DEVELOPMENT OF WASTE SEGREGATOR TO ENHANCE WASTE CLASSIFICATION BASED ON DEEP LEARNING APPROACH

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A report submitted in partial fulfilment of the requirements for the degree of Bachelor of Mechatronics Engineering

Faculty of Electrical Engineering
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2018

SUPERVISOR ENDORSEMENT

I hereby declare that I have read through this report entitled "Development of Waste Segregator to Enhance Waste Classification based on Deep Learning Approach" and found that it has complied the partial fulfilment for awarding the degree of Bachelor of Mechatronics Engineering.

Signature : ....

Supervisor's Name : ....

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DECLARATION

I declare that this report entitled “Development of Waste Segregator to Enhance Waste Classification based on Deep Learning Approach” is the result of my own research except as cited in the references. The report has not been accepted for any degree and is not concurrently submitted in the candidature of any other degree.

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DEDICATION

To my beloved Family

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ACKNOWLEDGEMENT

First of all, I am grateful to GOD for giving me the strength and health in completing this project. I also would like to express my gratitude to Pn. Nursabillilah Binti Mohd Ali my supervisor for final year project. Apart from being dedicated herself, she never fails to guide me through the entire project from the beginning until the end of the project. Although she is busy with her packed schedule, she always puts an additional effort to find a slot to review my progress and also guide on what to do next. I hereby thank her for all the knowledge and guidelines that she passed down to me.

Next, I definitely would like to thank the respective panels, Dr Mohd Shahrieel bin Mohd Aras and Pn. Nurdiana binti Nordin for sacrificing a part of their time to be my panels for FYP presentation. Credits for them for sharing all the knowledge and giving some feedback on my project during the presentation.

Last but not least, I grab this opportunity to convey my appreciation to everyone who helped me throughout this entire project including my family and friends.

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ABSTRACT

Malaysia is certainly one of the most successful nations in the changeover. The growth in industrialization and human population causes an increment in the solid waste materials. The intention of this research is to find an alternative way for waste disposal and develop a semi-automated recycling process. The common recycling method is manually picking and sorting the solid waste into categories, but due to the high cost to manage the waste generation and limited access to the recycling bin, deep learning based waste classification technique was proposed to solve this problem. The extent of this project is to use the depthwise separable convolutional neural network (MobileNets) for the plastic bottle and aluminium can classification. The system is also supported by Raspberry Pi and also python programming language. As a summary, the MobileNets based object detection is used to develop the waste segregator and able to achieve about 90% rate of success of waste detection. Aluminium can have a higher detection accuracy compare to the plastic bottle due to the transparency and also light reflectivity. The detection and segregation able to work as standalone but the aim to make fully automated is still not achieved.

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ABSTRAK

Malaysia sememangnya merupakan salah satu negara yang paling berjaya dalam perubahan. Pertumbuhan perindustrian dan populasi manusia menyebabkan kenaikan dalam bahan buangan pepejal. Tujuan penyelidikan ini adalah untuk mencari satu cara alternatif untuk pembuangan sisa dan membangunkan proses kitar semula separa automatik. Kaedah kitar semula biasa adalah dengan memetik dan mengasingkan sisa pepejal ke dalam kategori, tetapi kerana kos yang tinggi untuk menguruskan sisa buangan dan akses terhad kepada tong kitar semula, teknik klasifikasi sisa berasaskan "deep learning" telah dicadangkan untuk menyelesaikan masalah ini. Idea projek ini adalah menggunakan "depthwise separable convolutional neural network" (MobileNets) untuk mengklasification botol plastik dan tin aluminium. Sistem ini juga disokong oleh "Raspberry Pi" dan juga bahasa pengaturcaraan "python". Sebagai ringkasan, pengesanan objek berasaskan MobileNets digunakan untuk membangunkan segregator sisa dan dapat mencapai kadar kejayaan pengesanan sisa sebanyak 90%. Tin aluminium mencatat peratusan pengesanan yang tinggi berbanding dengan botol plastik ini disebabkan oleh ketelusan dan pemantulan cahaya.Pengesanan dan pemisahan dapat befungsi secara mandiri tetapi, matlamat untuk pemisahan automatik sepenuhnya masih belum tercapai.

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Municipal solid waste management (MSW) become splendid obstacles when setting up for advancement throughout the universe, specifically in rapidly developing towns. Solid waste can be any discarded or abandoned materials. It can be categorized into solid, semi-solid, liquid or gaseous materials. As per a report from World Bank's Urban Development division estimates that quantity of the solid waste materials will have bullish from 1300 million tonnes per year to 2200 million tonnes per year by 2025 [1].

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Malaysia is certainly one of the most successful nations in the changeover. Steady political circumstances and lots of assets ensuring good economic development and low unemployment rates thus, making it on par with a developed country [2]. The Multi-cultural nation is experiencing fast industrialization and urbanization offering an undesirable effect to the surrounding from the raising of waste materials [3]. Due to the industrialization excessive items are being manufactured and the majority of the people have a tendency to replace the items rather than restoring it. Therefore increasing the waste generated. In statistic based on Utusan Online, there are around 37000 tonnes of waste is being produced in one day, averagely 13.5 million tonnes per year. Table 1.1 below indicates the composition of waste in Malaysia for the year 1975 to 2005.

Table 1.1: Waste composition in Malaysia (% wet weight) [4]

Waste composition	1975	1980	1985	1990	1995	2000	2005
Organic	63.7	54.4	48.3	48.4	45.7	43.2	44.8
Paper	7	8	23.6	8.9	9	23.7	16
Plastic	2.5	0.4	9.4	3	3.9	11.2	15
Glass	2.5	0.4	4	3	3.9	3.2	3
Metal	6.4	2.2	5.9	4.6	5.1	4.2	3.3
Textiles	1.3	2.2	NA	NA	2.1	1.5	2.8
Wood	6.5	1.8	NA	NA	NA	0.7	6.7
Others	0.9	0.3	8.8	32.1	4.3	12.3	8.4

In the state of Malacca itself, each resident generates about 250kg of waste per year. The population of this state is around 872,900, it means that 218225 tonnes of waste are thrown per year [5]. Table 1.2 below displays the waste treatment procedure practised in Malaysia.

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Table 1.2: Waste treatment methods practised in Malaysia [4]

Treatment Method	2002	2006	2020 (target)
Recycling	5 %	5.5 %	22 %
Composting	0 %	1 %	8 %
Incineration	0 %	0 %	16.8 %
Inert landfill	0 %	3.2 %	9.1 %
Sanitary landfill	5 %	30.9 %	44.1 %
Other sites of disposal	90 %	59.4 %	0 %
Total	100 %	100 %	100 %

The another cause of waste generator is the city population which constitutes more than 65% of the overall population [4], in 1980, Malaysia populace was 13 million, increased tremendously to 17 million in 1991, 22 million in 2000 , 27 million in 2010 [6] and predicted 2017 populations are 32 million [7].

As the population of the country increases, the waste generated per year also increases. The figure 1.1 below shows the recycling rate for each country for the entire year of 2015, from that people, can know that Malaysia only have 17.5% recycling rate and in fact, it is considered to be very low. Another that we can see from that is our neighbourhood country Singapore, even smaller than Malaysia but still able to achieve 59% of recycling rate [8].

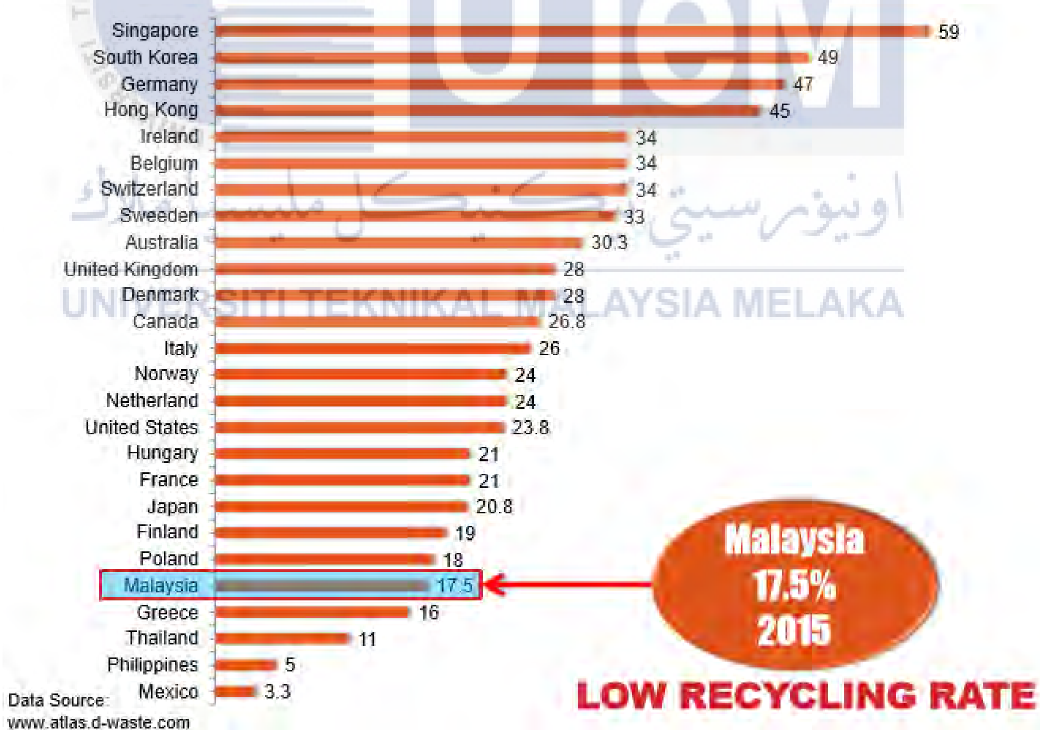

Figure 1.1: Recycle Rate for countries [8]

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Solid waste and public cleansing management believe that effective and efficient way fairly vital to ensure the high-quality lifestyle environment to stay clean, secure, and healthful. Regarding National Strategic Planning for solid waste Management Plan (2005), it had been highlighted that solid waste management is certainly founded on solid hierarchy as shown in figure 1.2. This hierarchy contains some of a few components that are essential [9].

Figure 1.2: Hierarchy of solid waste management [9]

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Efficient sorting of waste is a major issue in today society. Selective sorting is another approach, which is often implemented to improve recycling and reduce the environment [10]. When the waste is segregated into simple stream such as plastic bottles, metal cans it becomes easier to recycle and reuse. All of these are the proof shows that why need an alternative method to reduce the waste and increase the recycling rate. The "Development of Waste Segregator to Enhance Waste Classification based on Deep Learning Approach" might be one of the suitable systems to be used.

1.2 Problem Statement

Malaysia is very famous for the multi-ethnic festival celebration. When coming to any festivals, or celebration the soft drink becoming a compulsory drink. Not only during festival time, during sports also. For examples is energy drink such as 100plus, Revive and others. The soft drinks mostly manufactured and packed in aluminium cans, plastic bottle. A huge amount of waste is created if the used plastic bottle and cans are not disposed of using proper waste management.

The common approach of waste disposal is by unplanned and uncontrolled open dumping at the landfill sites. This technique is definitely injurious to living organisms such as humans, animal, and plants. This harmful approach of waste disposal can generate liquid leachate which contaminates surface and ground waters; can harbour disease vectors which separate harmful disease; can degrade the aesthetic value of the natural environment and it is an unavailing use of land resources [11].

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When wants to throw a trash, basically there are 2 problems. First one is the unavailability of the specific bin for the trash, and the second one needs to identify the type of the waste and put in each bin manually. Some places like universities, downtowns, subways, and malls have a different container for specific kind of a waste. Figure 1.3 below specify the recycling bins in Malaysia. The blue colour bin is used for the paper. The brown colour is used for the glass and the orange colour is used for aluminium, steel, and plastic [9]. But in most of the places, there only providing with one kind of bins and all the thrash being stuff inside it. Unfortunately, if even there are specific bin provided, there are some people who do not place waste incorrect bin [12]. Figure 1.4 proves the misuse of the recycling container.

Figure 1.3: Recycling bins in Malaysia [9]

Figure 1.4: Improper use of recycling cage [13]

In order to overcome the recycling problem, the initiative has been taken to implement a pre-trained convolutional neural network to replace the human brain to classify the waste and Raspberry Pi with Pi camera and with a set of the servo motor to segregate the waste automatically. The neural network will be trained with the custom dataset. The image of the waste will be captured and stored in a database. Then the database will be used to train the neural network.

1.3 Objective

The project will embark on the following objective:

1. To design a waste separation mechanism for non-deformed objects.
2. To classify plastic bottle and aluminium can using deep learning method.
3. To analyze the total loss during training process, detection accuracy and determine the reliable distance for the detection.

1.4 Scope and Limitations

Based on the process of designation and the consideration of limited time the scope of the project is limited as:

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The system will work on a depthwise separable convolutional neural network (MobileNets) to identify regular shapes bottles and cans. The system emphasizes on unbent 500ml F&N Season brand plastic bottle and 100plus bottle, 325ml and 300ml aluminium cans. Only 4 plastic bottles and 4 aluminium cans are used to do the analysis. Image of the waste object is captured and used for the detection. Black background is used throughout the whole project. The limitation of the project is the performance of the actual test will be affected by the intensity and reflectivity of the light. The classification and segregation of the waste is done one at a time. Area of application is limited to indoor area use such as small shops, restaurants, and malls.

CHAPTER 2

LITERATURE REVIEW

2.1 Theoretical Background

The chapter will explain the studies that have been conducted about the "waste segregation method". The studies start with the method used, the controller used, and the waste transmission method and suggested a place where the project will be implemented. There have been a lot of studies carried out in order to make the segregation as an automated process. This chapter will show all the previous study and comparison of the methods that related to the waste segregation. This chapter also will contain some explanation of machine learning and deep learning and comparison of the deep learning framework.

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2.2 Literature review of the previous study

2.2.1 PLC based automatic waste segregator

The researcher makes use the inductive sensor, photoelectric sensor, and a capacitive proximity sensor to identify the metal, plastic, glass/paper waste and Programmable Logic Controller (PLC) together with the mechanical actuator is used to segregate the waste accordingly [10]. A circuit interfacing used to connect between PLC and sensors. Sensor interfacing is performed to convert the analog transmission result from sensors into digital transmission before feeding into the controller. The PLC allows the separation to occur at the time of choice based on the sensors and coding embedded within it. The conveyor belt is used to transport the waste materials while 4 hydraulic cylinders are utilized as the mechanical flap.

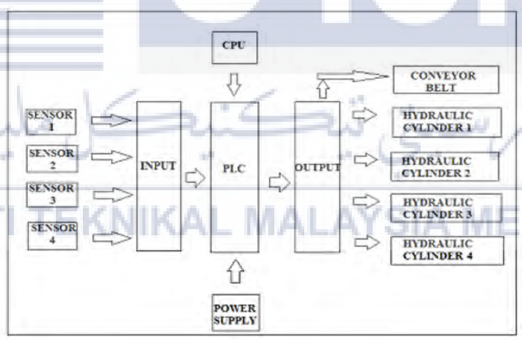

Figure 2.1: Block diagram of the AWS [10]

The system mainly concentrating on replacing the existing manual solid waste segregation as to decrease the waste that getting dumped as landfill. This reduces the manpower, period for the segregation. The usage of the hydraulic cylinder can be very expensive as the need to set up a small hydraulic system to power up the cylinder. Only 1 waste is being separated at the same time and also the limited option of I/O pin in the PLC cause issues in upgrading the task for future endorsement.

2.2.2 Microcontroller (MSP430G2553) automated waste segregator

The project uses microcontroller (MSP430G2553), parallel resonant impedance sensing system to recognize the metallic item, capacitive sensor copper plates to tell apart between wet and dry waste [11]. An IR-Proximity sense the input of the thrash and result in the Microcontroller to come out from low power setting and initialize all of the sensing modules. The analog signal converted to digital by LDC1000. The value of each capacitive plate is determined using the pin oscillator method. DC geared motored are accustomed to controlling the collector bin rotation and the flap position.

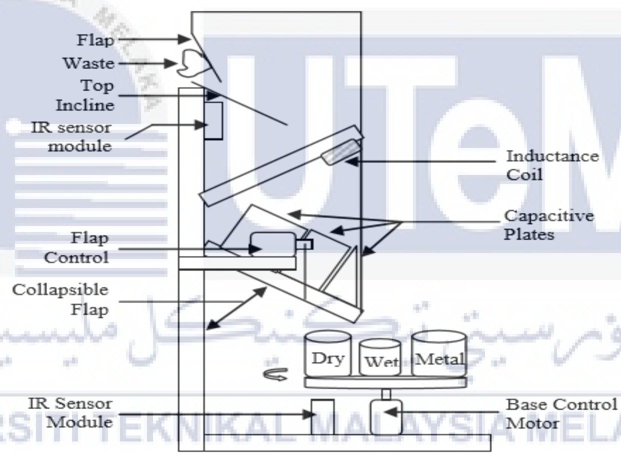

Figure 2.2: Automated Waste Separator [11]

The system is principally focused to split up the household waste. So that, the waste materials can be sent straight to the processing. The system struggling to differentiate the ceramic waste and able to segregate the waste one at a time. The project successfully implemented. The results show that the implementation is successful.

2.2.3 Intel Atom intelligent waste separator

This project emphasizes the advancement of the automated waste segregation using a multimedia embedded processor, image processing and machine learning [12]. The project not merely segregates the waste but it additionally rewards the people with some points. The system managed by the Intel Atom architecture, where a microcontroller is utilized to drive the electric motor and Microsoft webcam used to acquire the picture and convert it to grayscale. A guided user interface is applied for consumer and system communication and also to show the info on the waste.

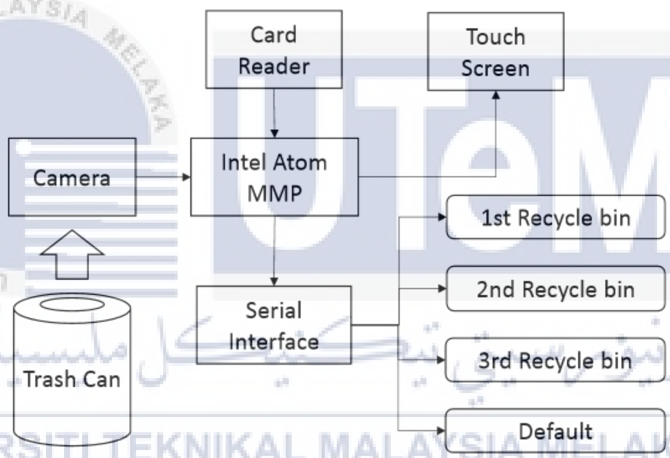

Figure 2.3: Block Diagram of the IWS [12]

The usage of guided user interface (GUI) in this project can be an advantage as an individual able know more details of the waste. People have a tendency to get some points if they used the system. It'll draw in the people to use it, but it struggles to determine the non-regular (deformed) and the design taking huge space and expensive. The project result shows an efficiency of 98.33%.

2.2.4 Computer vision based automatic waste classification

The project was focused on the application of the computer vision for waste classification. Image acquisition developed to capture the waste placed in the room [14]. Matlab software was used to process the captured image. The image converted into grayscale and compared with the images saved in the database. The image was compared using linear correlation coefficient. Then, the electrical signal will be produced to communicate to the robotic module. The function of robotics classification which converts the received electrical signal into a mechanical action. Arduino controller is used for the communication tool between image processing and robotic classification. The motor driver is used to control the motors.

The project is suitable for a small scale. For the industrial level, the image correlation method is not suitable. The process flow consumes a lot of time and the user needs to wait till the image is processed and selected bin opened. Even though the classification performance between the PET bottles, soda cans, cartoon boxes are 75%, 72%, and 87%, this will be a motivation for the school student to improve the project or apply or apply the technique in another field.

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2.2.5 Remote monitoring and sorting system using RFID

In this technique which applies radio frequency identification for on-line sorting of customer waste groups. The system not only robust but also accurate, it could handle vast quantities of plastic materials and e-waste [15]. Each waste will have identical types of RFID tags that contains the details about the object. The waste is transferred by conveyer belt. Whenever waste comes close to the RFID receiver, it transmits the essential details to the RFID receiver. Information is exchanged between the RFID receiver and RFID transmitter (tags). Data received from the RFID reader will be interpreted and redirected wirelessly to the remote master embedded program. The ZigBee receiver is connected to the computer.

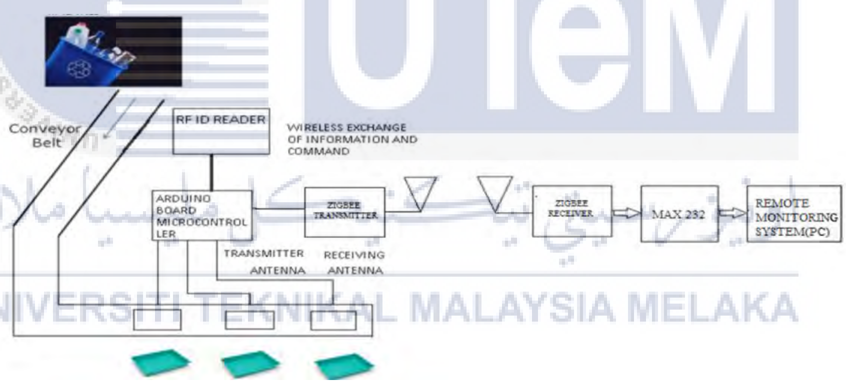

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Figure 2.4: RFID System Block Diagram [15]

The idea to mount RFID tags to each material during production, just to solve the issue of product segregation is not viable as not all companies would add to their cost of applying RFID tags to their products thus the implementation of such system is very challenging and not economical. Also, we are dealing with waste products so to use RFID scanner like devices in such severe and non-suitable condition would only add to the difficulty. The project objective is achieved.

