another example is the use of capacitive and inductive sensor to differentiate metal and non-metal waste [8]. The system was able to detect metal waste, but unable to sort plastic waste. Another research attempts to detect wet waste using capacitive sensor, based on the theory that wet waste will have larger dielectric constant than dry waste [9]. An alternative sensor that can be used is water level sensor, where the resistance value will change when the surface was exposed to the water [10].

On the other hand, an alternative approach for trash sorting is using image recognition technology. This is caused by limited amount of sensor types and types of wastes that can be detected. Visual analysis can be used to assist the sensors to make the trash identification become more accurate.

An example of the research that has been done is using a camera with Deep Neural Network (DNN) algorithm [11]. The algorithm was trained using *VN-trash datasets* to create a model, and then the model is tested for its accuracy. Another example is using CNN and transfer learning. The CNN that is used is the *DenseNet* Model. Other research uses *MobileNet*, a CNN architecture that was developed for mobile device with limited power supply. An example of the research is using *MobileNet* for application in Android system with limited computing capability [12]. The research states that the model reaches the accuracy of 87.2%. This architecture uses depthwise separable and pointwise convolution on the convolutional layer. Therefore, this reduces the computation value, and suitable for embedded applications [13].

The purpose of this research is to develop an automatic waste sorting system that is capable of sorting waste en masse. The waste sorting is expected to be able to separate metal waste, plastic waste, and wet organic waste from a pile of wastes. Inductive proximity sensor and water level sensor is used to detect metal and wet organic waste, while the plastic waste will be detected using image processing using MobileNet architecture.

II. METHODOLOGY

A. Design Concept

The concept of the system is a mass trash sorting system that is able to detect and sort waste types. The user placed the mass of trashes into the funnel. The funnel will open automatically to guide the trashes into the vibration machine. The vibration machine is used to make the trash fall one at a time into the detection chamber. The detection chamber contains sensors to identify and classify waste types. After then, the detection chamber opens and the trash will be guided to the separated waste bins. The system was provided with extra waste bin for the trash that was failed to be identified.

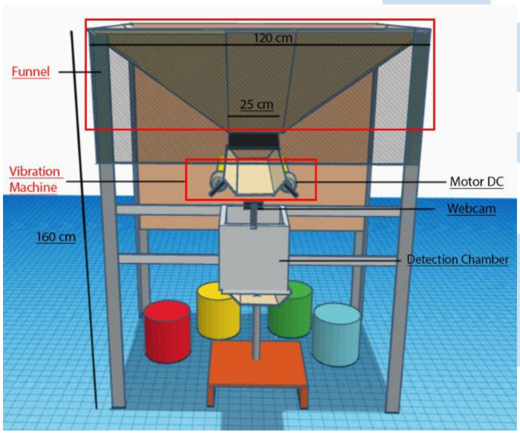

Fig. 1. The proposed design of the automatic mass waste sorting system

The proposed design is illustrated in Figure 1. The whole system has the area of 120 cm x 90 cm, with the height of 160 cm. For this research, only three types of wastes that will be tested to be identified, that is metal waste in the form of drinking cans, plastic waste in the form of drinking bottles, and organic wastes in the form of fruit peels. The size of the waste is limited to 25 cm x 25 cm x 25 cm. The whole system was powered using DC power supply.

There are three systems in the device; a system for trash guiding, a system for sensors, and a system for image processing. The overall block diagram is illustrated in Figure 2.

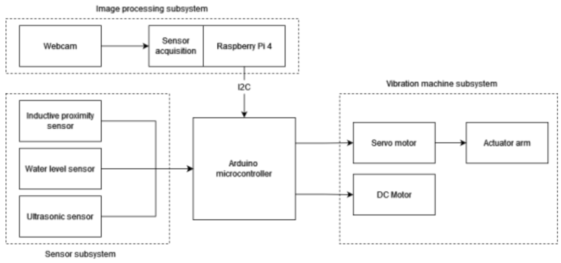

Fig. 2. The block diagram of the system

The trash was inputted to the large funnel on top. When the trash falls to the track, the vibration machine is active in order to make the trash fall to the detection chamber one at the time. When one of the trashes goes to the detection chamber, the vibration machine is inactive and the detection system starts classifying the type of waste. The detection chamber open and the trash will be guided to the waste basket according to the waste type. The process loops until there are no trashes left on the funnel. A fourth waste basket was provided in case the waste was not identified by the three types of waste already mentioned. Figure 3 provides the flowchart of the system.