2.2.6 Infrared camera technique

Aside from using sensors, one of the technique was using infrared camera [16]. The technique to acknowledge near infrared (NIR) spectra of plastic-type material was provided in Figure 2.2. Out of this spectrum, a coefficient set was obtained through the use of the wavelet analysis. After that, coefficients were utilized to create a quaternion number. This number would be weighed against the standard value to become in a position to determine the plastic material, which provides more detail about the plastic. The advantages of this technique included robust and insensitivity to the noise of the signal. However, this method was less accurate due to it structured on a simple Euclidean distance.

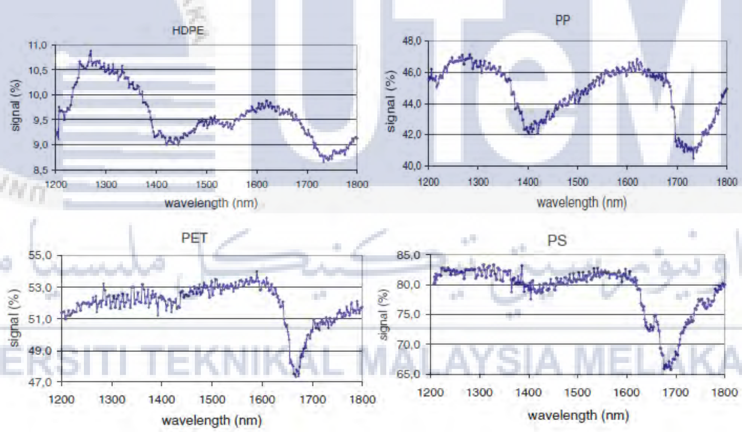

Figure 2.5: Spectra of HDPE, PP, PET, and PS by using NIR [16]

2.2.7 Inductive sensor array and colour vision

The effort taken by the researcher is to develop a sorting system to recycle metal scrap that is predicted based on colour vision and inductive sensor [17]. It is a combination of two systems in order to increase the capability of sensing a different kind of metal scraps. The colour detection was employing red channel as the common component which makes an evaluation of green and blue value in order to discover out the variation of colour as shown in Figure 2.4. Fluorescent light bulb with high quality is used to be able to reduce the system noise and maximize the effectiveness. Furthermore, the inductive system was used to measure the electrical properties of the metal for further confirmation. Therefore, it able to differentiate metals like steel, aluminium, copper, and brass. However, the inductive system contains 52 sensors that performed the sensing function which not only increased the manufacturing cost but also elevated the difficulty of machine learning. Sometimes, it had been adequate to use machine vision or deep learning.

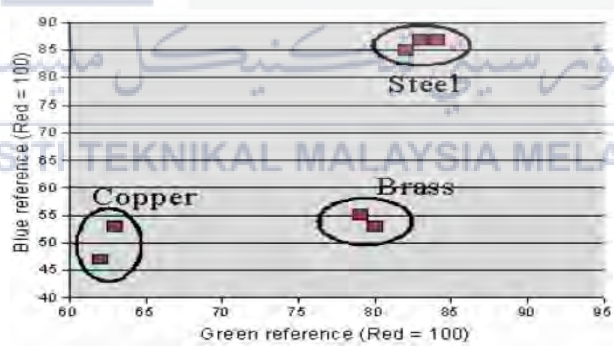

Figure 2.6: Two-dimensional classification [17]

2.2.8 Optical sensor based waste processing technology

In this paper, the mechanical isolating system was created and presented with the aid of operating sensor. In this system, the selecting criterion was based on particles position, size, shapes and colours of the waste particle. A visual sensor capable of measuring 3D visual parameters, positions and colour are selected [18]. A pressurized air flow was there in the mechanical sorting device nozzle which blows the targeted particles out of the mainstream which was sensed by the sensor and the entire process is controlled by a personal computer (PC). The experiment outcome proved the reliability of the system.

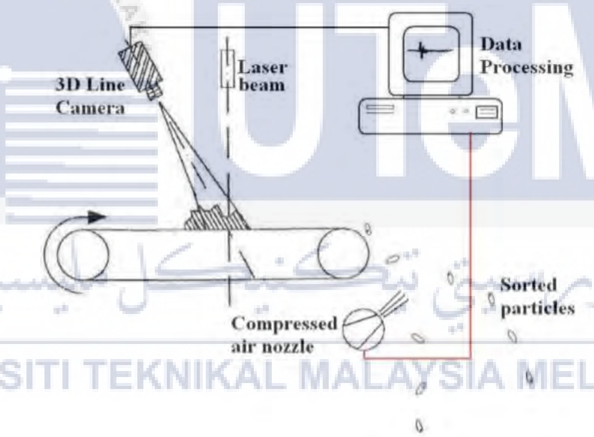

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Figure 2.7: Principle of Sorting System [18]

2.2.9 Frequency-based standalone waste segregator

Back in 2010, Jiu Huang proposed a standalone frequency based automated segregator in order to replace the old computer dependent system and analyse the accuracy and compare the performance [19]. Once the bottle or can is thrown on the galvanized iron platform, the sound of the object hitting the platform is recorded using the piezoelectric microphone. The analog signal is amplified and passed through the comparator in order to eliminate the noise and convert the signal into the digital signal. An average frequency value will be generated and displayed in the serial monitor. The observation indicates the frequency range of the plastic bottles and tin cans are 600Hz – 1900Hz, 1400Hz – 3000Hz respectively. To overcome the overlapping problem in 1400HZ-1900Hz the boundary is set to 1700Hz. This reduces the false acceptance.

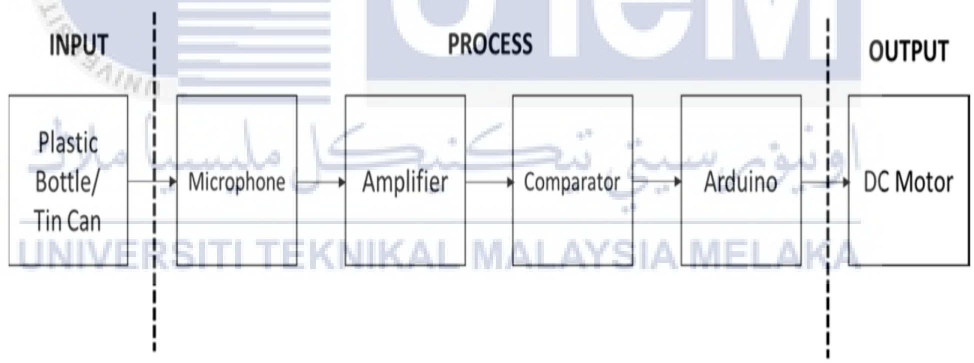

Figure 2.8: System Block Diagram [19]

The present studies also show a small improvement in comparison with the previous study. The accuracy of the system is improved and the project objectives are achieved. The overlapping frequency is quite a problem, so in order to prevent that, another condition should be set. There is also environmental sound which is can be considered to be a noise for the system and might affect the efficiency.

2.2.10 Near Infrared Spectroscopy based plastic sorting.

Madan Kumar along with some researchers emphasized the idea of using Near Infrared spectroscopy NIRS to automatically sort various kind of plastic [20]. A control system is build based on Raspberry Pi. Python programming language is used to process the (NIRS) data to collect details on the plastic category and also to communicate the spectrometer with the Raspberry Pi. A waste polymer is moved on the conveyor, the sample is irradiated by a 250 watts lamps and then optical device senses the sample and initiates the DAS to capture the signal. After collects the spectrometer statistic, scatter correction, baseline correction and pattern recognition are performed and decision supporting system is used for classification. The process flow is shown in the figure below.

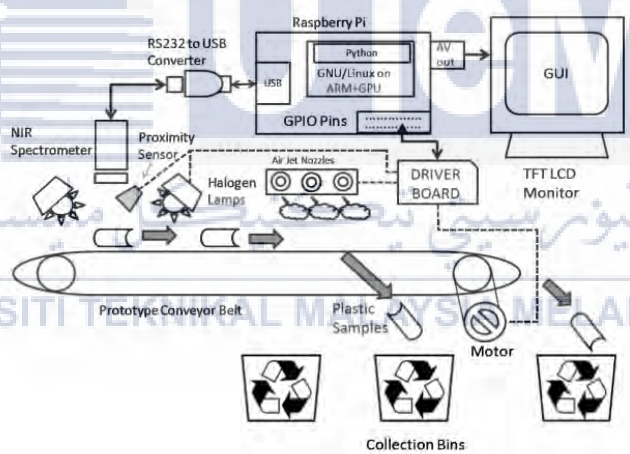

Figure 2.9: Architecture of Complete System [20]

The system only focusing on separating type of plastic waste. It able to sort five groups of polymers and capable of sorting 80 plastic item per minute.

2.3 Summary of the previous study

2.3.1 Summary of the waste separation technique used

Table 2.1: summary of the waste separation technique

Technique Used	Description	Advantages	Disadvantages
1. Sensor Mechanism			
a. Photoelectric sensor (plastic) [10]	The photoelectric sensor consists emitter to emit light and receiver to receive the light. When emitted light is interrupted or reflected, it causes changes to the amount of light arrive at the receiver, thus, the changes are converted into electrical output.	+ able to detect plastic bottle + detect a wide range of bottles + simple installation + non-stop detection + robust and waterproof housing + long life	- must install at 2 points on the system. - expensive - over the course, the lens gets contaminated - sensing range affected by colour and reflectivity of the target. - unable to detect other waste
b. Inductive proximity sensor (metallic waste) [10,11]	High magnetic field frequency generated by the coil in the front face. When a metallic	+ high accuracy +high switching rate	- limited operating range - cannot detect object other than metal

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	object is introduced on its surface, the oscillator field is affected and once threshold value reached the output switches.	+ compatible with the harsh environment + long life	
c. capacitive proximity sensor (glass and paper) [10,11]	The sensor generates an electrostatic field and response to changes in capacitance value when a target enters the field. Once the specific threshold is reached, the oscillator is activated, triggering the switch	+ ability to detect both metallic and non-metallic + stable output + high speed + low cost + low power	- affected by temperature and humidity - not accurate as an inductive sensor
e. Optical sensor [18]	The sensor converts light ray to an electrical signal. It analyses the physical quantity of light and then converts it to a form that is readable by an instrument.	+ detects particles sizes, and positions, colours and shapes.	- can be easily set to off an can cause problems - expensive than inductive and capacitive sensors.

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f. Piezoelectric microphone [19]	It's a form of microphone that senses audio vibrations through contacts with solid objects.	+ high impedance + sharp resonance + waterproof + pressure tolerant	- null frequency response - high-temperature sensitivity - environment noise might affect the performance
2. Hu's invariant moments (HIM) [12]	Based on the work of the nineteenth-century mathematician. This method used for selection of a set of numerical attributes to be extracted from the waste [21].	+ independent	- vary with the image geometry - complex
3. k-NN classification [12]	It is called as a lazy classifier. It classifies new thing by searching for its nearest training items according to a distance metric[22].	+ it is simple + easy to implement + can be exploited/modify easily	- high computational cost - computational cost depends on the training set.
4. Linear correlation [14]	The linear correlation method used to compare the capture and database images. the metric used to calculate the		- the image must be captured with high light intensity. - poor performance for low light intensity capture image

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	dependence of 2 matrices. Values close to (+/-1) indicates strong relation and vice versa.		- very sensitive
5. RFID [15]	Radio Frequency Identification (RFID) consists of one tag and one scanner. The tag contains the electronic information about the object and the scanner used to read the tags. It uses an electromagnetic field to track the objects.	+ more precise + efficient + able to identify all the materials.	- Not viable as the manufacture need to attach RFID in each of their product - Not Economical - more expensive - need to have a scanner (cannot be in a harsh environment)
6. Infrared Camera technique (plastics) [16]	The infrared camera was used to identify the near-infrared (NIR) spectra of the plastic material.	+ very robust and insensitivity to the noise of the signal	- Less accurate due to based on a simple Euclidean distance. - Cannot recognize the overlapping object.
7. Inductive Sensor Array and colour vision (metals)	The use of 2 functions in 1 method. The colour detection used to compare the colours	+ more accurate and reliable in detecting aluminium metal	- a complex set up mechanism - complex program - high manufacturing cost

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[17]	presence, while, the inductive sensor used to measure the electrical properties of the metal.	+ can differentiate another type of metals	
8. NIRS (Near-infrared Spectroscopy) [20]	A spectroscopy method that uses the near-infrared region of the electromagnetic spectrum.	+ able to differentiate types of plastic (PET) (HDPE) (PVC) + very fast and well suited for transparent polymers + reliable	- long execution time

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2.3.2 Summary of controllers used

Table 2.2: Summary of controllers used

Controllers	PLC [10]	Intel Atom [12]	Microcontroller [11,14,15]
Advantages	+ Low error rate + Small amount of cabling + High Productivity, Reliability and efficiency. + rugged	+ Small in size + Low power consumption + designed for multimedia embedded application + can work with windows and Linux (OS)	+ flexible + faster speed of execution + less expensive + rigid
Disadvantages	- difficulty when changes or replacement required. - difficult to find the error	- poor 3D performance - overheat problems	- Prone to damage when exposed to a harsh and rough condition - consume more processing time

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2.3.3 Summary of actuators used

Table 2.3: Summary of actuators used

Actuator	Hydraulic cylinder [10]	DC Motor [11,12,14]	Servo Motor [19]	Jet Air Nozzle [15,18,20]	Blower [14]
Advantages	+ robust + more reliable + constant force and torque	+ easy operation + can be controlled using PWM + cheap + high RPM	+ easy operation + can be controlled using PWM + accurate angle rotation + high torque + very rugged	+ separate waste with any weight/density	+ low pressure + suitable to separate dry waste.
Disadvantages	- expensive (components) - high maintenance	- cannot be used for linear actuation - applicable for lightweight load	- limited size available - noisy - consume current	- high pressure - might cause injury/hazards - high noise - (expensive)	- less efficiency

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2.3.4 Summary of the waste transportation method and proposed area (scope) of application

Table 2.4: Summary of waste transportation method

Waste Transmission			
1.Conveyor mechanism [10,15,18,20]	2. Inclined plane/tunnel mechanism [11]	3. Ramp & Chamber [12]	4. Manually [14]
The waste is transmitted in a conveyor belt from beginning till end.	The waste is transported in the inclined/ tunnel in vertical movement.	The ramp is used to switch the ways between the chambers.	The object is manually thrown in the selected bin after the process.

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Table 2.5: Summary of proposed area for project application

Area of application					
Municipal Corporation [10]	Recycling plants [14,18]	Household levels [11]	Public Areas [12,19]	School compound [15]	Plastic segregation plant [20]

2.4 Introduction to Machine Learning

Machine learning is using algorithms to acquire details form raw data and symbolize it in some type of the model. Arthur Samuel, a pioneer in artificial intelligence (AI) at IBM and Stanford, described machine learning as, “the field of research that gives computers the ability to learn without having to be explicitly programmed” [23].

How does the machine learn? Learning means something like “gaining knowledge by studying, experience, or being taught.” Machine learning is certainly using some algorithm for obtaining structural information from the example data. A computer learns something about the framework that represents the information in the raw data. Deep learning is a sub-discipline of machine learning field of study as shown in figure 2.10 [23].

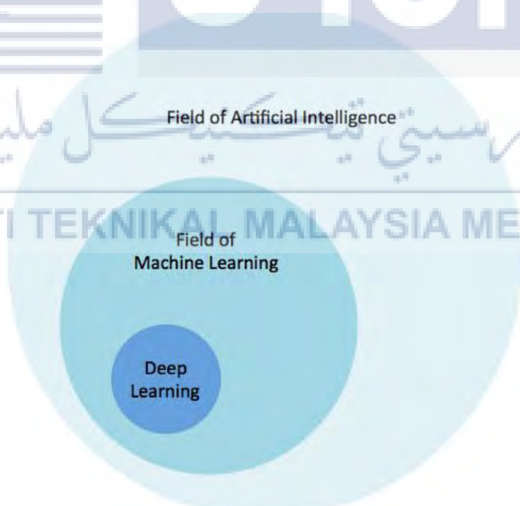

Figure 2.10: The relationship between AI, ML and DL [23]

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2.5 Types of Machine Learning systems

2.5.1 Supervised learning

The training data feed to algorithm includes the desired solution, called labels as shown in figure 2.11 below. A typical supervised task is object classification. It is being trained with many examples, and it must learn how to classify new items.

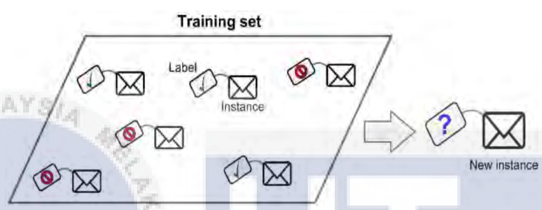

Figure 2.11: A labelled training set for supervised learning [24]

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2.5.2 Unsupervised learning

In unsupervised learning, the training data is unlabeled. It can be said like students (system) tries to learn without a teacher guidance as shown in figure 2.12.

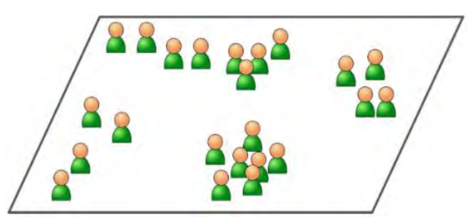

Figure 2.12: An un-labelled training set for unsupervised learning [24]

2.5.3 Semi-supervised learning

In semi-supervised learning, it contains partially labelled data and partial unlabeled data.

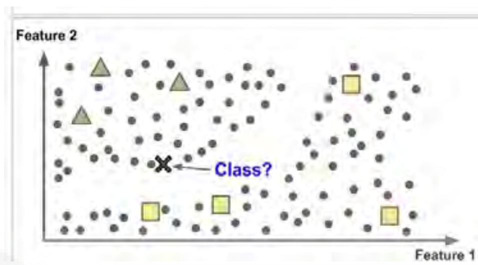

Figure 2.13: Semi-Supervised Learning [24]

2.5.4 Reinforcement learning

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Reinforcement learning is a very different beast. The learning system, called an "agent" can observe the environment, select and perform actions, and get rewards in return s shown in figure 2.14 below.

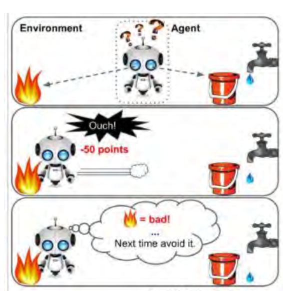

Figure 2.14: Reinforcement Learning [24]

2.6 Deep Learning

Deep learning is a sub-discipline of the machine learning, it is more complex since dealing with neural networks. This is in part due to how it has shown not only top-flight accuracy in machine learning modelling but also demonstrated generative mechanics that fascinates even the non-computer scientist. One useful definition specifies that deep learning deals with "neural network with more than two layers" [23].

2.6.1 The Biological Neuron

The biological neuron is a nerve cell that provides the fundamentals functional unit for the nervous system of all animals. Neuron exists to communicate with one another and pass electro-chemical impulses across synapses, from one cell to the next, as long as the impulse is strong enough to activate the release of the chemicals across a synaptic cleft.

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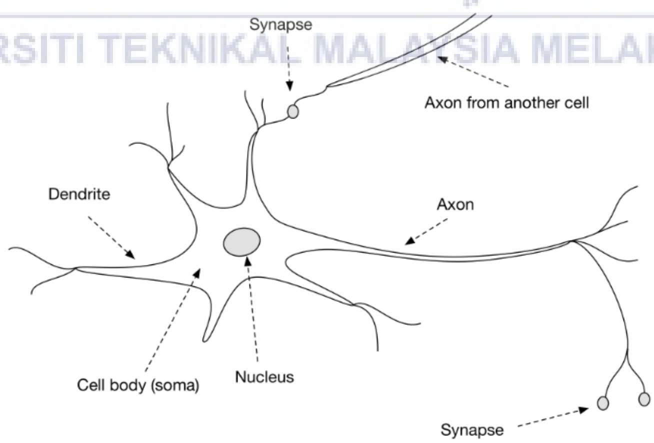

Figure 2.15: The Biological Neuron [23]

2.6.2 Artificial Neural Network (ANN)

ANN is the foundation of the Deep Learning. The network is versatile and powerful making them ideal to tackle large and highly complex machine learning task. The Perceptron is one of the simplest ANN architecture, "invented in 1957 by Frank Rosenblatt". It happens to be slightly different artificial neuron called linear threshold Unit (LTU) [24].

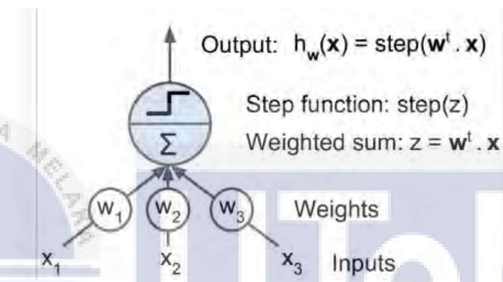

Figure 2.16: Linear Threshold unit (LTU) [24]

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2.6.3 Deep Neural Network (DNN)

When ANN consists of two or more hidden layers then it is called as a deep neural network. Multilayer perceptron with backpropagation is an example of the deep neural network.

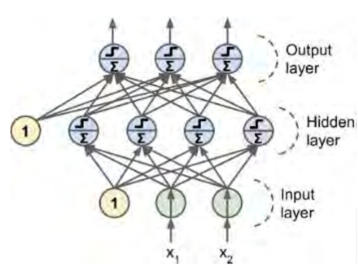

Figure 2.17: Multilayer perceptron [24]

2.6.4 Recurrent Neural Network

Recurrent neural networks take their input, not just current input they see, but also what they have perceived previously in time. So, the Recurrent Neural Network has two sources of input, the present and the recent past, where it will be combined to determine to new data as shown in figure 2.18.

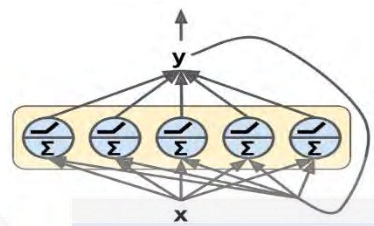

Figure 2.18: A Layer of Recurrent Neurons [24]

2.6.5 Convolutional Neural Network (CNN)

The convolutional neural network is mainly used for image classification. The architecture of the CNN consists of the convolutional layer, pooling layer, and fully connected layer. An example of typical CNN is shown in figure 2.19.

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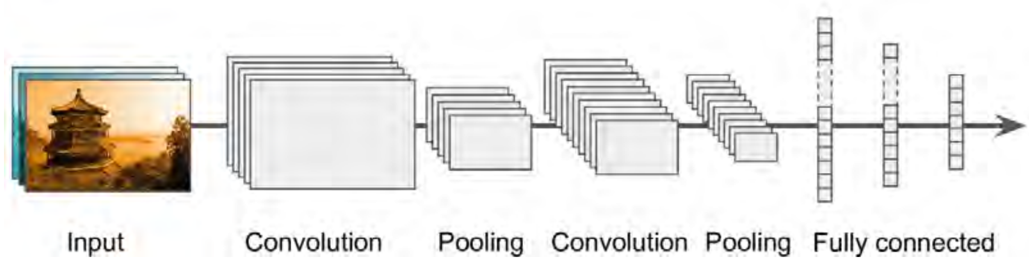

Figure 2.19: Typical Convolutional Neural Network [24]

2.6.6 Comparison between Deep Learning Framework [25]

Table 2.6: Comparison between Deep Learning Framework

Deep Learning Framework	Pros	Cons
Pytorch & Torch	➢ Lots of modular pieces that are easy to combine ➢ Easy to write your own layer types and run on GPU ➢ Lots of pre-trained models	❖ Need to write own custom training code ❖ No conventional support ❖ Spotty documentation
Tensorflow (Google)	➢ Python & Numpy ➢ Computational graph available ➢ Train model without writing any code ➢ Able to be implemented on small devices (Android)	❖ Slower than other frameworks. ❖ Not many pre-trained models. ❖ No commercial support ❖ Not very tool able
Caffe	➢ Good for feedforward networks and image processing ➢ Good for fine-tune existing network	➢ Need to write C++/CUDA for new GPU layers ➢ Not suitable for RNN ➢ Not extensible

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	➢ Train model without writing any code ➢ Useful python interface	➢ No commercial support ➢ Slow development
Deeplearning4j	➢ Python & Numpy ➢ Computational graph available ➢ RNN fit nicely in a computational graph	➢ The error message cannot help ➢ compile times increases as the model size ➢ Much fatter than torch ➢ Single GPU
DSSTNE (Deep scalable sparse tensor network engine) (Amazon)	➢ Fast ➢ Written largely in C++ ➢ Handle sparse encoding	❖ Amazon may not be sharing all information necessary. ❖ Amazon has chosen another framework for use on.
Keras	➢ Compatible with Theano, tensorflow and Deeplearning4j ➢ Fast growing frameworks	❖

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2.7 Summary of chapter

As a summary of this literature review, recycling is the only way to separate waste accordingly and to reduce the waste management cost. Pre-trained convolution neural network able to replace human brain to recognise and separate used drinking bottles or cans. All these materials have its own unique reflective of light and colour. These parameters are the key point to develop an algorithm in next chapter. After having a useful parameter, some important techniques in object detection are needed. In next chapter, depthwise separable convolutional neural network (MobileNets) is elaborated for object detection. A flap and funnel-based separation mechanism are discussed. Last but not least, these reviews are the fundamental and guiding line for this project to run smoothly.

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CHAPTER 3

METHODOLOGY

In this chapter, will be discussed further the methodology that's used in accomplishing the project. The technique and tools are properly planned and selected to guarantee the project success within the time and fulfil the objective that been outlined before. To develop this technique, it required knowledge and understanding in the deep learning (convolutional neural network), and Python programming language. This chapter will discuss the type of software program used, and the equipment being utilized for the Development of Waste Segregator to Enhance Waste Classification based on Deep Learning Approach. The project flowchart and Gantt chart planning will be discussed in the next part. Other than that, this chapter also will explain the experimental setup required to obtain the data.

3.1 Hardware Development

3.1.1 Raspberry Pi

Based on chapter 2, table 2.2 shows the comparison between the controllers used in the previous study. The reason of choosing Raspberry Pi instead of those controllers is because Raspberry Pi is a small computer that able to process large data independently and it also equipped with camera serial interface (CSI) which enable the camera modules. It also has a large community support compared to other board. This making the learning process to be easier for the beginner. Other than that, this small computer able runs multiple operating systems (one at a time). The main official operating system is raspbian. The other supported operating systems are Ubuntu mate, Ubuntu core, Windows 10 IoT.

3.1.2 Pi Camera

The Pi camera is chosen for this project as its compatibility with the Raspberry Pi. The version 1.3 is the latest model. The pi camera can be plugged directly into the camera serial interface (CSI) connector on the Raspberry Pi. It able to deliver a crystal clear 5MP resolution image, or 1080p HD video recording.

3.1.3 Servomotor

Servo motors (MG995) is selected to be used in this project. One to control the flap motion. The flap is acting as opening and closing of the waste entrance. The second motor is used to control the path to the selected bin. Servo motor is chosen because of its ability to move in required angle and can be controlled using the PWM.

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3.2 Software Development

3.2.1 Convolutional Neural Network

The correct method has to be chosen to guarantee the success of the project. The convolutional neural network is chosen for the image classification. It is also one of the most famous techniques used in Artificial Intelligence (AI). The CNN can be split into 2 separate categories as shown in figure 3.2. The first category is feature learning, it occupied the head and middle of the network and second category or the end of the network is classification. The feature leaning can have tens or hundreds of hidden layers that learns to detect different features of an image. Another advantage of the CNN is it very easy to train. The feature learning consists of 3 layers, called as Convolutional, ReLu, Pooling which are repeated for several times.

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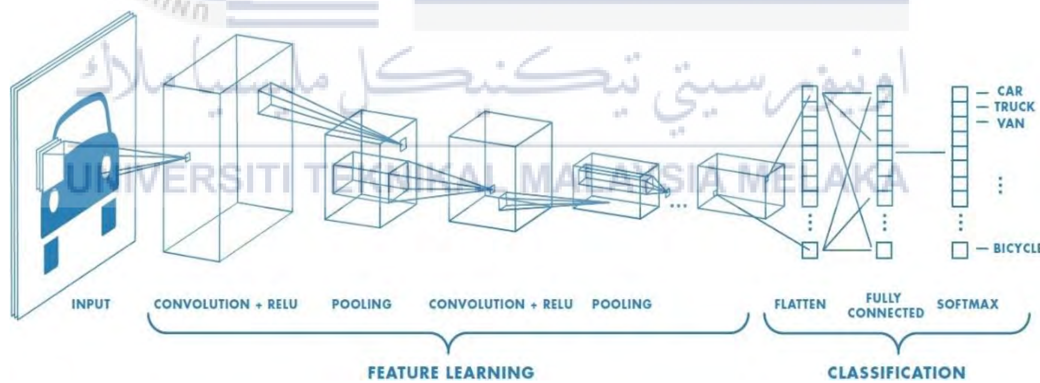

Figure 3.2: Convolution Neural Network

For image processing, an image is called as a matrix of pixel values consists of row and columns. For convolution, the image can be presented as a 3 dimension matrix, (Length x Width x Depth). The depth represents the channels. There are 3 channels known as Red, Green, and Blue (RGB).

3.2.1.1 Convolution

The main purpose of the convolution is to extract the features from the input image. Convolution preserves the spatial relationship between pixels by learning image features using small squares of input data. The working method of the convolution step for a 5 x 5 input image and with 3 x 3 filter is explained below.

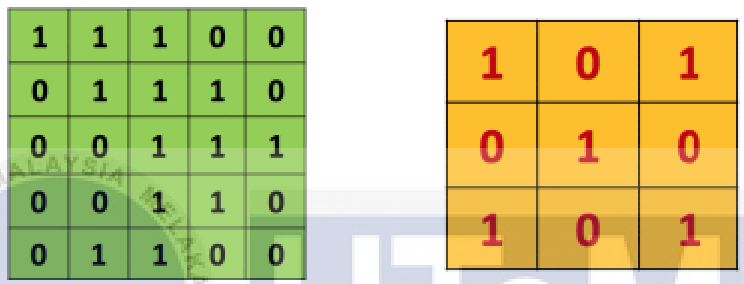

Figure 3.3: Input Data (left) and Filter (right)

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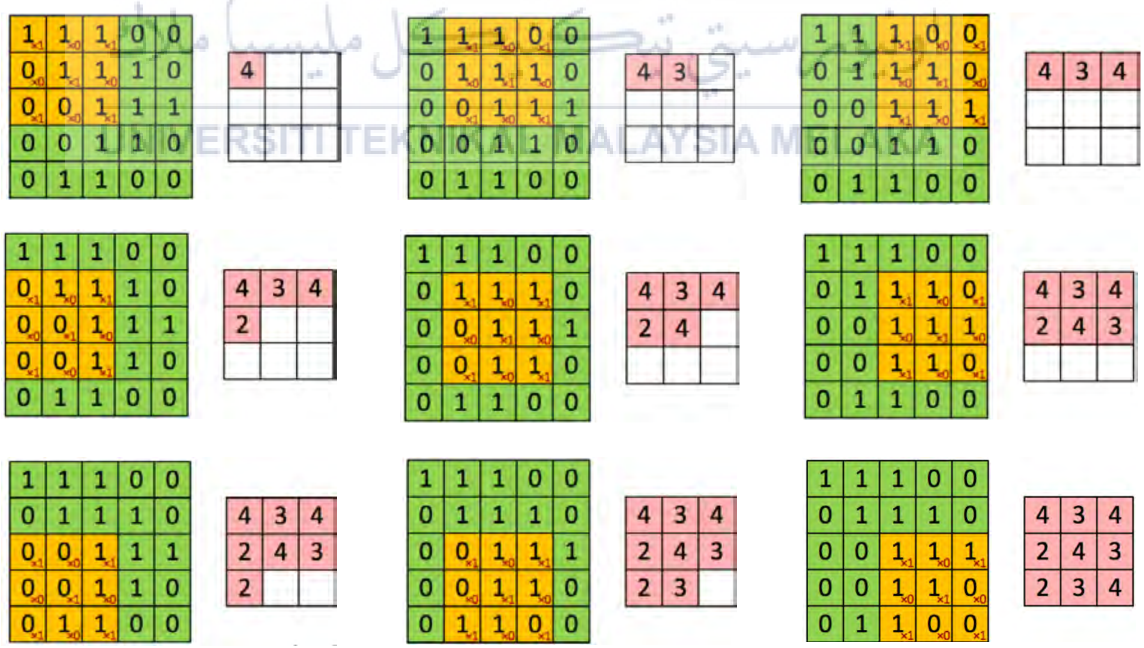

Figure 3.4: The convolutional computational

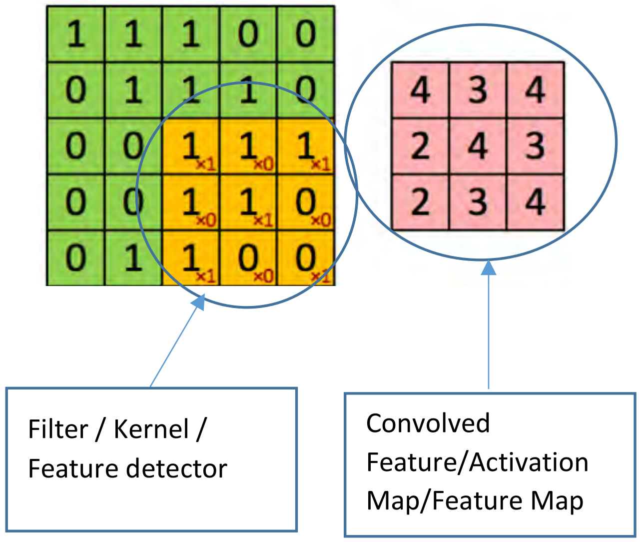

Figure 3.5: Common Names

3.2.1.2 ReLU

ReLU is stands for Rectified Linear Unit and is it a non-linear operation. It is an element-wise operation where it will replace all the negative pixel values in the convolved feature by zero. The output of the ReLU can be referred as Rectified feature map.

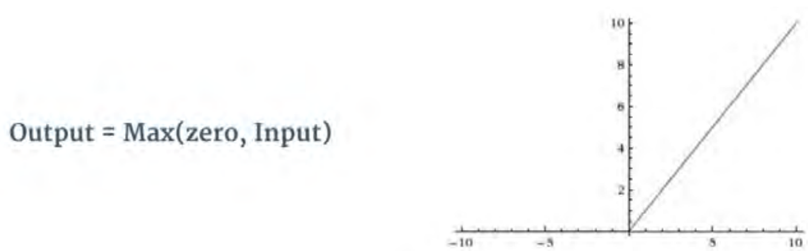

Figure 3.6: ReLU operation

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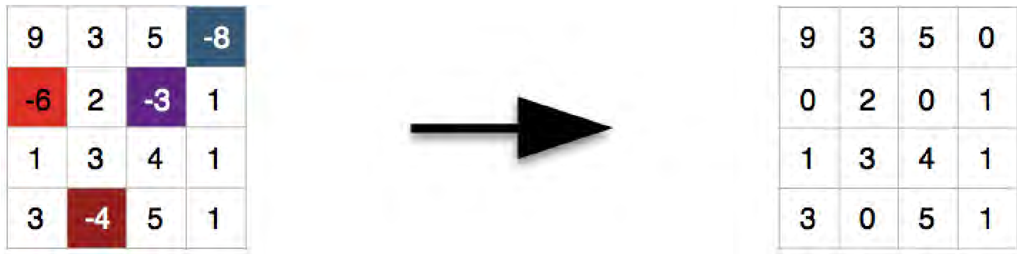

Figure 3.7: ReLU layer

3.2.1.3 Pooling

Spatial Pooling is used to reduces the dimensionality of each feature map but maintain the most important information. This step also called as subsampling or downsampling. Example of spatial pooling is Max pooling, Average pooling, Sum pooling etc. Max pooling is the commonly used step. A spatial neighbourhood (2 x 2 matrix) is defined and take the largest elements from the rectified convolved map. Figure 3.8 shows the example Max Pooling operation.

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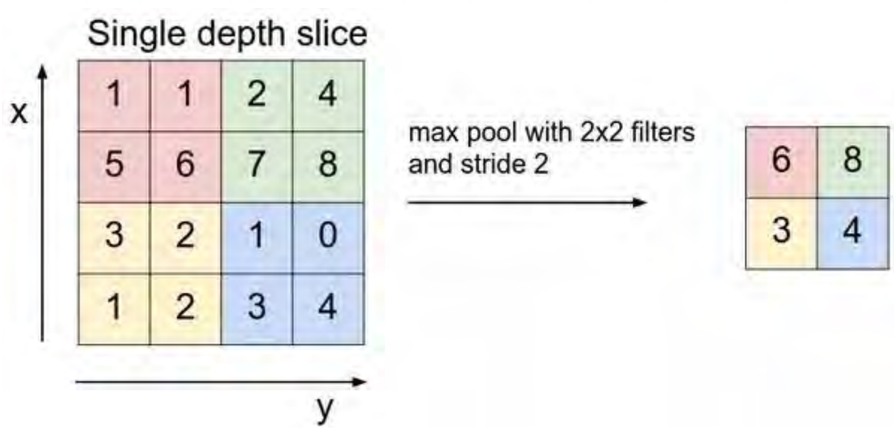

Figure 3.8: Max Pooling operation

3.2.1.4 MobileNets CNN

The pre-trained MobileNets convolutional neural network is chosen for this project. The primary reason for selecting this neural network is it is extremely light and very less in size and also the network is provided by the Google Inc. The network is mainly created for the mobile vision.

This network runs on the depth-wise separable convolutions. The depth-wise separable convolutions are made of two factorized convolution layers which factorize a standard convolution into depthwise convolutions and 1x1 pointwise convolutions as shown in figure 3.9 below. The depthwise convolutions are used as a filtration system to each input channel (input depth). The result of the depthwise convolutions the simply feed as input for the pointwise convolution. Pointwise convolution uses basic 1x1 convolution to make a linear combination. The network uses both batchnorm and ReLU nonlinearities for both layers. Figure 3.10, 3.11 and 3.12 shows the difference between standard convolution and depthwise separable convolution [26].

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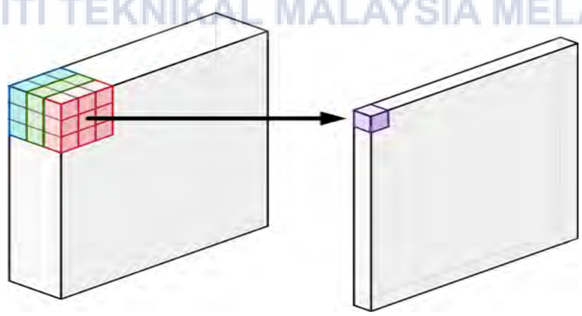

Figure 3.9: Normal Convolution

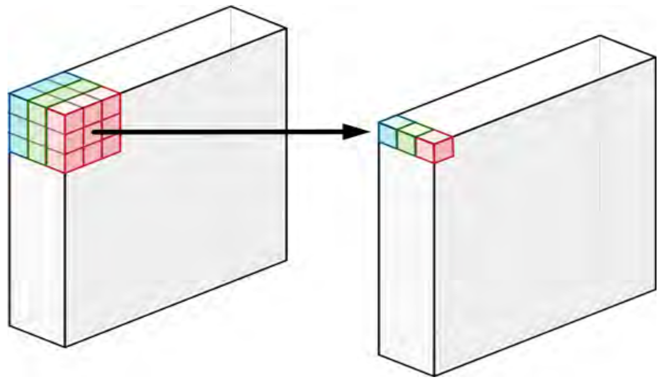

Figure 3.10: Depth-wise Convolution

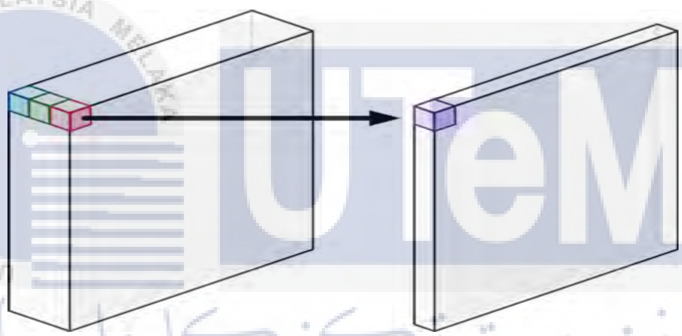

Figure 3.11: Pointwise Convolution

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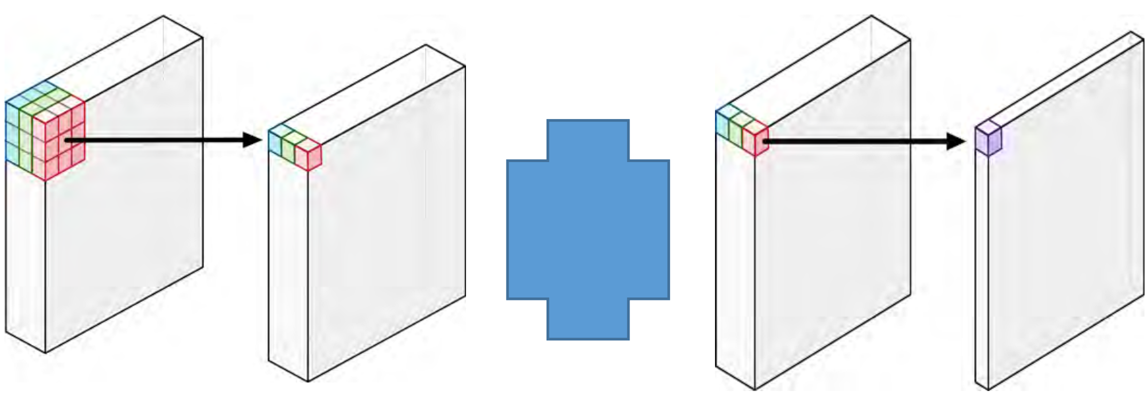

Figure 3.12: Depthwise Separable Convolution

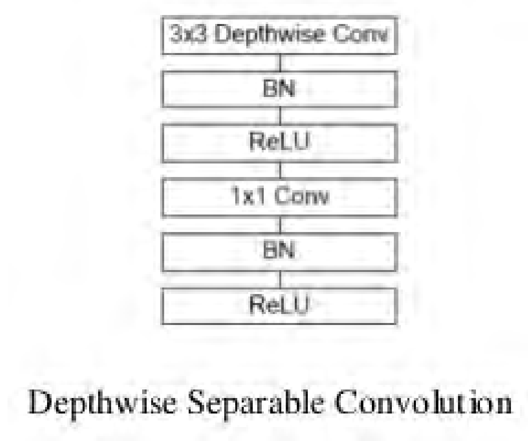

Figure 3.13: MobileNets Model depthwise separable convolutions [26]

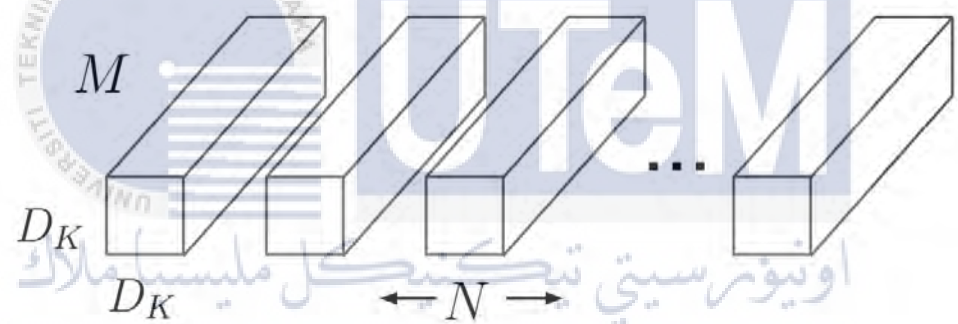

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Figure 3.14: Standard convolution filters [26]

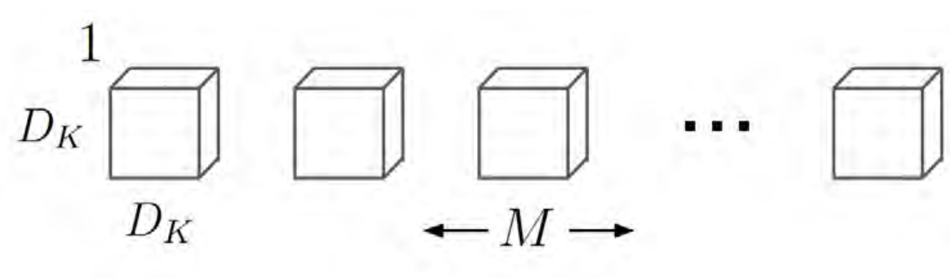

Figure 3.15: Depthwise convolutional filters [26]

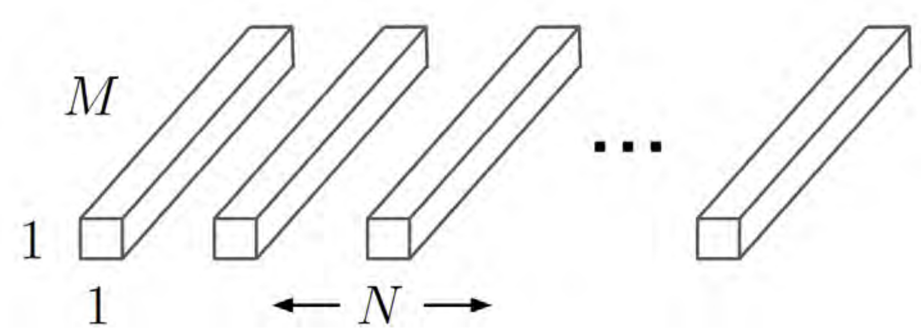

Figure 3.16: Pointwise convolution [26]

By assuming the output and input feature map as a square. The standard convolution network takes the input of a $D_F \times D_F \times M$ feature map **F** and produces a $D_F \times D_F \times N$ feature map **G** [26].