The trash that fall into the detection chamber will be read by the ultrasonic sensor, stopping vibration machine to prevent more trash falling into the chamber. The image processing subsystem will start first, determining the waste types using algorithm that is stored in Raspberry Pi. If the confidence level of the image processing is below 50, the sensor subsystem will take over to determine the waste types. When the detection is done, the microcontroller will move the waste track using servo motor to the waste baskets.

B. Testing and validation method

Testing is done to evaluate how the sensors able to identify the waste type. In this system, the proximity sensor and water level sensor starts reading the data when the distance of waste and the ultrasonic sensor is less than 5 cm. 10 types of wastes, with 5 types of metallic drinking cans and 5 types of organic wastes such as fruit peels are placed one-by one in random order. Then the sensor will responds how the data is evaluated. Based on the research done on waste management system, it is expected to have 61% accuracy rate and 85% precision rate.

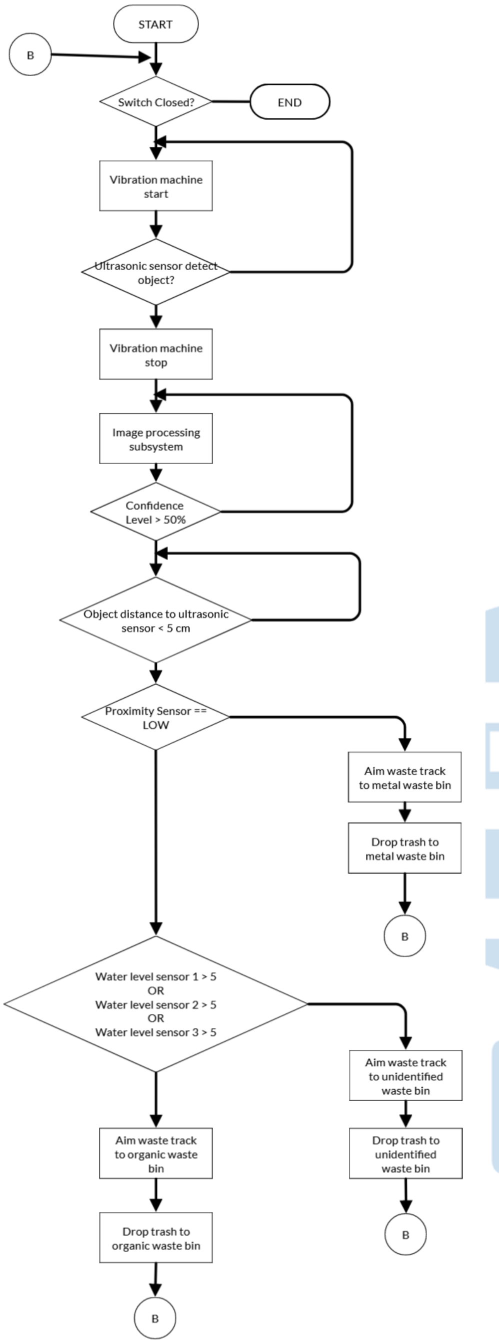

Fig. 3. The block diagram of the system

For image processing system, several testing steps were done. The first step is the preparation step, where the webcam was connected to Raspberry Pi 4. The second step is activating image processing program, object introduction in real time, and running tests on 20 different objects to evaluate the classification output from the program. The third step is the training and accuracy validations; where the datasets was put in the *Teachable Machine* application. In the application, the basic model that is used is *MobileNet*. This model was chosen due to its compatibility with Raspberry Pi 4. By default, the model that is used in *Teachable Machine* is *MobileNet* version 1, or *MobileNetV1*. The model has the size of 224x224 pixels. The accuracy was calculated using equation (1) to (4):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 = \frac{1}{\frac{1}{Precision} + \frac{1}{Recall}} \quad (4)$$

Where TP is true positive, TN is true negative, FP is false positive and FN is false negative. After training, the model is converted in *tflite* form and run in Raspberry Pi 4.

Based on the research done on image processing for identifying waste types using similar systems; it is expected to have 90% accuracy rate and 85% precision rate.

III. Analysis

Data analysis will be separated for each subsystem.

A. *Trash guiding system*

The whole system is constructed on a steel frame, with triplex wood as the body. The funnel part is constructed using galvanic plate. The vibration machine track was constructed using MDF plate on two PVC pipes as the frame. This vibration track will be moved using a cam driven from a 5V DC motor. On the side of the vibration track is a rack for housing the Arduino MEGA 2560, Raspberry Pi 3, and the circuitry for powering the whole system. The final track for trash separation was constructed using MDF plate on a wood, driven by MG996 servo motor. The constructed design can be seen in Figure 4.