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Where: D_F = spatial width x height of a input feature map

D_G = spatial width x height of a output feature map

M = input channel (depth)

N = output channel (depth)

The standard convolution network is parameterized by convolutional kernel **K** of size $D_K \times D_K \times M \times N$.

Where: D_K = kernel dimension

M = input channel

N = output channel

For the convolution, the output feature map assuming stride one and padding is computed as:

$$G_{k,l,n} = \sum_{i,j,m} K_{i,j,m,n} \bullet F_{k+i-1,j-1,m} \tag{3.3.1}$$

The computational cost for standard convolutions is:

$$D_K \bullet D_K \bullet M \bullet N \bullet D_F \bullet D_F \tag{3.3.2}$$

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MobileNets models address each of these terms and interactions. Firstly, in order to break the interactions between output channel and the size of the kernel depthwise convolutions is used.

The standard convolutions have the effect of filtering features based on the convolutional kernel and combined in to produce a new representation. In MobileNets this filtering and combining steps can be split into two steps using depthwise separable, in order to reduce the computational cost [26].

Depthwise convolution with one filter per input channel can be written as:

$$\hat{G}_{k,l,n} = \sum_{i,j,m} \hat{K}_{i,j,m,n} \bullet F_{k+i-1,j-1,m} \tag{3.3.3}$$

where $\widehat{\mathbf{K}}$ is the depthwise convolution kernel of the size $D_K \times D_K \times M \times N$ where the m_{th} filter $\widehat{\mathbf{K}}$ is applied to m_{th} channel in **F** to produce the m_{th} channel of the filtered output feature map $\widehat{\mathbf{G}}$.

The computational cost of depthwise convolution is:

$$D_K \bullet D_K \bullet M \bullet D_F \bullet D_F \tag{3.3.4}$$

Depthwise convolutional is very effective compared to the standard convolution. The depthwise convolutional only filter input channel, and doesn't combine it to create new features. So an additional 1 x 1 convolution is added to computes the linear combination of the output of depthwise. This combination is called as depthwise separable convolution. The depthwise convolution cost :

$$D_K \bullet D_K \bullet M \bullet D_F \bullet D_F + M \bullet N \bullet D_F \bullet D_F \tag{3.3.5}$$

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which is the sum of the depthwise separable convolution (depthwise + 1 x 1 pointwise). by expressing convolution as a two-stage procedure of filtering and combining we get a reduction in the computation of:

$$\frac{D_K \bullet D_K \bullet M \bullet D_F \bullet D_F + M \bullet N \bullet D_F \bullet D_F}{D_K \bullet D_K \bullet M \bullet N \bullet D_F \bullet D_F} = \frac{1}{N} + \frac{1}{D_K^2} \tag{3.3.6}$$

All layers of the MobileNets convolutional neural network are followed by a batchnorm and ReLU non-linearity with the exception of the final fully connected layer which has non-linearity and feeds into a softmax layer for classification. Figure 3.13 shows a layer with normal convolution, batchnorm and ReLU non-linearity to the factorized layer with depthwise convolution, 1x1 pointwise convolution as well as batch norm and ReLU after each convolutional layer. Downsampling is handled with stridden convolution in the depthwise convolution as well as in the first layer. A final average pooling reduces the spatial resolution to 1 before the fully connected layer. MobileNets consists of 28 layers as shown in table 3.2 [26].

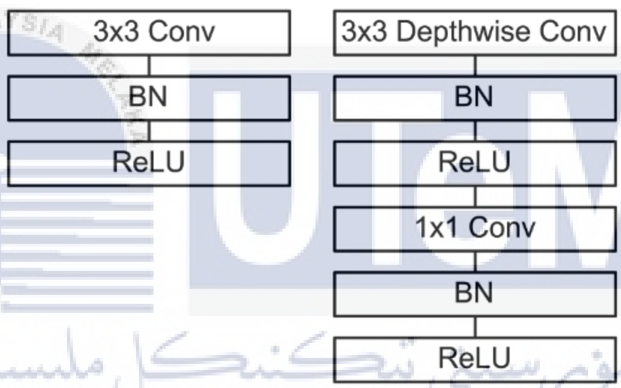

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Figure 3.17: left shows standard convolution. Right shows depthwise separable convolution [26]

Table 3.1: MobileNets Network Architecture [26]

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

3.2.2 SSD Single Shot Multibox Detector [27]

The SSD approach is based on the feed-forward CNN that produces a fixed-size collection of bounding box and scores for the presence of object class instances in those boxes, followed by a non-maximum suppression step to produce the final detections [27]. Single shot means that the tasks of object localization and classification are done in a single forward pass of the network. Multibox means the technique for the bounding box regression [28]. Detector means classifier.

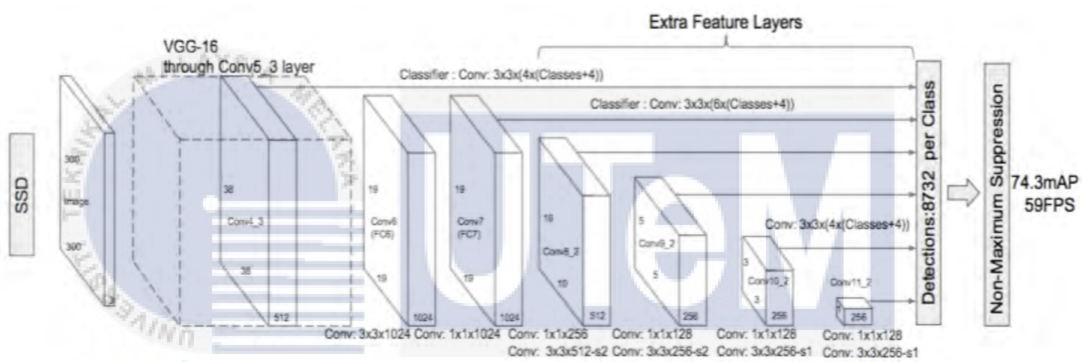

Figure 3.18: Architecture of the SSD [27]

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From figure 3.18, the architecture is build on the VGG-16 architecture but discards the fully connected layers. The first part is the feature extraction part where consist of a bunch of convolutional blocks from some other networks. The outputs are feed into the next part which is detection part. It is a sequence of the detection blocks, with each block having its own output that contributes to the final output.

There are 3 branches in each detection block known as box generation, classification and localization correction. Box generation is responsible for the cropping rectangle of various aspect ratio centred in regular grid nodes over the feature map. The branch is responsible for predicting class + 1 confidence score for each generated box.

Last part is responsible for the fines adjustment of positions for all boxes generated. Then the outputs are collected a last layer where the smart filtering of the prediction happens. Classification loss and Localization losses calculated only for boxes with same class label as the ground truth.

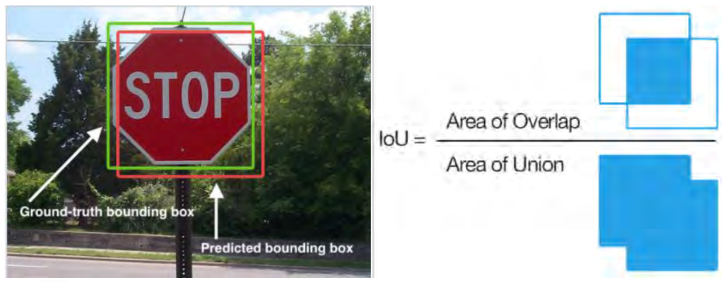

Figure 3.19: Diagram describing IoU

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Localization Loss

$$L_{loc}(x,l,g) = \sum_{i\in Pos}^{N} \sum_{m\in\{cx,cy,w,h\}} x_{ij}^{k}\,\mathrm{smooth}_{\mathrm{L1}}(l_i^m - \hat{g}_j^m)$$
$$\hat{g}_j^{cx} = (g_j^{cx} - d_i^{cx})/d_i^w \qquad \hat{g}_j^{cy} = (g_j^{cy} - d_i^{cy})/d_i^h$$
$$\hat{g}_j^{w} = \log\left(\frac{g_j^w}{d_i^w}\right) \qquad \hat{g}_j^{h} = \log\left(\frac{g_j^h}{d_i^h}\right) \tag{3.3.7}$$

Classification Loss

$$L_{conf}(x,c) = -\sum_{i\in Pos}^{N} x_{ij}^{p} log(\hat{c}_i^p) - \sum_{i\in Neg} log(\hat{c}_i^0) \quad \text{where} \quad \hat{c}_i^p = \frac{\exp(c_i^p)}{\sum_p \exp(c_i^p)} \tag{3.3.8}$$

The Overall objective loss

$$L(x,c,l,g) = \frac{1}{N}(L_{conf}(x,c) + \alpha L_{loc}(x,l,g)) \tag{3.3.9}$$

3.2.3 Tensorflow

Tensorflow is an open source software library for machine intelligence which provided by the well-known organization Google Inc. Tensorflow can be utilized for statistical calculation using data flow graphs. The versatile architecture allows deploying computation to one or more CPUs or GPUs in a desktop, server, or mobile devices with a solitary API (Application Programming Interface). The library generally developed by the Google brain team within Google's Machine Learning Intelligence research organization for the purposes of performing machine learning and deep neural networks research. There are a lot of businesses and system that using tensorflow such as; Airbnb, Nvidia, Uber, Dropbox, eBay, Google, Snapchat, Intel, Twitter, Airbus, MediaTek, and Mi.

3.2.4 Python Programming Language

Python is an interpreted, object-oriented, high-level programming language with dynamics semantics. It is certainly a high-level built-in data structures. The language is very simple, easy to learn, and easy to read. The python interpreter and the comprehensive standard library are available in source and it is totally free of charge. It also gives an easy method to debug the program errors. The Python programming language is mainly used compared to other language is because the tensorflow library works well in this language.

3.2.5 LabelImg

LabelImg is a graphical annotation software that can be used for label bounding boxes around the objects in the images. it is written in python. The annotation will be

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saved as XML files in PASCAL VOC format, The XML file will contain the image size, the depth and the xmax , y max x-max coordinate that highlights the bounding boxes [29].

3.2.6 OpenCV

OpenCV is also known as "Open Source Computer Vision", is a software library. It provides high-level computer vision and machine learning functionalities. OpenCV not only provides a common infrastructure for computer vision applications but also to decrease the software developing time. It is so different and suitable under-graduate student because it guarantees free to be used. Besides that, it has about 2500 optimized algorithms. Algorithms are usable in face detection and recognition, object recognition, classify human actions in videos, track camera movements, track moving objects, extract 3D models of objects.

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3.3 Gantt Chart FYP 1

Table 3.2 below indicates the planned activities and allocated duration for each activity for FYP 1.

Table 3.2: Gantt chart for FYP 1

FINAL YEAR PROJECT 1	SEMESTER 1													
	WEEK													
PROJECT ACTIVITIES	1	2	3	4	5	6	7	8	9	10	11	12	13	14
MEET PROJECT SUPERVISOR														
FYP TITLE CONFIRMATION														
LITERATURE REVIEW														
PROBLEM IDENTIFICATION														
METHODOLOGY SELECTION														
DESIGN PROCESS														
SELECTION OF COMPONENTS														
EVALUATION														
REPORT WRITING (FYP1)														
PRESENTATION (FYP1)														
SUBMISSION REPORT (FYP1)														

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3.4 Gantt Chart FYP 2

Table 3.3 below indicates the planned activities and allocated duration for each activity for FYP 2.

Table 3.3: Gantt chart for FYP 2

FINAL YEAR PROJECT 2	SEMESTER 2													
	WEEK													
PROJECT ACTIVITIES	1	2	3	4	5	6	7	8	9	10	11	12	13	14
MEET PROJECT SUPERVISOR														
FABRICATE HARDWARE														
DATA ACQUISITION														
TRAINING AND TESTING CNN														
TESTING ELECRIC CIRCUIT														
EXPERIMENT ANALYSIS														
MODIFICATION														
FINAL ANALYSIS														
REPORT WRITING (FYP2)														
PRESENTATION (FYP2)														
SUBMISSION REPORT (FYP2)														

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3.5 Project Flowchart

3.5.1 Creating Datasets, Training and Testing process.

Figure 3.20 shows the flows and steps to create the required datasets, training and testing process.

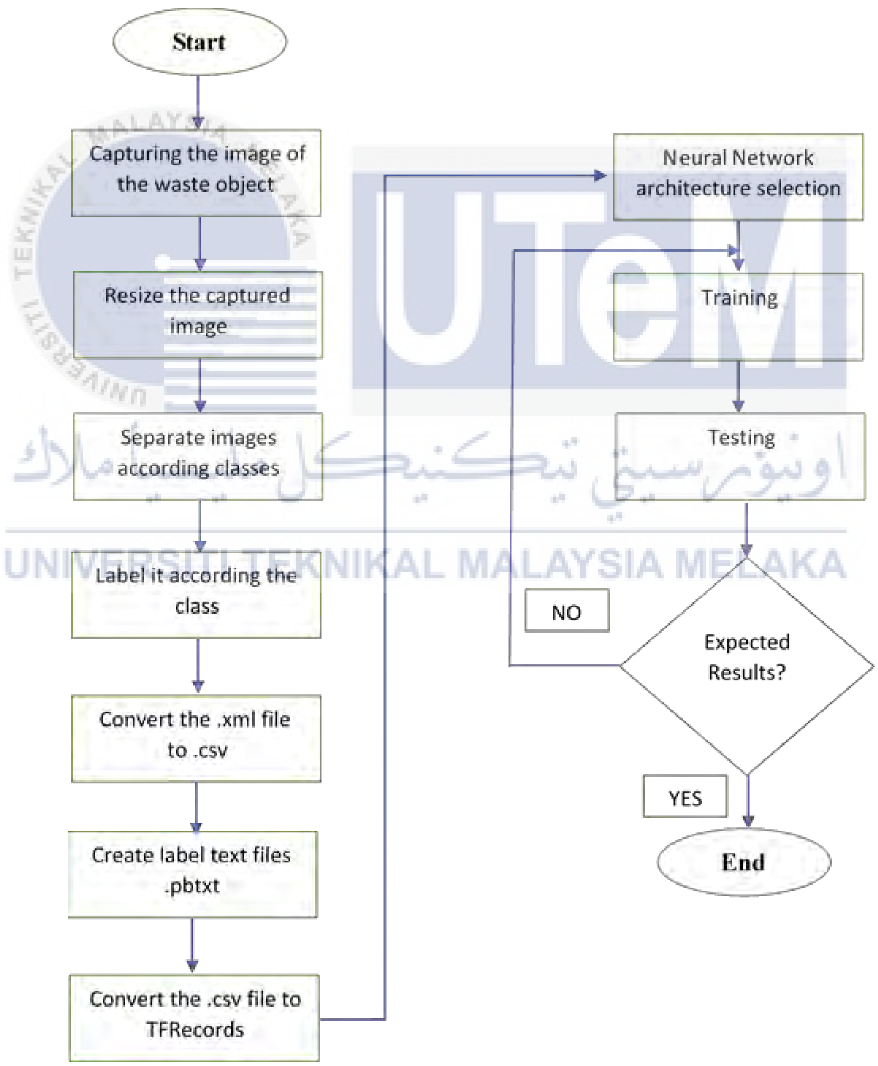

Figure 3.20: Steps creating the Dataset until Testing

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3.5.1.1 Capturing the image

Firstly, all the required plastic bottle and aluminium cans are collected. Then, the image of the all the collected waste object is captured. The device used to acquire all this image is iPhone 7. The images are captured with random distance, random orientation and with a black background. All the photo then, filtered and 120 photos for each class are selected and put together in a folder named “images” as shown in the figure 3.21.

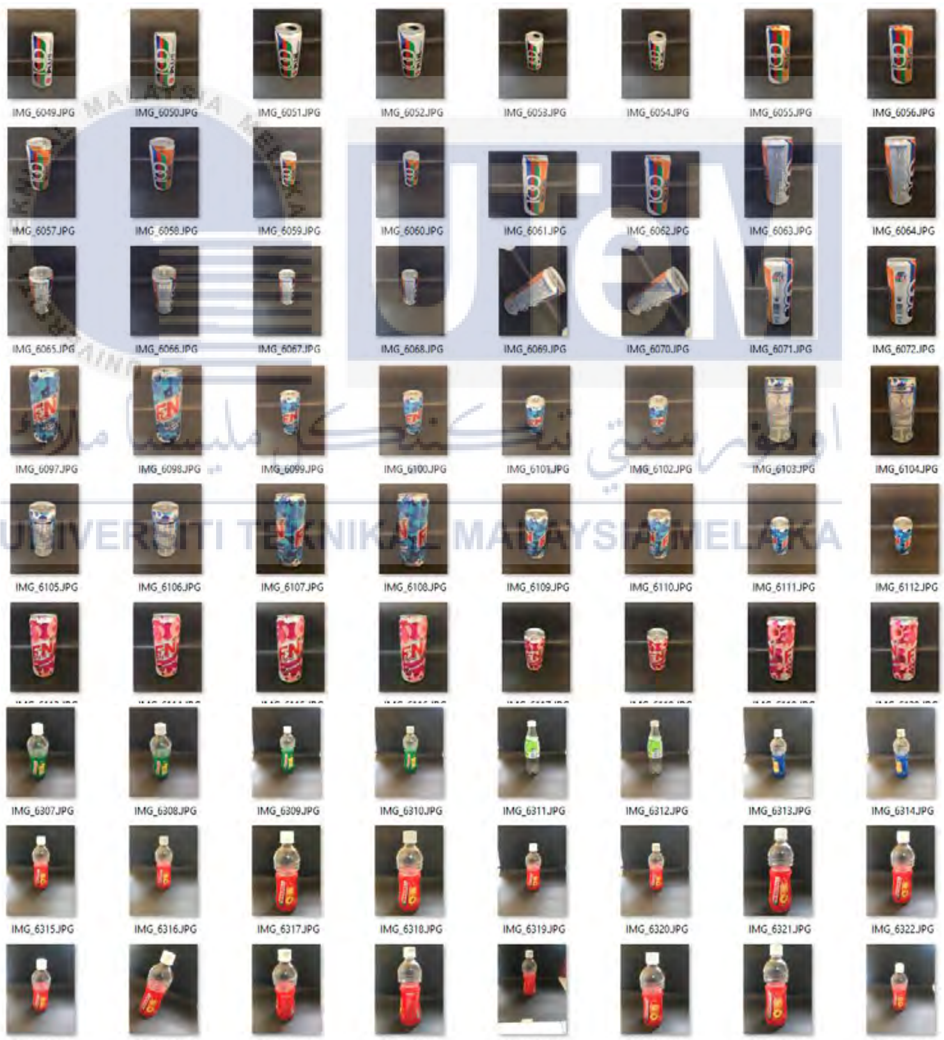

Figure 3.21: Dataset of the aluminium cans and plastic bottles

3.5.1.2 Resizing the image

The image resolution of captured photos is 3024 x 4032. This resolution is then reduced to 5 different resolution. There resolutions are 300 x 400, 600 x 800, 900 x 1200, 1200 x 1600 and 1800 x 2400. Python Imaging Library (PIL) is used to resize the images. All the resized images are put into a different folder under the folder name images. The coding used for the image resizing process is shown in figure 3.22 and the folder arrangements are shown in the figure 3.23.

```
#!/usr/bin/python
from PIL import Image
import os, sys

path = "/root/Desktop/Venoth Database/"
dirs = os.listdir( path )

def resize():
    for item in dirs:
        if os.path.isfile(path+item):
            im = Image.open(path+item)
            f, e = os.path.splitext(path+item)
            imResize = im.resize((1200,900), Image.ANTIALIAS)
            imResize.save(f + ' venoth3.jpg', 'JPEG', quality=100)

resize()
```

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Figure 3.22: Code to resize the image to 900x 1200

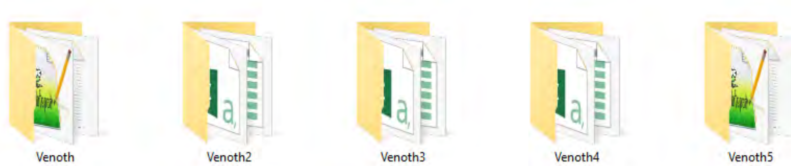

Figure 3.23: resized images folder arrangements

3.5.1.2.1 Pseudocode

Initialize the libraries

Initialize the path

define resize()

for :

All the items in the directory.