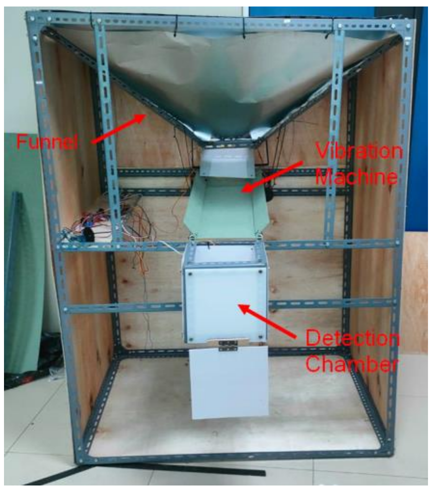

Fig. 4. Front view of the constructed system

For the detection chamber system, steel frame is used along with 5 mm acrylic glass as its body. The Logitech webcam was mounted on top of the chamber for image processing subsystem. The lid is mounted with water level sensor and inductive sensor. Placed near the lid was an ultrasonic sensor for trash detection. The inside of the chamber, along with the position of the sensors is illustrated in Figure 5.

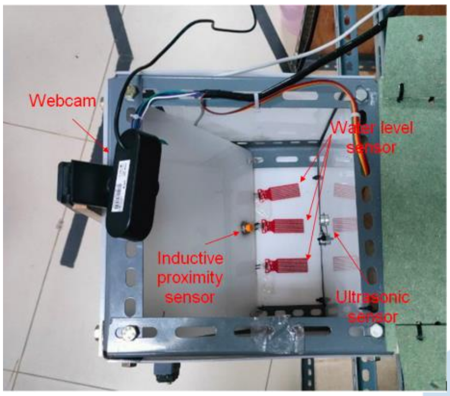

Fig. 5. The inside view of the detection chamber, showing the placement of the sensors

Testing is done to evaluate whether the system is capable of guiding the wastes into the detection chamber one by one. During the testing, the system was able to completely guide metal and plastic wastes with 100% accuracy, however it completely failed to guide organic waste to the detection chamber. One of the possible reason is the organic waste might be too sticky to the surface, and the vibration was not strong enough to move the waste.

B. *Trash identification system using sensor*

Testing is done to evaluate how the sensors able to identify the waste type. In this system, the proximity sensor and water level sensor starts reading the data when the distance of waste and the ultrasonic sensor is less than 5 cm. For testing purposes, the microcontroller is connected to the laptop, using Arduino IDE serial monitor to display the results from sensor reading. Figure 6 shows the output from the serial monitor.

```
distance: 1.96 cm

CLASSIFICATION = LOGAM
distance: 2.18 cm

CLASSIFICATION = LOGAM
distance: 2.28 cm

CLASSIFICATION = LOGAM
```

Fig. 6. Serial monitor output from the sensor subsystem

The random waste samples were prepared to evaluate the system accuracy. The samples are shown in Figure 7, where M denotes metallic waste and O denotes organic wastes, and the number indicates the different waste such as drinking cans from other brand and different fruit peels. For each evaluation, the samples will be dropped inside the detection chamber in random order.

Fig. 7. Waste samples with each respective labels

Table 1 illustrates the result of random samples, “Good” indicates the sample is able to be identified correctly by the system and “Bad” indicates that the sample is failed to be identified.

TABLE I. RESULT OF THE READING FROM ELECTRICAL SENSOR SUBSYSTEM

Test set 1		Test set 2		Test set 3		Test set 4	
M1	Good	M4	Bad	O1	Good	M3	Good
O1	Good	O3	Bad	O2	Good	O5	Bad
M2	Good	M5	Good	M1	Good	O3	Bad
O2	Bad	O4	Bad	M3	Good	O4	Bad
M3	Bad	O5	Bad	O4	Bad	M4	Good
O3	Good	O1	Good	M4	Good	O2	Good
M4	Good	M1	Good	O3	Good	M2	Good
O4	Bad	O2	Good	M5	Bad	M1	Good
M5	Good	M2	Good	M2	Good	O1	Good
O5	Bad	M3	Good	O5	Bad	M5	Good
Average accuracy = 70%		Average accuracy = 70%		Average accuracy = 70%		Average accuracy = 70%	

From the results, the accuracy of the device is around 65%. On the overall score, it shows relatively no improvement to the similar researches in waste sorting systems using electrical sensors. The factors that involving such result might from the trash size that was relatively too small, therefore the ultrasonic sensor failed to recognize the object. This statement was identified by the failed result produced by the metal samples that is relatively small compared to the other samples, and the organic wastes which were relatively flat. Some metal sample also gives inconsistent results due to the metal cans might land on a different position; some of the position may not trigger the ultrasonic sensor which makes the system failed to identify the sample.