Images are opened as a file. Metadata is read from the opened file.

The pathname path split into a pair.

The image is resized to 1200,900.

The image saved with current name + venoth3.jpg as JPEG format with a quality of 100.

The resized images and original images are saved in the same directory.

end for

end resize()

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The required libraries will be initialize. Then user need to set the path for the image database. That path will be the directory of the original images. Then a image will be opened as a file and the metadata is read from the file. The file remain open until the end. Then the path name is split into a pair (root, item). Then the opened image is resized to the desired size which, in this case is to 1200,900. Then the resized image is saved current name together with venoth3.jpg. for example, if the original name of the images is IMG6001 then it will be saved as IMG6001 venoth.jpg. A high quality down sampling filter is used to maintain the quality of the image. The process will loop until the last image.

3.5.1.3 Labelling the images

This is the time taking process where all the images need to be labelled with the respective class. Each class consist of 120 images with 5 different resolution. LabelImg software was used for labelling. The output of this labelling is a text file with format of .xml. This .xml file will contain all the necessary information of the labelled image. The labelling procedures are shown in the figure 3.25. The example of the .xml content is shown in the figure 3.26.

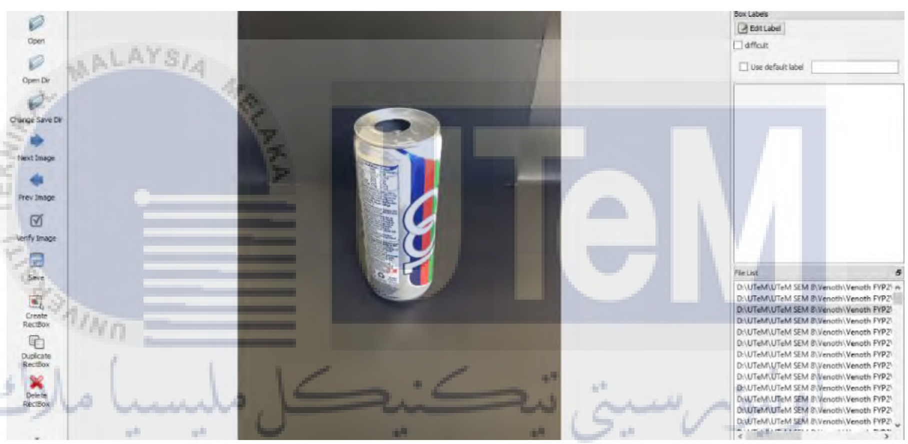

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Figure 3.24: LabelImg software interface

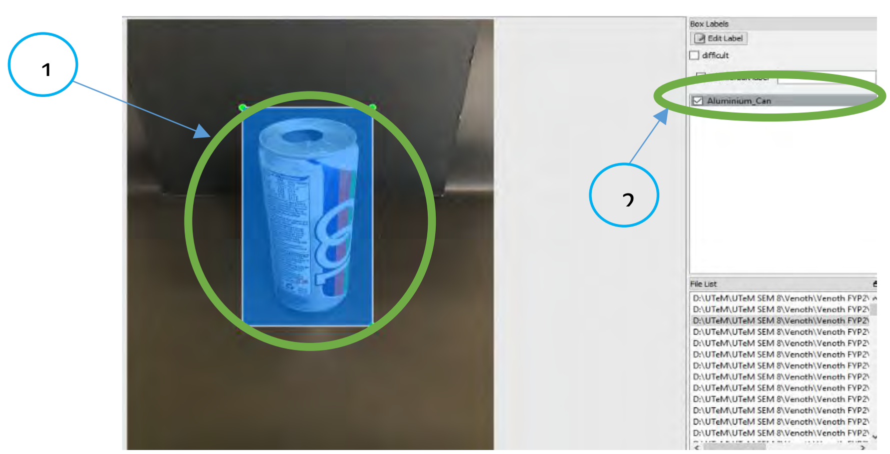

Figure 3.25: Image labelling and class selection

```
1  <annotation>
2      <folder>Venoth4</folder>
3      <filename>IMG_6001 venoth4.jpg</filename>
4      <path>D:\UTeM\UTeM SEM 8\Venoth\Venoth FYP2\Venoth4\IMG_6001 venoth4.jpg</path>
5      <source>
6          <database>Unknown</database>
7      </source>
8      <size>
9          <width>1200</width>
10         <height>1600</height>
11         <depth>3</depth>
12     </size>
13     <segmented>0</segmented>
14     <object>
15         <name>Aluminium_Can</name>
16         <pose>Unspecified</pose>
17         <truncated>0</truncated>
18         <difficult>0</difficult>
19         <bndbox>
20             <xmin>369</xmin>
21             <ymin>460</ymin>
22             <xmax>803</xmax>
23             <ymax>1448</ymax>
24         </bndbox>
25     </object>
26 </annotation>
```

Figure 3.26: .xml file content

Line 2 shows the directory of the image. Line 3 indicates the name of the image. Line 4 shows the path of the image from the root. Line 9 and 10 records the image height and width. Line 15 shows the name of the class. The class should be same to all aluminium can images. Line 20 to 24 indicates the dimension of the labelled class.

3.5.1.4 File conversion and label text

TensorFlow library is used for this project. TensorFlow requires a file format of TFRecord in order to proceed to the training process. All the .xml files for each image, classes, and resolution will be converted into .csv files and then into TFRecord. The .csv contents are shown in the figure 3.27. Before converting to TFRecord a label text is required. This label text with the format of .pbtxt will contain the name of the classes as shown in the figure 3.28.

1	filename	width	height	class	xmin	ymin	xmax	ymax
2	IMG_6101 venoth4.jpg	1200	1600	Aluminium_Can	391	470	774	1314
3	IMG_6285 venoth4.jpg	1200	1600	Plastic_Bottle	320	119	825	1548
4	IMG_6143 venoth4.jpg	1200	1600	Aluminium_Can	317	165	873	1221
5	IMG_6229 venoth4.jpg	1200	1600	Aluminium_Can	332	531	756	1209
6	IMG_6370 venoth4.jpg	1200	1600	Plastic_Bottle	325	58	837	1555
7	IMG_6283 venoth4.jpg	1200	1600	Plastic_Bottle	349	146	830	1377
8	IMG_6275 venoth4.jpg	1200	1600	Plastic_Bottle	432	233	832	1141
9	IMG_6249 venoth4.jpg	1200	1600	Plastic_Bottle	295	55	893	1533
10	IMG_6245 venoth4.jpg	1200	1600	Aluminium_Can	395	565	793	1224
11	IMG_6024 venoth4.jpg	1200	1600	Aluminium_Can	173	268	1010	1172
12	IMG_6059 venoth4.jpg	1200	1600	Aluminium_Can	439	382	778	1090
13	IMG_6292 venoth4.jpg	1200	1600	Plastic_Bottle	373	104	812	1582
14	IMG_6316 venoth4.jpg	1200	1600	Plastic_Bottle	398	160	810	1170
15	IMG_6359 venoth4.jpg	1200	1600	Plastic_Bottle	430	219	815	1248
16	IMG_6087 venoth4.jpg	1200	1600	Aluminium_Can	395	409	747	1163
17	IMG_6314 venoth4.jpg	1200	1600	Plastic_Bottle	437	336	791	1309
18	IMG_6043 venoth4.jpg	1200	1600	Aluminium_Can	300	146	844	1416
19	IMG_6113 venoth4.jpg	1200	1600	Aluminium_Can	295	158	851	1431

Figure 3.27: .csv file content

```
item {
  id: 1
  name: 'Aluminium_Can'
}

item {
  id: 2
  name: 'Plastic_Bottle'
}
```

Figure 3.28: Label .pbtxt

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The label.pbtxt should follow the name used when labelling the image. An incorrect format will cause an error during the conversion.

3.5.1.5 Network Selection, Training and Testing.

Mobilenet-SSD was selected for this project and the training steps is restricted to 5000 steps. For the testing process, new images are captured and used to test the network detection accuracy.

3.5.2 Waste Segregation Process Flowchart.

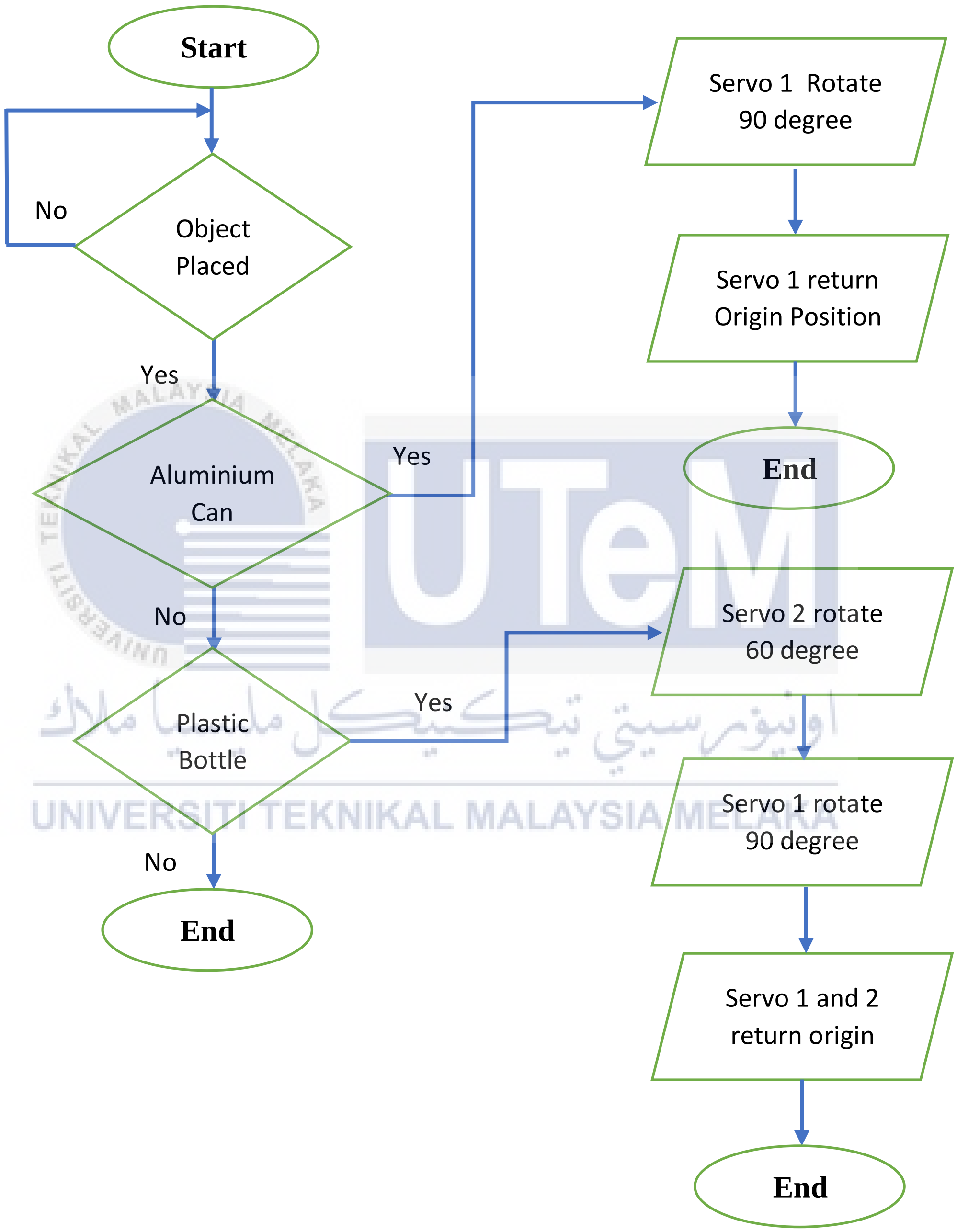

Figure 3.29: Segregation Flowchart

3.6 Experimental Setup

3.6.1 Experiment 1

Objective

1. To train the pre-trained Mobilenet network to detect plastic bottle and aluminium can
2. To determine the loss of the network by varying the resolution of the image.

Procedures

1. The resized image 300 x 400 was trained using the network
2. The training steps are restricted to 5000 steps.
3. The loss data are collected.
4. The step 1 to 3 is repeated for the image 600 x 800 , 900 x 1200 , 1200 x 1600 and 1800 x 2400.
5. All the data are recorded and tabulated.

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3.6.2 Experiment 2

Objective

1. To analyse the classification accuracy using the various distance from the object.
2. To determine the reliable distance for detection.

Procedure

1. The reference distance for aluminium can to the camera was set to 20 cm while for plastic bottle is 30cm.
2. For aluminium cans, the distance was increased 5cm for each test till 40cm.
3. Step 2 is repeated for plastic bottles till reach 50cm.
4. All the required images were collected
5. The images are classified using the re-train network model.
6. The results are tabulated into the table.
7. The data recorded are analysed.

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3.6.3 Experiment 3

Objective

1. To determine the classification of the aluminium can and plastic bottle.
2. To get the accuracy of the system.

Procedure

1. The required input images are gathered.
2. The input image was analysed using the re-trained model.
3. The results are tabulated into the table.
4. The experiment is carried out for 20 trials.
5. The step 2 -5 are repeated for all the input images.
6. The data is recorded and analysed.

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CHAPTER 4

RESULTS AND DISCUSSION

This chapter will discuss about the hardware development and also the results of experiments that has been carried out in order to test the accuracy and to identify the reliable detection distance of the system. The experiments are conducted indoor, with a black background and will be including several parameters that are taken to test the system. From the experiment that was conducted, several data are collected and tabulated into the table as result. The data taken will be analysed and briefly discussed in this chapter.

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4.1 Hardware Design

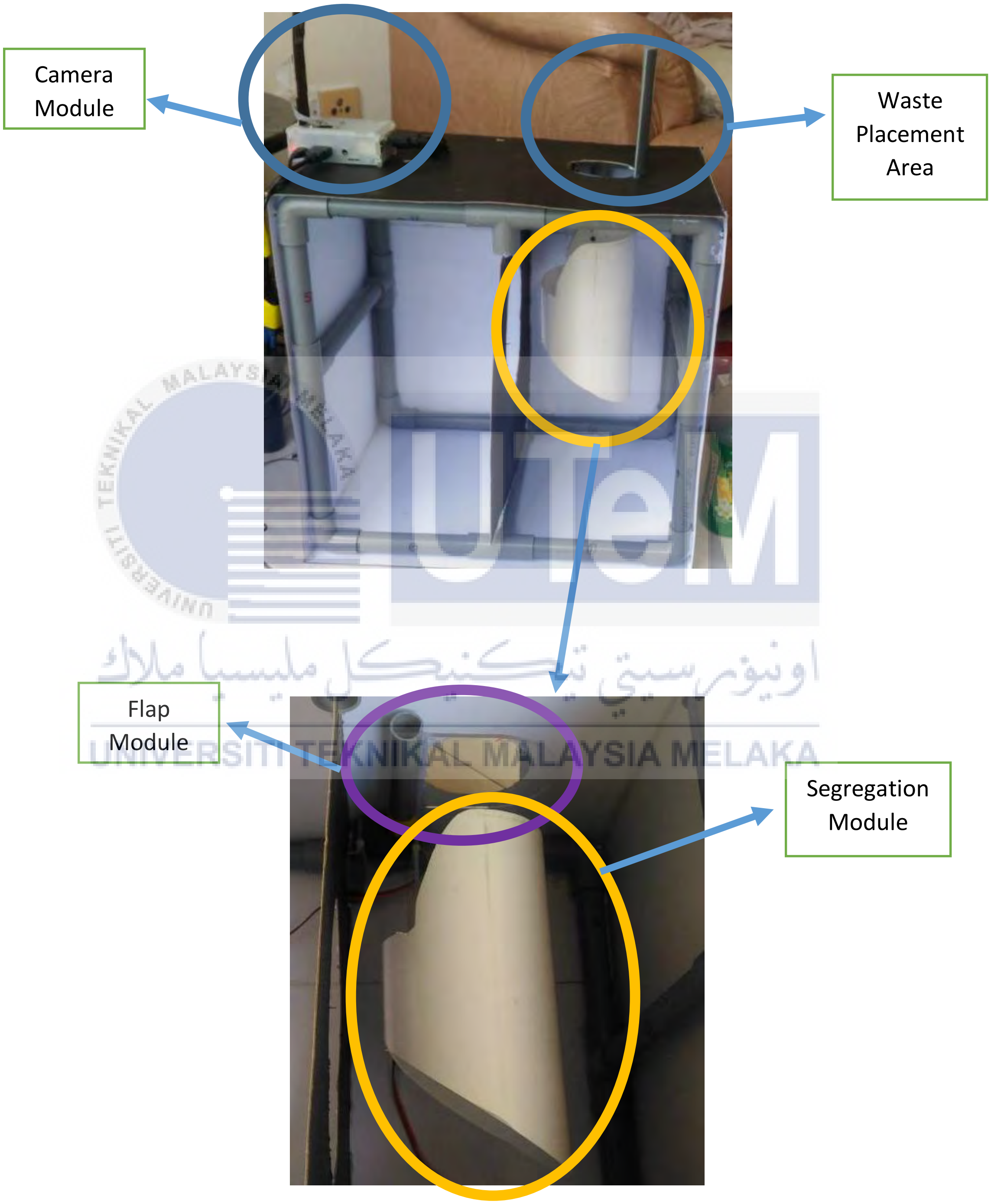

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Figure 4.1: The project (a) isometric view (b) front view (c) side view (d) top view

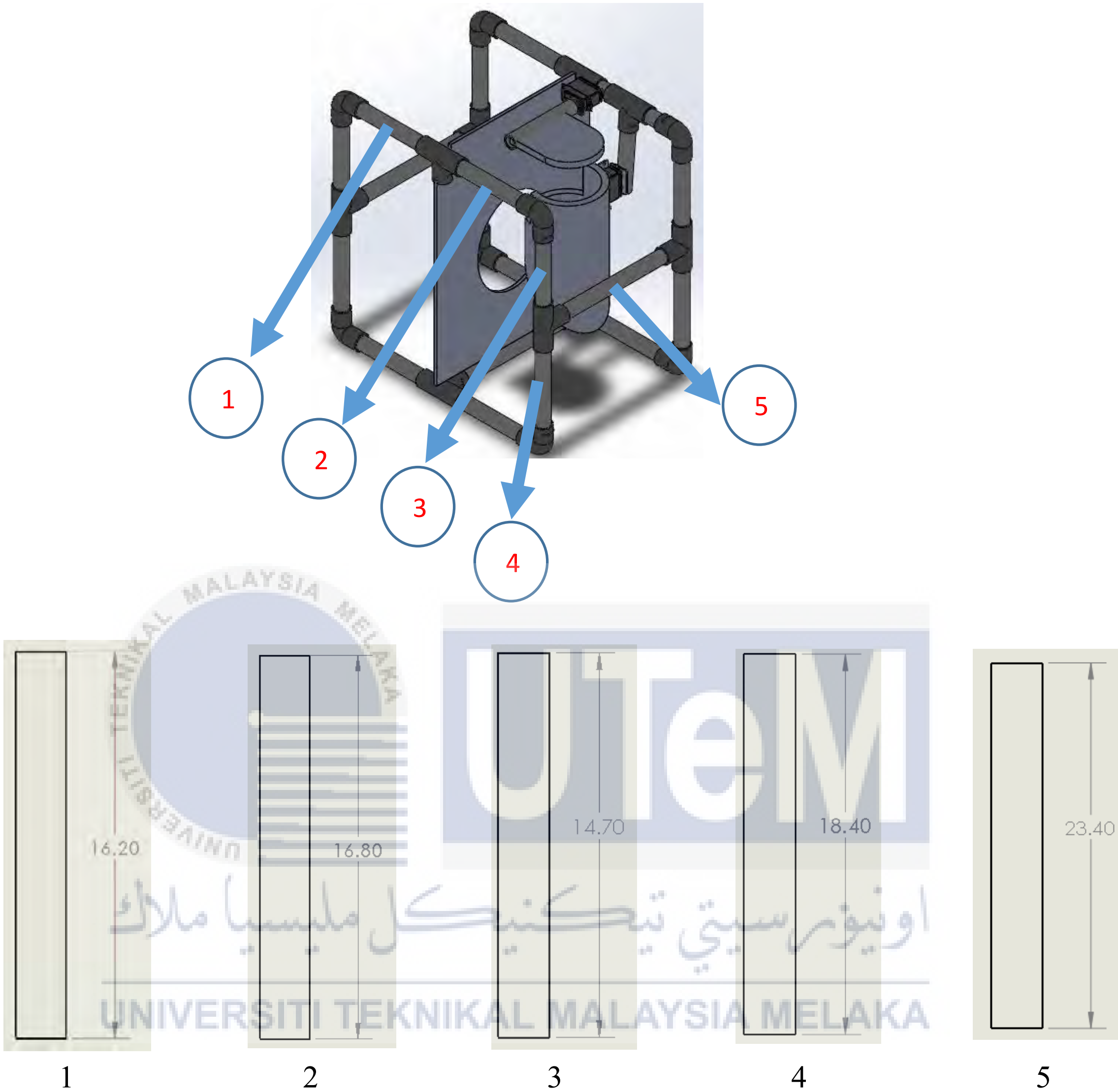

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Figure 4.2: Dimension of the projects

Figure 4.1 shows the fully covered projects view. A shows the isometric view of the project, B shows the front view, C indicates the side view and D shows the top view. Figure 4.2 shows the detailed view of the project including the dimension. This whole project is made up from PVC pipe of 0.5 inch, while the segregation module is made from 2 and half inch PVC pipe. The whole project is covered by using A3 sized Black Color Cardboard.

4.2 Experiment 1

Experiment 1 is carried out to estimate the total loss in the network during the training process. The training step is fixed for 5000 steps while the image resolution varied. The training is conducted locally (Notebook). The specification of the hardware is described in table 4.1 and the software specifications are described in table 4.2. Figure 4.3 shows the image of the hardware used.

Table 4.1: Hardware specifications

Notebook Model	Asus - A456U
Processor	Intel i5-6200U (Sixth-Gen)
Graphics Card	Nvidia-930m
RAM	12GB (4 + 8)

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Figure 4.3: Asus A456U

Table 4.2: Software Specifications

Library	**Version**
OS	Ubuntu 17.04
Python	3.6.3 / 2.7.14
Tensorflow	1.7.0 – CPU (build from source)
CUDA Toolkit	No
cuDNN	No
OpenCV	3.4.1
Protobuf	3.5.1
Pillow	5.1.0
Lxml	4.0.0
Matplotlib	2.2.2
Numpy	1.14.2
GCC* (GNU Compiler Collection)	7.2.0

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4.2.1 Experiment 1 results

The experiment 1 results are shown in table 4.3. The results for each resolution are interpreted in the form of the line graph and shown in figure 4.4 until figure 4.8.

Table 4.3: Total Loss results for all image resolutions

Steps	Picture Resolution				
	300 x 400	600 x 800	900 x 1200	1200 x 1600	1800 x 2400
1	14.610	15.016	16.964	15.747	N/A
250	2.765	3.415	4.724	3.189	N/A
500	2.940	3.331	2.112	3.686	N/A
750	2.862	2.271	2.605	3.300	N/A
1000	2.549	2.185	2.196	2.634	N/A
1250	2.541	1.852	3.015	2.138	N/A
1500	1.783	2.816	2.577	1.405	N/A
1750	2.387	2.055	2.880	2.532	N/A
2000	1.740	2.228	2.335	1.844	N/A
2250	1.657	2.054	1.340	4.698	N/A
2500	2.164	2.645	2.268	1.962	N/A
2750	1.088	1.404	1.343	1.959	N/A
3000	1.272	3.232	1.951	2.446	N/A
3250	0.790	1.566	1.745	2.938	N/A
3500	0.907	1.641	1.585	1.395	N/A
3750	2.392	1.751	1.544	1.284	N/A
4000	1.279	1.304	1.738	1.311	N/A
4250	1.371	2.556	1.706	1.692	N/A
4500	2.348	2.844	1.444	1.567	N/A
4750	1.915	1.256	2.168	1.534	N/A
5000	1.768	2.177	1.256	1.220	N/A

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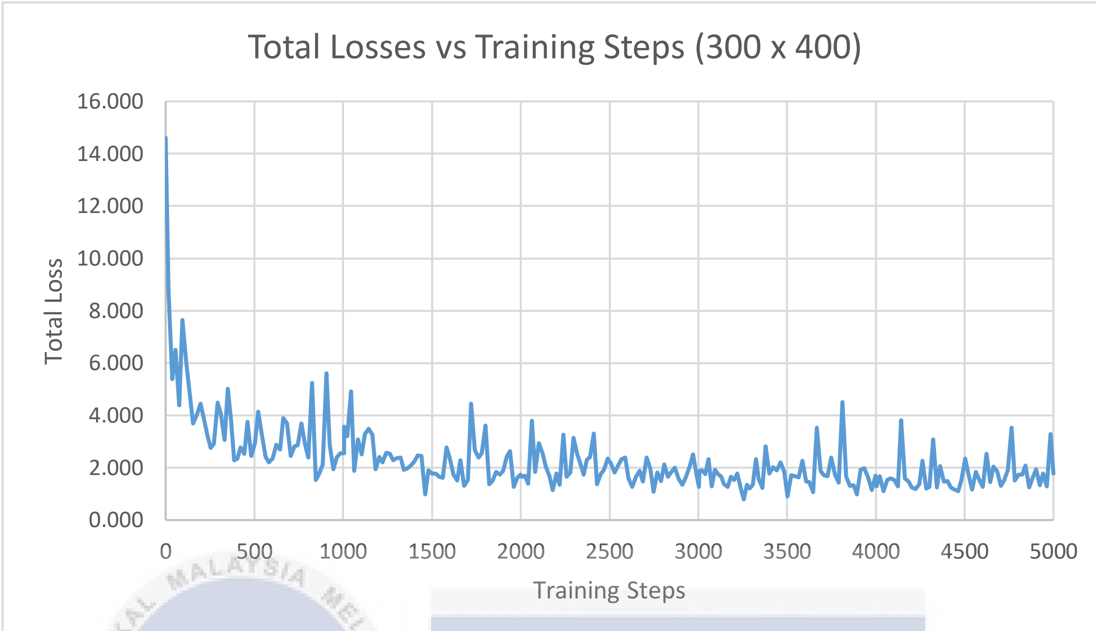

Figure 4.4: Total loss graph for image resolution 300 x 400

Figure 4.5: Total loss graph for image resolution 600 x 800

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Figure 4.6: Total loss graph for image resolution 900 x 1200

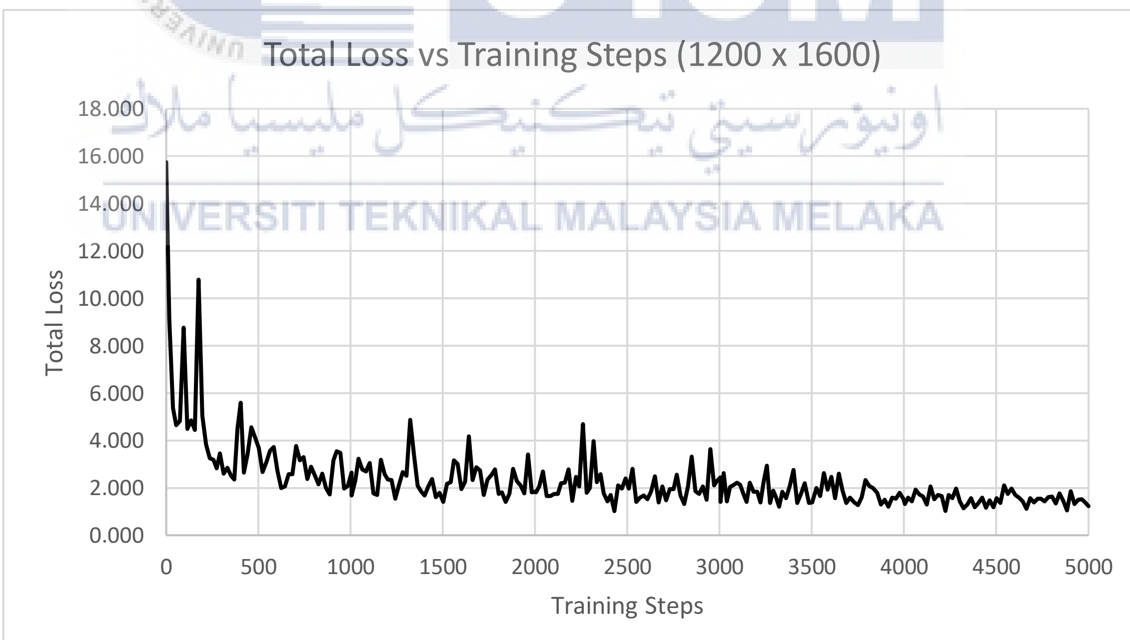

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Figure 4.7: Total loss graph for image resolution 1200 x 1600

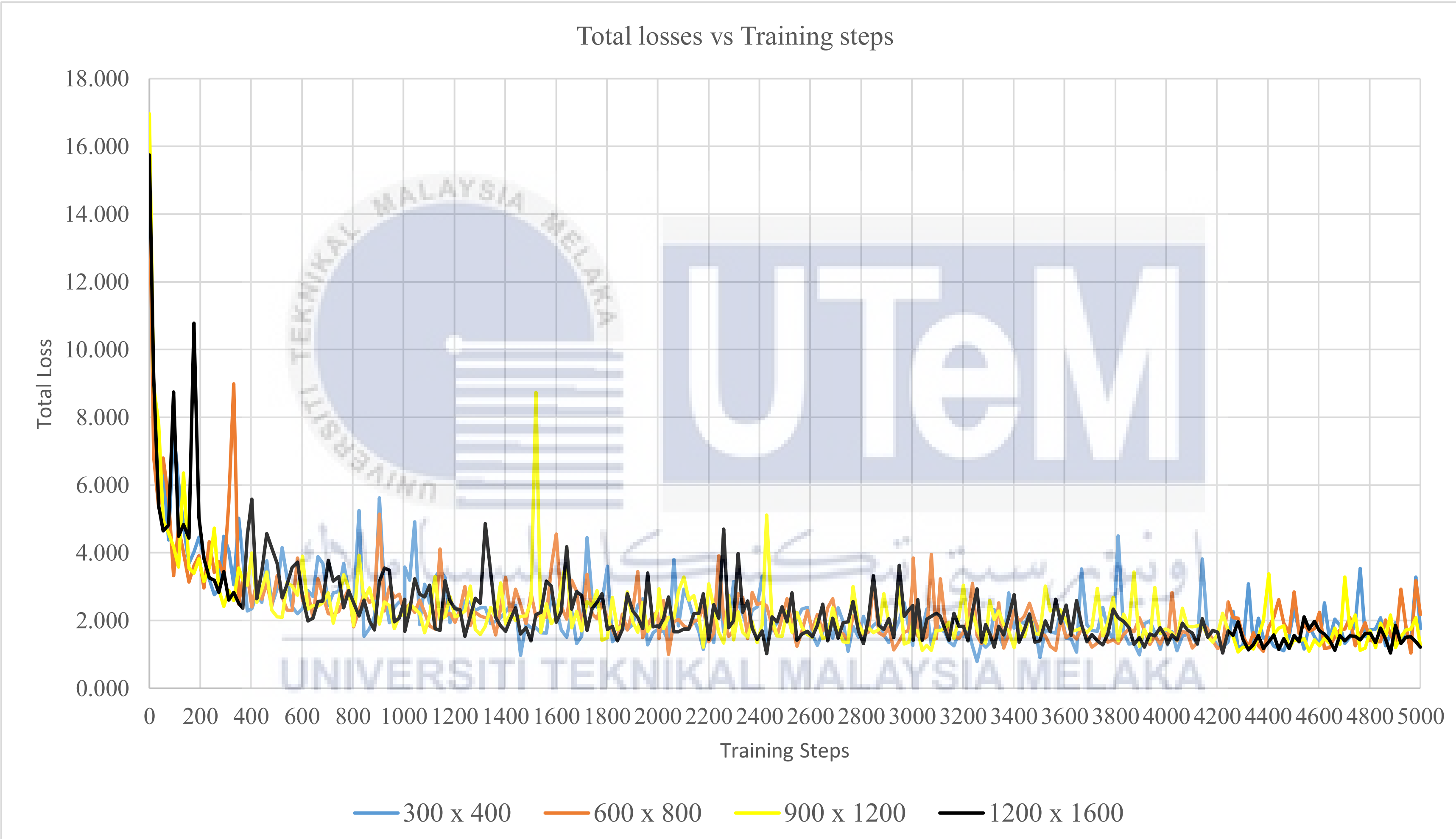

Figure 4.8: Combination of all total loss graph

4.2.2 Experiment 1 discussion

Total loss data collected for this experiment was for 5000 steps. Due to space limitation, only limited data are shown in table 4.3. The data shown in the table started with 1 till 5000 an increment of 250. On the other hand, the graph shown in figure 4.4 till figure 4.7 includes all the recorded data.

From the graph shown in figure 4.4, total loss of the network for image resolution of 300 x 400 at step 1 was recorded at 14.610. Then the loss decreased to 2.765 at 250 steps then, there is a slight increase to 2.940 at step 500. From the graph observation, the loss value from step 17 to step 115 fluctuates between the range of 8 to 4. From step 135 to step 500 the fluctuating range decrease between range 6 and 2. Starting from step 522 till 2000 the values fluctuated between 5.6 till 0.9. The loss values are fluctuated below 4 starting from step 2005 till the end except for step 3812 where the loss value exceeds the range.

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From the graph observed in figure 4.5, the total loss for the image resolution 600 x 800 started at 15.016 then followed 3.415 and 3.331 for the step 250 and 500. There is a drastic fluctuation at step 332 there the loss value increase drastically to 8.9. Starting from step 500 to 3238 the loss is maintained under a range of 4, except for step 905 and 1601 where, there recorded values are 5.135 and 4.556 respectively. However, the network shows a consistent loss from step 3500 till 4963 where the loss value maintained below 3.

For image resolution 900 x 1200, the loss graph is shown in figure 4.6. The loss started with 16.964 and then followed by 4.724 for step 250 and 2.112 for step 500. The observation from the graph shows that the after step 500 the total loss recorded until the end is maintained below 4, except for step 1521 and step 2429 where the loss is observed to at 8.740 and 5.118 respectively.

The results for the image resolution 1200 x 1600 is shown in figure 4.7 total loss recorded for step 1 is 15.747. Before reach 500 steps, there is a high fluctuation in loss values. At step 55 the recorded value is 4.646 then its fluctuated to 8.755 at step 95. The loss value again reduced to 4.438 at the step of 155 and at step 175 the value drastically increased to 10.778. Starting from step 500 the loss value is being maintained below 4 until step 4000. There is 3 times the loss value exceeds the range of 4. The steps are 1322, 1641 and 2250. The recorded values are 4.864, 4.177 and 4.698. The loss value between 4000 and 5000 steps are consistently recorded below the range of 2.

The data for 1800 x 2400 image resolution couldn't be obtained. This is due to the limited hardware resources. The CPU with 12GB of RAM able to train the lowest resolution without any problems. But for the 1800 x 2400 image resolution, the training process took a long time and even sometimes unable to complete it due to the memory restriction.

Last but not least, the training step for each resolution took around 6 to 8 hours to complete the 5k steps. Figure 4.8 shows the combination of all the loss graph. The higher image resolution graph shows a low loss compared to other low image resolutions. Since the 1200 x 1600 graph shows a low total loss, the trained model is used for the detection accuracy.

4.3 Experiment 2

This experiment is carried out to calculate detection accuracy of the waste object over a distance. The distance between the camera and waste object is varied. The tabulated data and results are shown in table 4.4 to 4.11. Figure 4.9 shows the experimental setup for this experiment and waste objects used for this experiment.

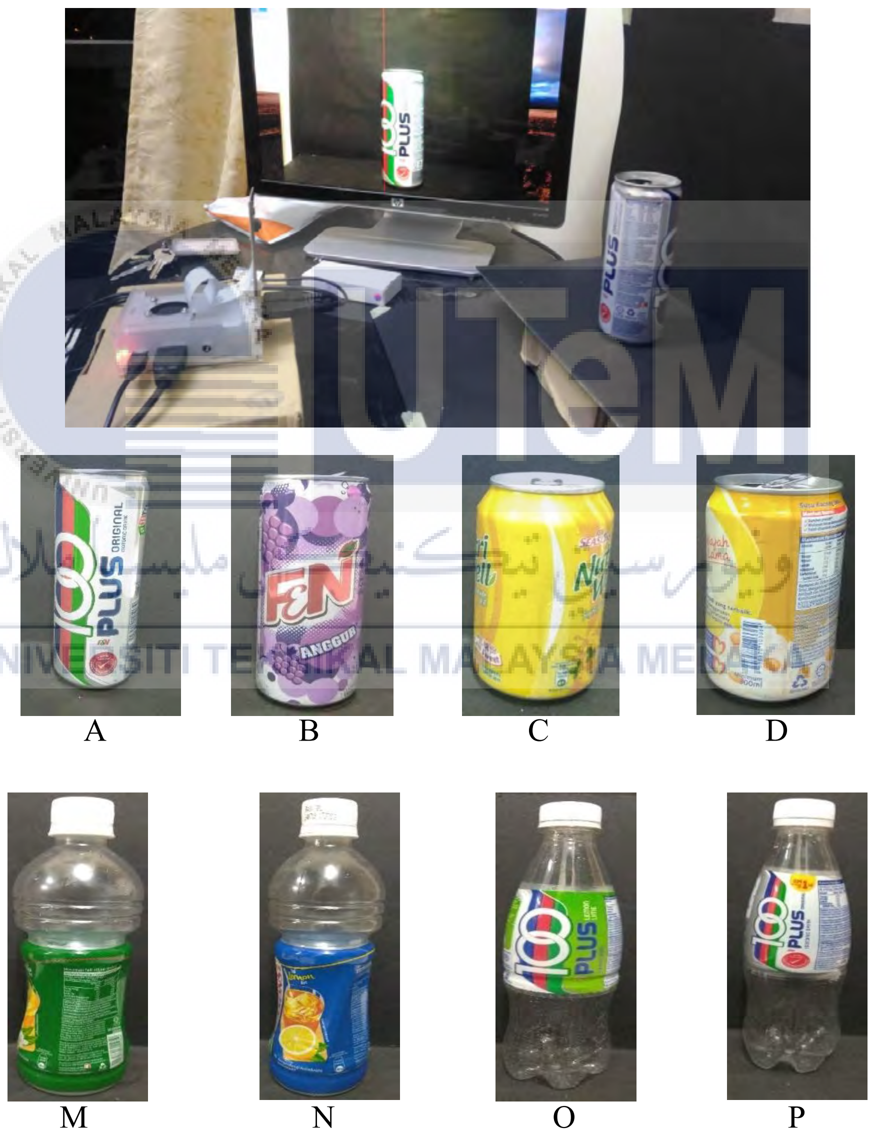

Figure 4.9: Experimental setup and waste used in the experiment

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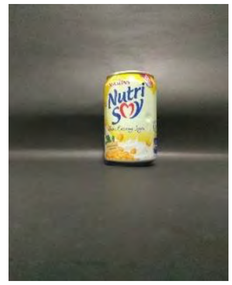
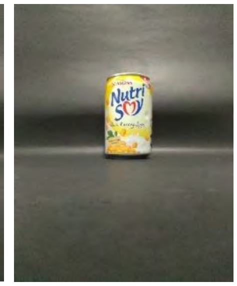
20cm


25cm


30cm


35cm


40cm

Figure 4.10: Aluminium Can with various distance.

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30cm


35cm


40cm


45cm

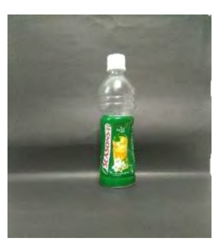
50cm

Figure 4.11: Plastic bottle with various distance

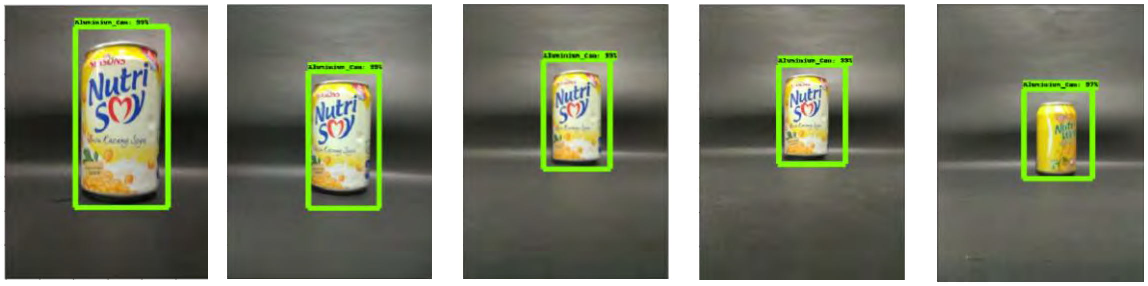

Figure 4.12: Aluminium Can detection results

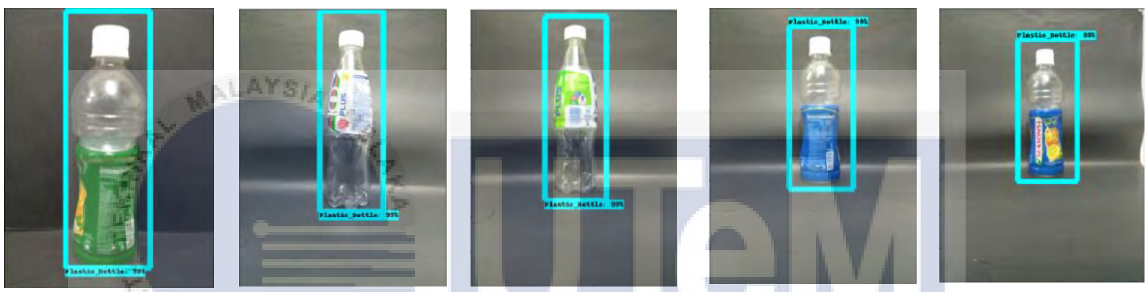

Figure 4.13: Plastic Bottle detection results

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4.3.1 Experiment 2 results

Table 4.4: Aluminium Can A detection results

Distance (cm) / Trials	Aluminium Can A						
	1	2	3	4	5	Average	Standard Deviation
20	99	99	99	99	99	99	0
25	99	99	99	99	99	99	0
30	98	98	99	98	97	98	0.70711
35	99	98	98	97	97	97.8	0.83666
40	99	97	97	97	97	97.4	0.89443

Table 4.5: Aluminium Can B detection results

Distance (cm) / Trials	Aluminium Can B						
	1	2	3	4	5	Average	Standard Deviation
20	99	99	99	99	99	99	0
25	99	99	99	99	99	99	0
30	99	98	98	99	97	98.2	0.83666
35	98	99	97	98	98	98	0.70711
40	97	97	97	99	97	97.4	0.89443