To prove this statement, an alternative script was used by bypassing ultrasonic sensor reading to identify the waste types. Sample used are the only samples that produce failed result in previous testing. Based on the alternative script testing, the successful result is 66.7%. Some organic wastes failed to be detected because the waste lands on the side where no water level sensors are present. It can be concluded that the sensor placement needs to be redesigned in order to increase its detection capability.

C. Trash identification system using image processing

During testing, the Raspberry Pi was connected to a display monitor for monitoring the result. The program was shown in figure. The display shows the image taken from the camera, along with text for displaying waste type and confidence level in percent. The program and the view of the webcam can be seen in Figure 8.

Fig. 8. View of the webcam capturing the sample image in the detection chamber, showing identification result along with the confidence level score

Using epoch value 50, batch size in range of 16-32 and learning rate value 0.001, the system works well. This is based on the score of recall, accuracy, precision and F1 score of 100%. However, using learning rate value of 0.01, the whole score decrease significantly. It is observed that a learning rate value that is too high will cause unstable model and decrease of detection capability.

On the other hand, increasing epoch value to 70 will results in stable and good score for each parameter change. However, large epoch value doesn't guarantee stability of the model. An epoch value of 80 with learning rate of 0.01 resulting in the model incapable of classifying waste types to "nothing". Therefore, an epoch value of 70 is considered optimal in this research. The summary of the model training result is illustrated in Figure 9.

After accuracy test were done, the model was downloaded in *tflite* form, and the architecture was extracted from said model. The model uses 3x3 kernel for *depthwise* layer and 1x1 for Conv2D layer. The activation used for this model is *ReLu* and *Softmax* for *Dense*, and *Linear* for other layers. From the extraction results, the total parameter is 538,608 with trainable parameter is 524,528 and non-trainable parameter is 14,080.

Fig. 9. Result of model training with various variables on epoch 50, 70, and 80

The created model was tested to evaluate its capability of classifying wastes in terms of shape, background, and color. Each waste identification testing was repeated seven times, to evaluate whether the identification still accurate whether the trash lands on the detection chamber in different positions. The samples that were used is shown in Figure 10.

Fig. 10. Waste samples with each respective labels

Table 2 shows the result of the image training. “Success” indicates the samples were identified correctly, and “Fail” indicates the samples were identified wrong, regardless of confidence level score.

TABLE II. RESULT OF IMAGE PROCESSING USING TRAINED MODEL

Metal waste		**Plastic waste**		**Organic wastes**	
M1	Success 7 Fail 0	P1	Success 7 Fail 0	O1	Success 6 Fail 1
M2	Success 6 Fail 1	P2	Success 7 Fail 0	O2	Success 5 Fail 2
M3	Success 7 Fail 0	P3	Success 3 Fail 3	O3	Success 5 Fail 2
Average success = 95%		Average success = 85%		Average success = 80%	

For waste sample testing, the average of the accuracy of the subsystem was 86.67%, with 85% precision. This accuracy was relatively low compared to other research. There are several reasons. The first one is the need to increase training data. During testing, the amount of the training data is 900 samples. The second reason is the training image variety. The images used for training are not varied enough in terms of positions, which make the failure of identification when the object is in the other positions. The third reason is the use of Tensorflow lite. This is the program that is compatible with Raspberry Pi, however the use of this program needs higher compression of the model. The compression process reduces the complexity of the model.

Another problem was found during the whole system testing. Based on the live testing, the image processing system always gives high number of confidence level, even with the wrong identification. This makes the sensor subsystem doesn’t work to help image processing subsystem to give a better results. The program flow needs to be re-evaluated to solve this problem.

IV. CONCLUSIONS

The system was capable of classifying wastes with the overall accuracy of 75.83%, based on the average accuracy of the two subsystems. Several improvements needs to be done for the device, such as increasing training data, redesign sensors placement and reorganize the program flow so the subsystem can work together to improve the accuracy. Even so, it is hoped that this research may inspire future researches on mass waste sorting systems.

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