Table 4.6: Aluminium Can C detection results

Distance (cm) / Trials	Aluminium Can C						
	1	2	3	4	5	Average	Standard Deviation
20	99	99	99	99	99	99	0
25	99	99	99	99	99	99	0
30	97	98	98	97	98	97.6	0.54772
35	99	97	97	97	98	97.6	0.89443
40	99	97	97	98	99	98	1

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Table 4.7: Aluminium Can D detection results

Distance (cm) / Trials	Aluminium Can D						
	1	2	3	4	5	Average	Standard Deviation
20	99	99	99	99	99	99	0
25	99	99	99	99	99	99	0
30	97	98	97	97	99	97.6	0.89443
35	99	97	98	99	97	98	1
40	97	97	99	97	97	97.4	0.89443

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Table 4.8: Plastic Bottle M detection results

Distance (cm) / Trials	Plastic Bottle M						
	1	2	3	4	5	Average	Standard Deviation
30	99	99	99	99	99	99	0
35	99	99	99	99	99	99	0
40	97	98	98	98	99	98	0.70711
45	97	97	98	99	98	97.8	0.83666
50	99	97	97	97	97	97.4	0.89443

Table 4.9: Plastic Bottle N detection results

Distance (cm) / Trials	Plastic Bottle N						
	1	2	3	4	5	Average	Standard Deviation
30	99	99	99	99	99	99	0
35	99	99	99	99	99	99	0
40	99	98	99	98	97	98.2	0.83666
45	99	97	98	98	97	97.8	0.83666
50	99	98	99	97	97	98	1

Table 4.10: Plastic Bottle O detection results

Distance (cm) / Trials	Plastic Bottle O						
	1	2	3	4	5	Average	Standard Deviation
30	99	99	99	99	99	99	0
35	99	99	99	99	98	98.8	0.44721
40	97	99	98	97	98	97.8	0.83666
45	97	98	97	99	97	97.6	0.89443
50	97	99	99	97	98	98	1

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Table 4.11: Plastic Bottle P detection results

Distance (cm) / Trials	Plastic Bottle P						
	1	2	3	4	5	Average	Standard Deviation
30	99	98	99	98	99	98.6	0.54772
35	97	98	98	99	98	98	0.70711
40	99	97	97	98	97	97.6	0.89443
45	97	98	97	99	98	97.8	0.83666
50	99	97	98	97	99	98	1

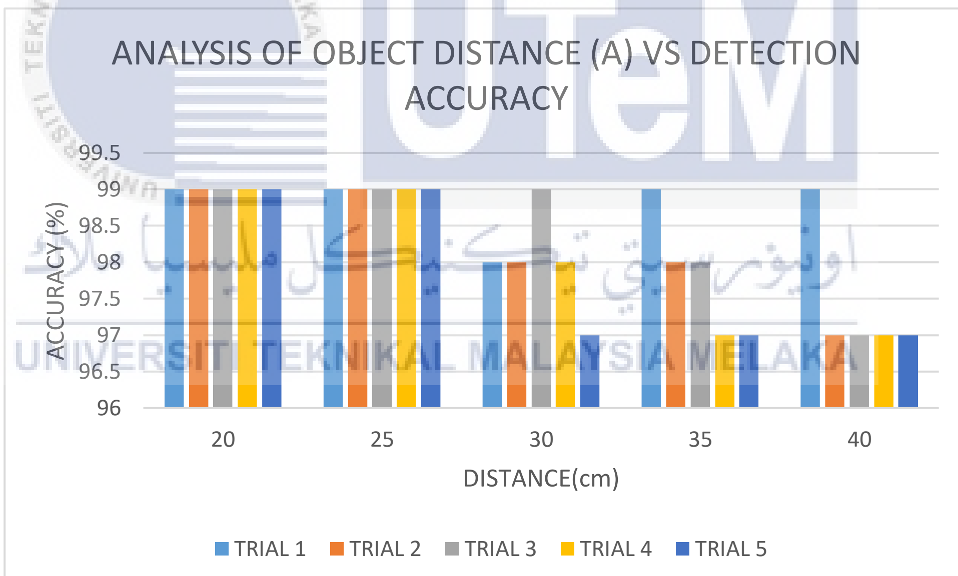

Figure 4.14: Aluminium Can A various distance accuracy

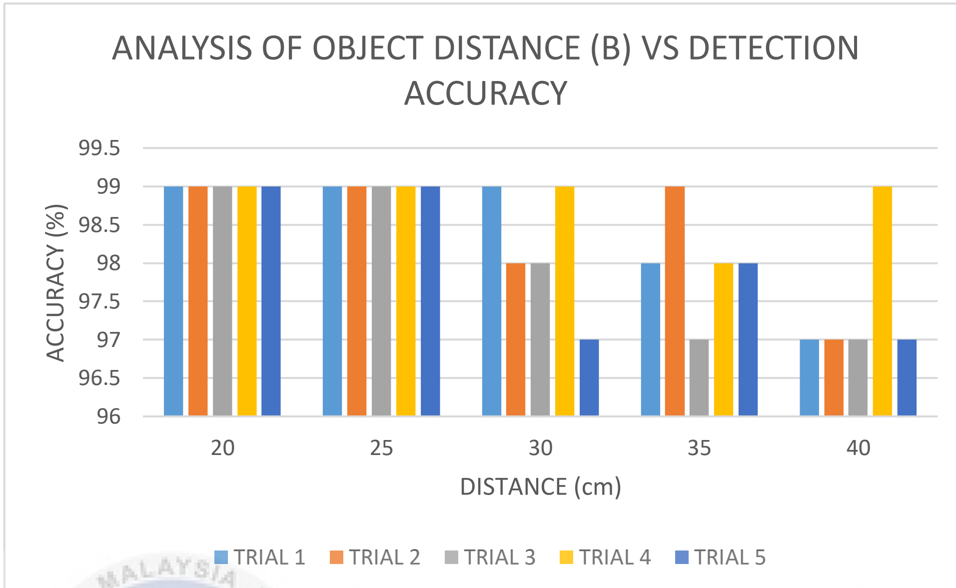

Figure 4.15: Aluminium Can B various distance accuracy

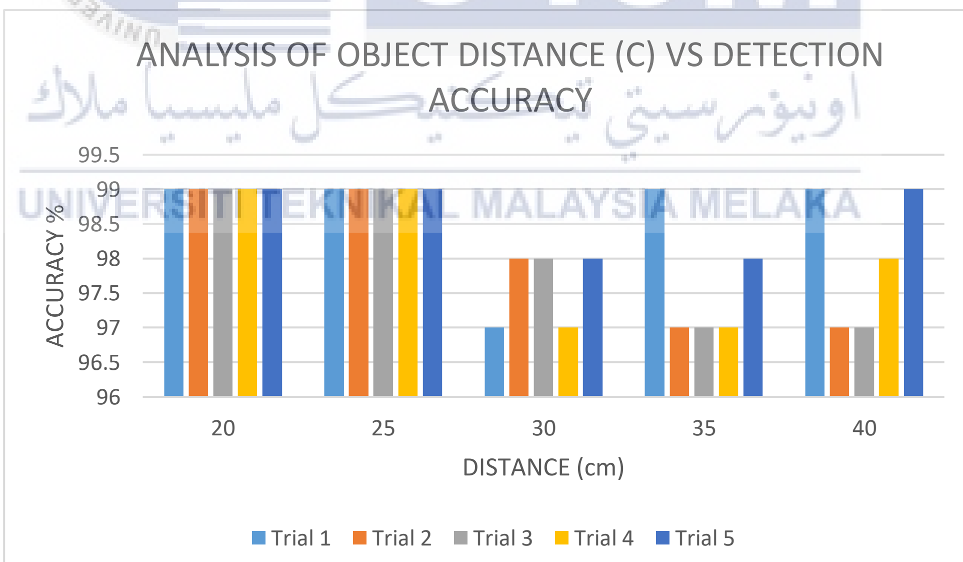

Figure 4.16: Aluminium Can C various distance accuracy

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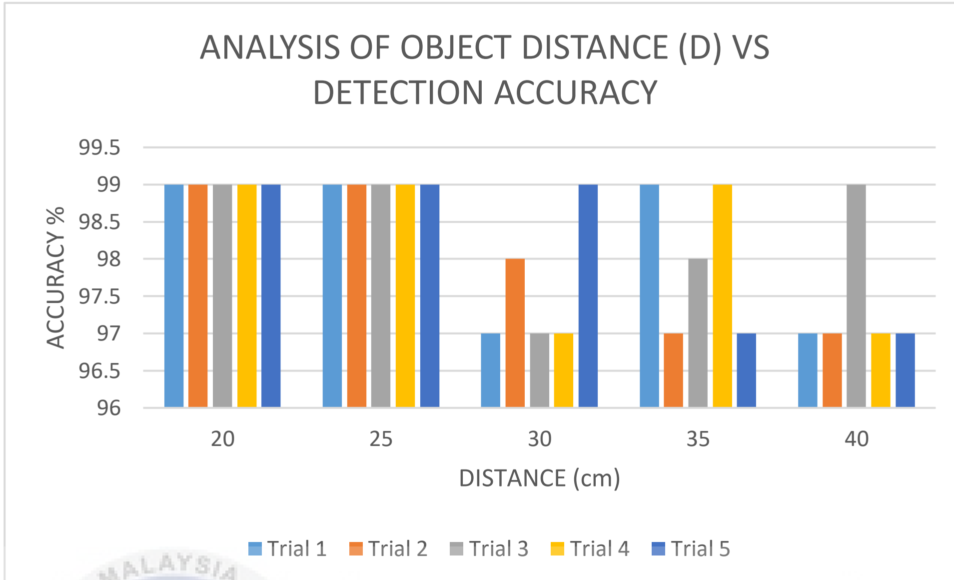

Figure 4.17: Aluminium Can D various distance accuracy

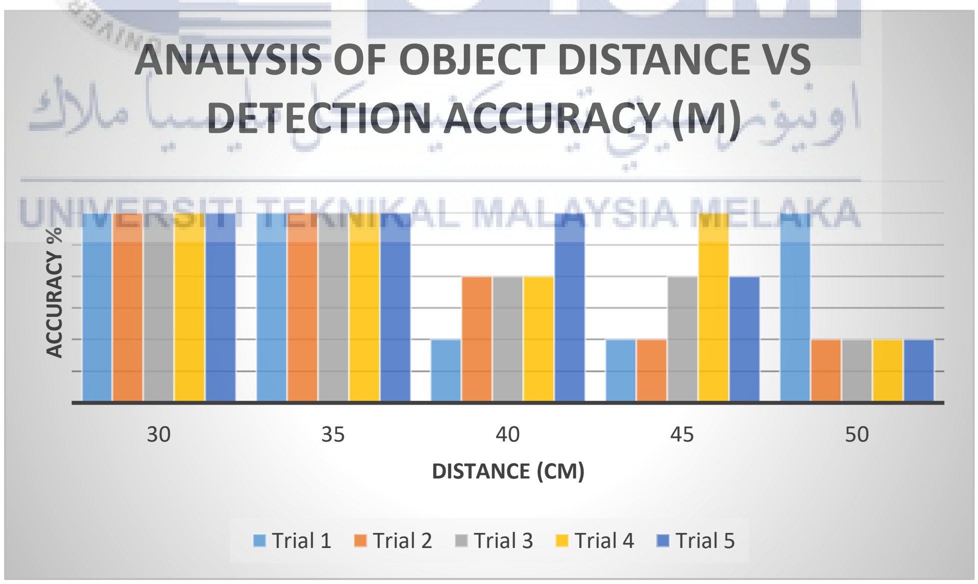

Figure 4.18: Plastic Bottle M various distance accuracy

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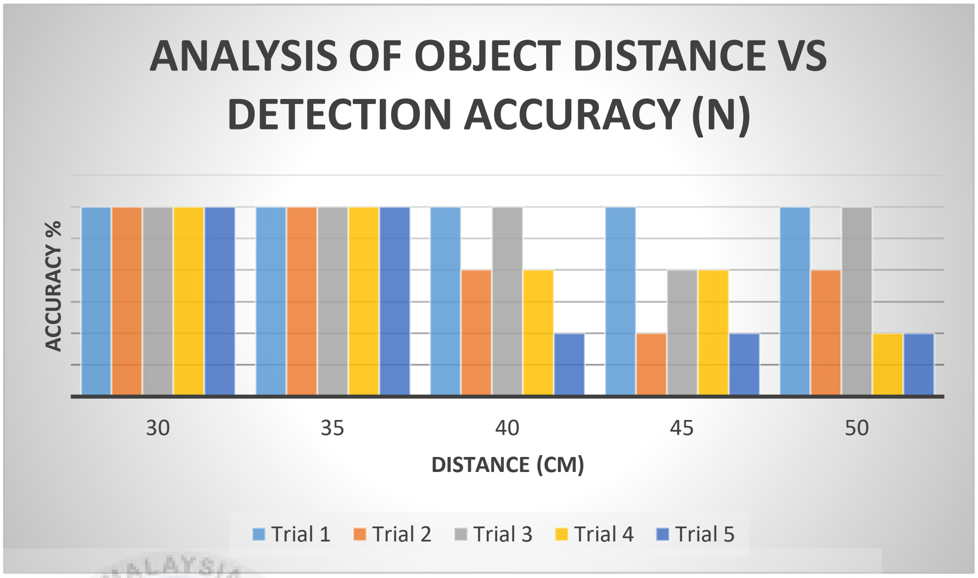

Figure 4.19: Plastic Bottle N various distance accuracy

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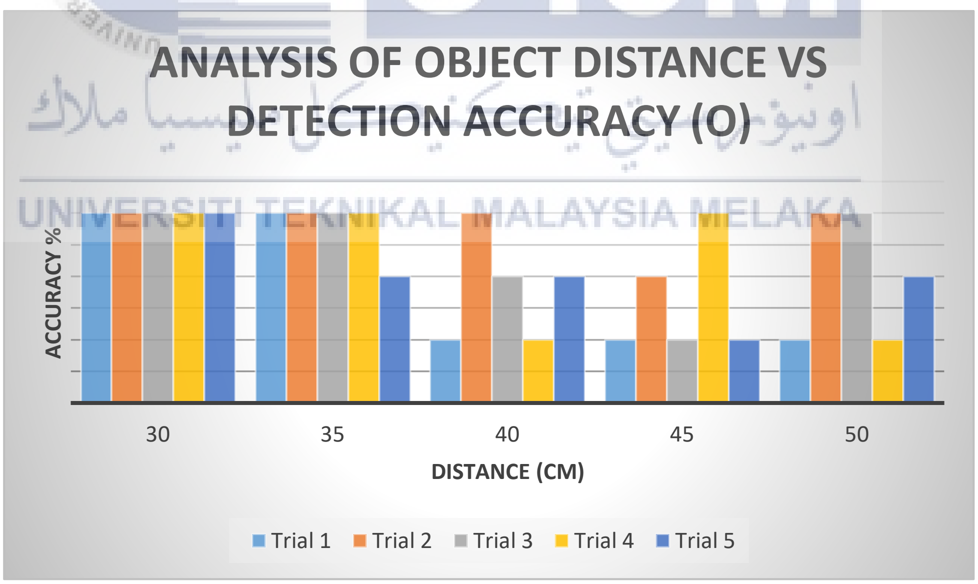

Figure 4.20: Plastic Bottle O various distance accuracy

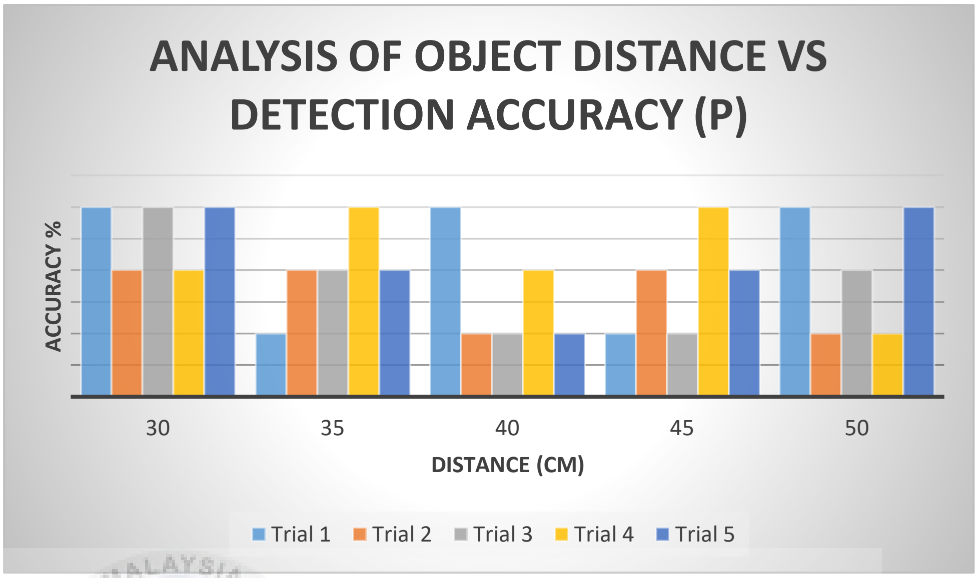

Figure 4.21: Plastic Bottle P various distance accuracy

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4.3.2 Experiment 2 discussion

Table 4.4 above shows the experimental data and figure 4.14 shows detection results for Aluminium Can A distance over a number of trials. The detection of the distance of 20cm and 25cm shows a higher and constant result compare to other three distances, for the 30cm distance the detection results decreased by 1 for each trial. The average detection for 20cm and 25cm remain the same while for others it decreases. The shorter the distance the better the detection. The distance of 20cm, 25cm are considered to be more reliable than others. Again, the light intensity and reflectivity do play a role for the results fluctuation.

Table 4.5 above shows the experimental data and figure 4.15 shows detection results for Aluminium Can B distance over a number of trials. The detection for the distance 20cm and 25cm shows constant result compare to other three distances which have some drop-in result, for the 35cm distance the detection results rocketed at 2nd trial and dropped on the 3th trial. As the distance increases, there is higher fluctuation in the detection results. The detection at 20cm and 25cm distance resulted higher compare to others. The reliable distance is same as for Aluminium Can A.

Table 4.6 shows the experimental data and figure 4.16 shows detection results for Aluminium Can C. The detection for the 20cm and 25cm distance for 5 trials remain the same which is 99%. For a distance of 30cm and 35cm the detection results varied around 1%. Again, the reliable distance for Aluminium Can C is 20cm and 25cm.

Table 4.7 above shows the experimental data and figure 4.17 shows detection results for Aluminium Can D. The detection at 20cm and 25cm shows constant result compare to other three distances which have some drop-in result, at 30cm the detection results rocketed at 2nd trial and dropped on the 3rd trial and again rocketed ad last trial. At distance of 35cm, there is some fluctuations. The first detection is 99% then dropped to 97% then again reached the 98% then increased to 99% and again dropped to 97%. There is no stability in the detection at the distance of 35cm. The reliable distance still maintained at 20cm and 25cm.

Table 4.8 above shows the experimental data and figure 4.18 shows detection results for Plastic Bottle M. Compare to the aluminium can the initial distance start with 30cm due to the size difference. The detection at 30cm and 35cm shows constant result compares to other three distances which have some fluctuating result. At 40cm and 45cm the value fluctuated between 97% and 99%. For the 50cm the initial result rocketed to 99% the dropped to 97% and remain constant until the end. Similar to the aluminium can, the 1st and 2nd distance shows a great accuracy and reliability.

Table 4.9 shows the experimental data and figure 4.19 shows the detection results for Plastic Bottle N. 1^{st} and 2^{nd} distance results similar to the previous bottle. The detection at 40cm shows that the accuracy dropped 1% from 4^{th} to 5^{th} trial. As the distance increases, there is slight decrease in the accuracy.

Table 4.10 shows the experimental data and figure 4.20 shows the detection results for Plastic Bottle O. The detection at 30cm shows constant result compare to other four distances which have some drop-in result, for the 35cm the detection results dropped at 4^{th} trial. As the distance increases, the accuracy fluctuates. Again, as the distance increase, the stability also decreases. The reliable distance for plastic bottle O is 30cm only.

Table 4.11 above shows the experimental data and figure 4.21 shows detection results for Plastic Bottle P. Compare to other bottle at 30cm distance the accuracy has dropped 1%. This du the transparency of the bottle and also white label on it. For each distance out of 5 trials, there is 99% accuracy at least for once.

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For aluminium can and plastic bottle detection, as the distance increases the accuracy decreases. The stability of detection also decreases as the distance increases. The reliable detection distance for aluminium can is 20cm and 25cm, while for a plastic bottle is 30cm and 35cm. This distance will be used for the next experiment to determine the accuracy of the detection.

4.4 Experiment 3

The experiment is carried out to test the accuracy of the waste detection. Only 4 aluminium can and 4 plastic bottles are used for this experiment. The experiment is carried out for 20 trials. The data collected for aluminium cans are shown in table 4.4, while table 4.5 shows the data collected for the plastic bottles. Figure 4.22 shows the experimental setup for the experiment.

Figure 4.22: Experimental setup

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A B C D

Figure 4.23: Aluminium Can used for the experiment

M N O P

Figure 4.24: Plastic Bottle used for the experiment

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4.4.1 Experiment 3 results

A B C D

Figure 4.25: Aluminium Can detection results

M N O P

Figure 4.26: Plastic Bottles detection results.

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Table 4.12: Aluminium Can detection data

Trial	Aluminium Can A	Aluminium Can B	Aluminium Can C	Aluminium Can D
1	99	99	99	99
2	99	99	99	99
3	98	99	99	99
4	99	99	97	98
5	98	97	99	99
6	99	97	98	99
7	99	98	99	99
8	99	99	98	98
9	99	98	98	97
10	99	99	97	98
11	99	97	98	98
12	99	98	99	99
13	99	97	98	97
14	99	98	97	99
15	98	98	97	97
16	99	98	97	98
17	98	99	98	99
18	99	99	98	97
19	98	99	99	98
20	99	98	99	98
AVG	98.8	98.4	98.3	98.5
S.D	0.421637	0.843274	0.8232726	0.70710678

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Table 4.13: Plastic Bottle detection data

Trial	Plastic Bottle M	Plastic Bottle N	Plastic Bottle O	Plastic Bottle P
1	99	99	99	99
2	99	98	98	98
3	99	98	97	97
4	99	98	97	96
5	99	98	97	96
6	99	98	97	96
7	99	97	97	96
8	99	97	97	97
9	98	97	97	97
10	98	97	98	98
11	99	97	97	98
12	98	98	97	98
13	99	98	99	98
14	98	99	98	99
15	99	99	98	99
16	98	99	97	98
17	99	98	97	97
18	98	98	97	97
19	98	98	99	97
20	99	99	99	98
AVG	98.65	98	97.6	97.45
S.D	0.48936	0.725476	0.820783	0.998683

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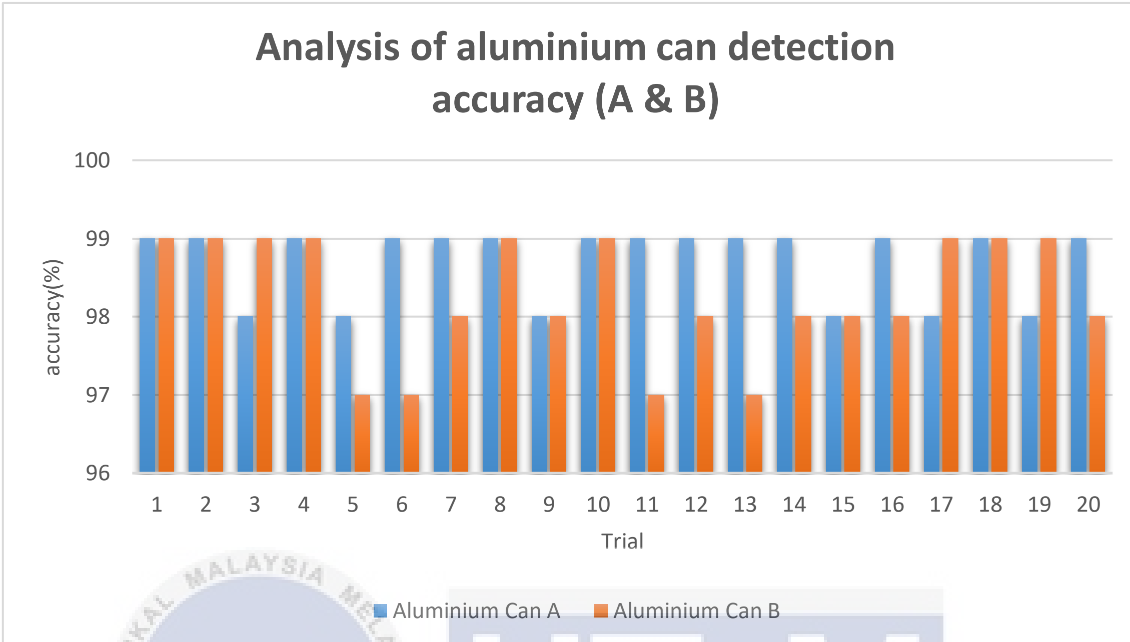

Figure 4.27: Aluminium Can A & B detection results

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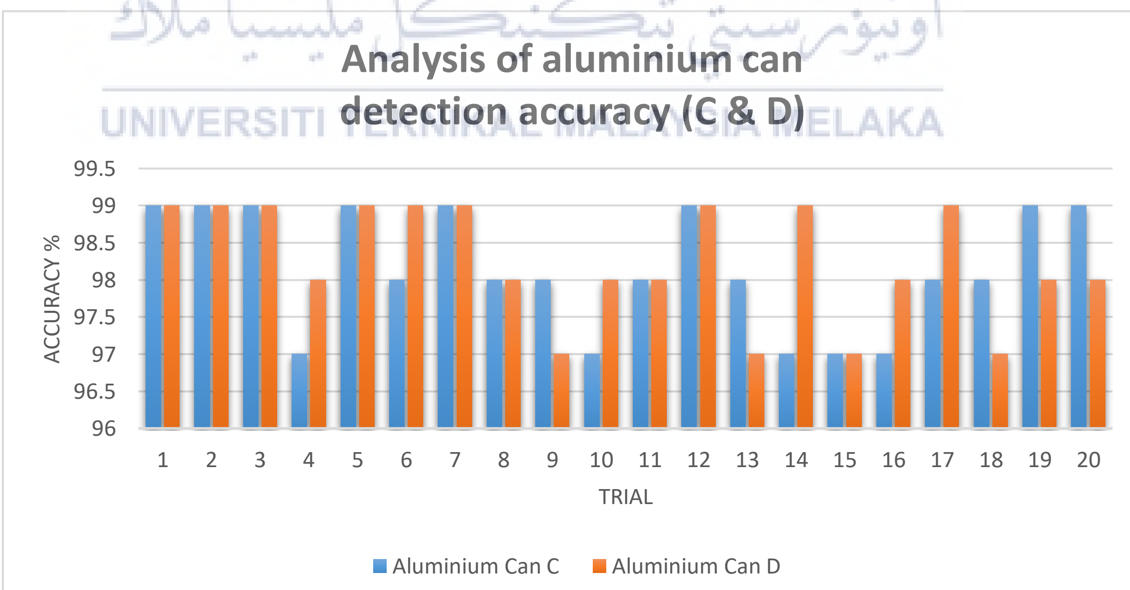

Figure 4.28: Aluminium Can C & D detection results

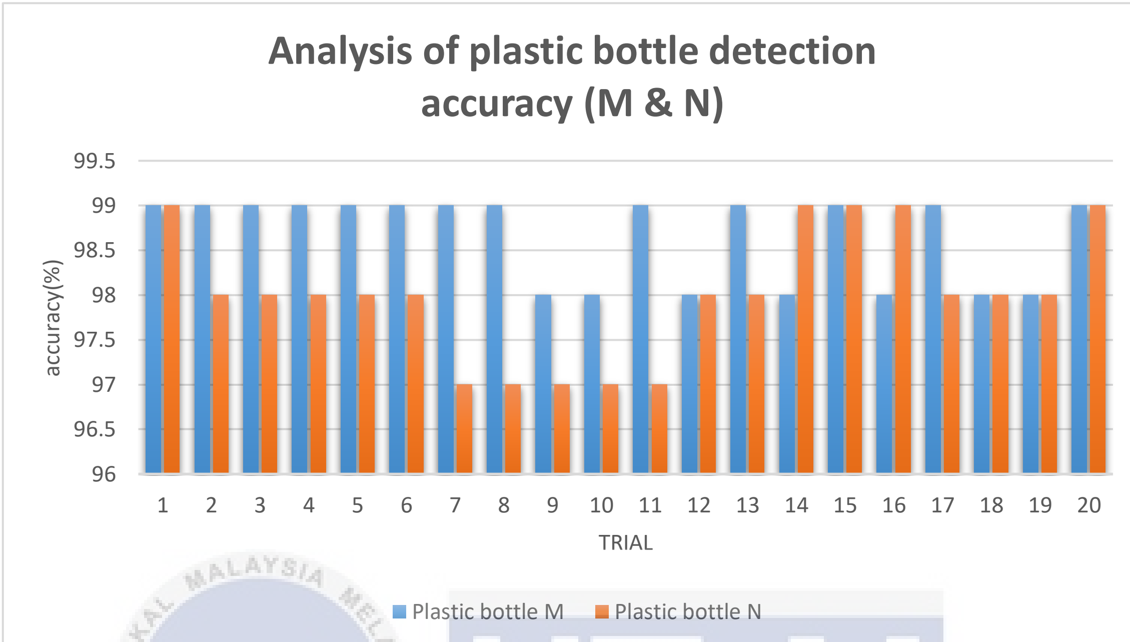

Figure 4.29: Plastic Bottle M & N detection results

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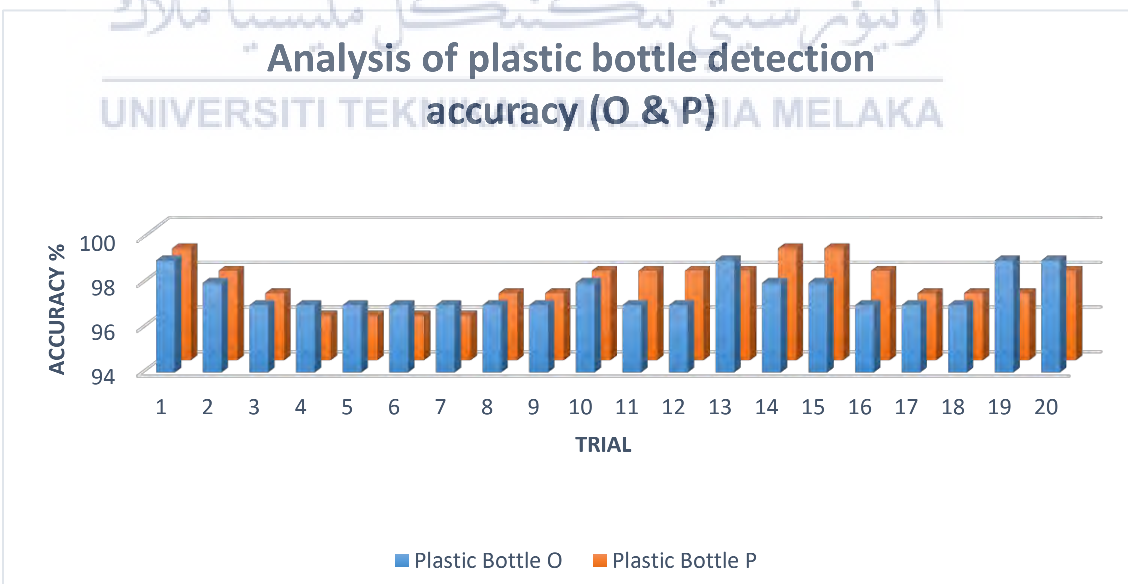

Figure 4.30: Plastic Bottle O & P detection results

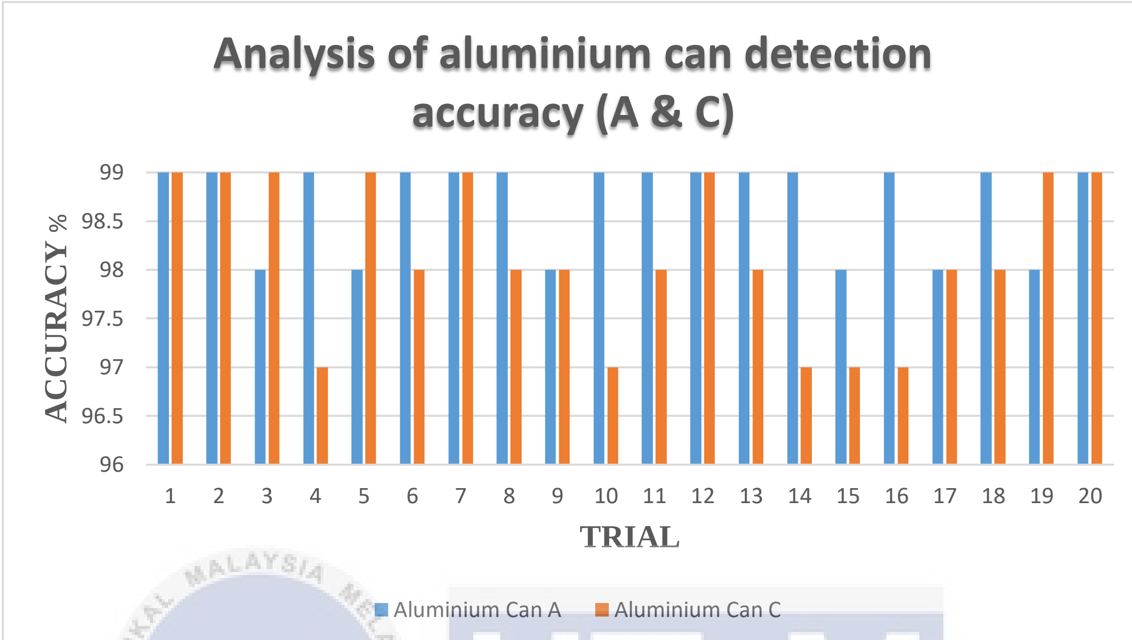

Figure 4.31: Aluminium Can A & C detection results

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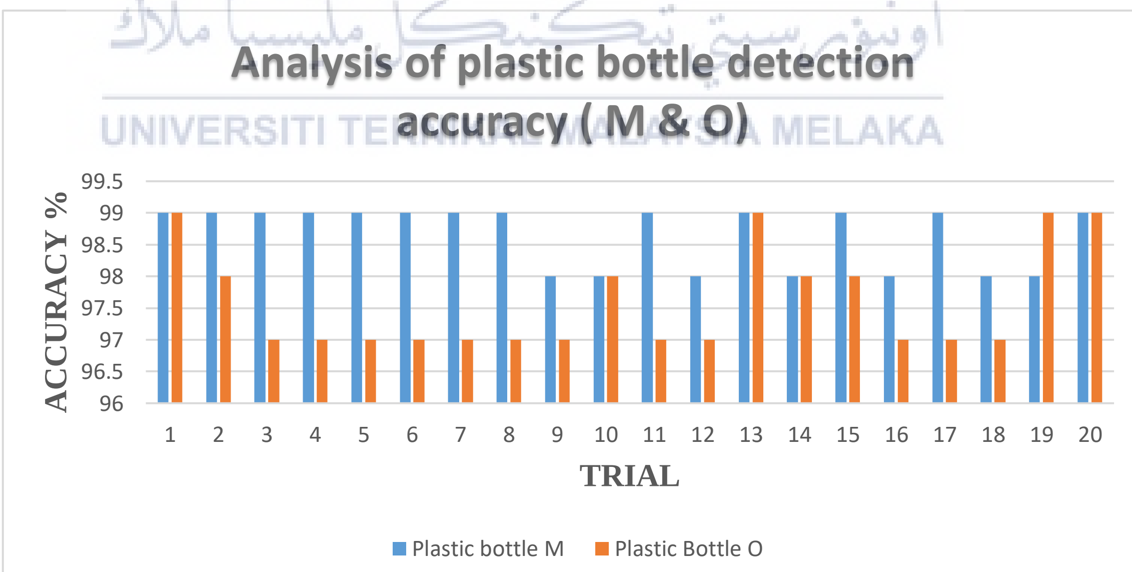

Figure 4.32: Plastic Bottle M & O detection results

4.3.2 Experiment 3 discussion

The graph at figure 4.27 shows the analysis result of aluminium can detection for 325ml types of can's over the number of trials run. As shown figure 4.23 above both cans having similarity in size and different in colour. Based on the data shown on table 4.12 and also the graph trend shown in figure 4.27, the result analysis for Aluminium Can A detection accuracy shows average of 98.8% which is higher compare to Aluminium Can B which the detection accuracy is 98.4%. The difference is 0.4%. From the 6th trial to 14th trial, the Aluminium Can A detection accuracy is recorded consistently at 99% while for the Aluminium Can B the detection varies. The light intensity and also the colour difference between the both aluminium can affect the detection results.

The graph at figure 4.28 shows the analysis result of aluminium can detection for 320ml types of can's over the number of trials run. Based on the data shown on table 4.12 and also the graph trend, the result analysis for Aluminium Can C and D shows that the first three trial run results for both aluminium can remain constant. After that, there is some drops in number of value for the next trials for both cans. The average accuracy detection for Aluminium Can D is higher than Can C. Aluminium Can C average accuracy is 98.3% and for Aluminium Can D is 98.5%. The difference of the detection is due to the light intensity and colour difference of both aluminium can.

The graph at figure 4.29 shows the accuracy analysis result for plastic bottle M and N as shown in figure 4.14. Both bottles are selected from F&N season brand with difference colour of labels. Based on graph trend, the result analysis for plastic bottle M shows constant accuracy until 8th trial run whereas drop in the amount of value on the 9th and the 10th trial, whereas plastic bottle N shows a moderate accuracy. The average detection result for Plastic Bottle M went up slightly compared to N. The calculated average for Bottle M is 98.65% while for Bottle N is 98%.

The figure 4.30 above shows the accuracy analysis result of 100 plus plastic bottle over the number of trials run. The plastic bottle O and P has constant accuracy result for the 1^{st} run while the next run dropped slightly until the 9^{th} trial run. The average detection accuracy for plastic bottle O went up slightly 0.15% compare to plastic bottle P.

Figure 4.31 shows the comparison between 325ml aluminium can (A) and 320ml aluminium (C). There is fluctuation in the detection accuracy. This is due to the colour, size and position of both objects are different. The light reflectivity for both objects also differs. Figure 4.32 shows the comparison between 500ml F&N season bottle and F&N 100plus. Both bottles are from same brand but, the detection accuracy is not the same. This is because the plastic bottle O much more transparent than bottle M and the light reflectivity differs for both objects.

Based on table 4.12, the average detection for Aluminium A, B, C, and D are 98.8, 98.4, 98.3 and 98.5 respectively. Average detection for Plastic Bottle M, N, O, and P are 98.65, 98, 97.6 and 97.45 respectively. Even though there is a slight difference between each value, the network does provide a better detection accuracy. Compare to plastic bottle detection, aluminium can have high detection accuracy. Aluminium Can A and Plastic Bottle M provide a good repeatability results which each result has the standard deviation of 0.42163 and 0.48936. This proves the test provides a capable result over a repeatable period.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The Development of Waste Segregator to Enhance Waste Classification based on Deep Learning Approach is designed to be a system that equipped with Deep Learning technology which is capable of performing waste classification and segregations. This system is designed in order to replace the manual way of waste recycling. The first objective is partially achieved as the design is successfully developed. However, there is a problem with the segregation process. This is because there is a communication problem between the detection and also separation mechanism. The problem is that the camera able to capture and the system able to recognise the waste but the actuator which is servo motor is unable to work. The troubleshooting as been done by altering and changing the coding however the system unable to segregate the waste. There are some problems with the software installation, but all the software installation problem able to solved by troubleshooting. Another problem arise is lagging. The raspberry equipped with limited resources, when running the classification process the raspberry pi become vey lag and very slow processing.

Second objective is achieved as the trained MobileNets Convolutional Neural Network able to recognise the waste whether it is plastic bottle or aluminium can. Last objective also achieved as the system performance is well analysed. Data and results shown in Chapter 4 revealed that the developed system able to sort the waste into their respective classes. The results also show that the image resolution does affect the classification. As the image resolution increase, the total loss in the network is reduced and the accuracy increase.

However, this design is a fundamentals mechanism only emphasize only on certain volume and brand of drinking containers. The specific drinking containers are 320ml and 325ml aluminium can, 500ml F&N season brand and 100plus. But this is not the limitation of this developed project. A new waste class can be added in the network through training. For examples, can add new target such as KFC, MCD paper cup and coffee cup. Styrofoam also can be added. A new object dataset is created by obtaining required images and retrain the network compare the performance.

There are a lot of techniques that can be used for the object detection. This project uses MobileNets Convolutional Neural Network together with python to process and recognise the waste.

In conclusion, all the objectives are achieved as the developed system can process and recognize the waste. A lot of experienced is gained especially in the deep learning and also mechatronic design. This project does have a greater capability to become a reliable helper in the recycling process if further improvement is considered and implemented.

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5.2 Recommendation

There are some parts that can be improved for the future usage. First of all is to troubleshoot the segregation problem and replace the on-image detection to the real time detection. Secondly is to add more classes for the recognition. This developed project has a limitation of 500ml of plastic bottle. In future this volume can be increases into 1.5l plastic bottle. The developed system also can be added with some additional classes like food cans, plastic cup, paper cup, and etc.

This project is developed using Google MobileNets v1 and currently there is a new version of MobileNets is introduced. The new MobileNets is known as MobileNetV2: Inverted Residuals and Linear Bottlenecks. A project can be developed based on the new version and the performance of the system can be analyzed and compared with the version 1. Other than that, the deep learning framework used in this system is tensorflow. A new project can be developed using another deep learning framework that has been discussed in chapter 2.

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This project is developed using Convolutional Neural Network. A new project can be developed using Artificial Neural Network or Recurrent Neural Network and the performance of the system can be analyzed and compared.

Last but not least, a fully cover black box with built in lighting can be fabricated and install at the waste placement area. This because light intensity and reflection of the light become the manipulated variables that affecting the accuracy of the mechanism. The fluctuated accuracy values are due to the experiment done in different position. Deep learning is one of the good tool to recognize object.

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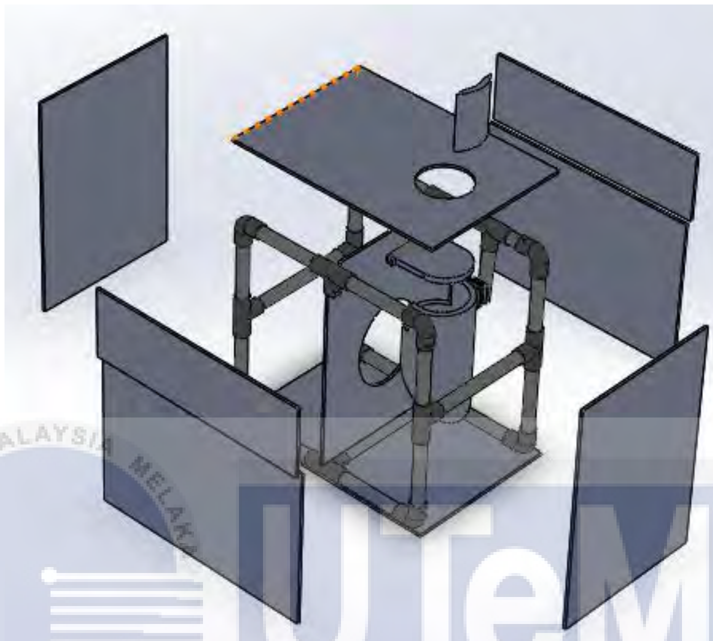
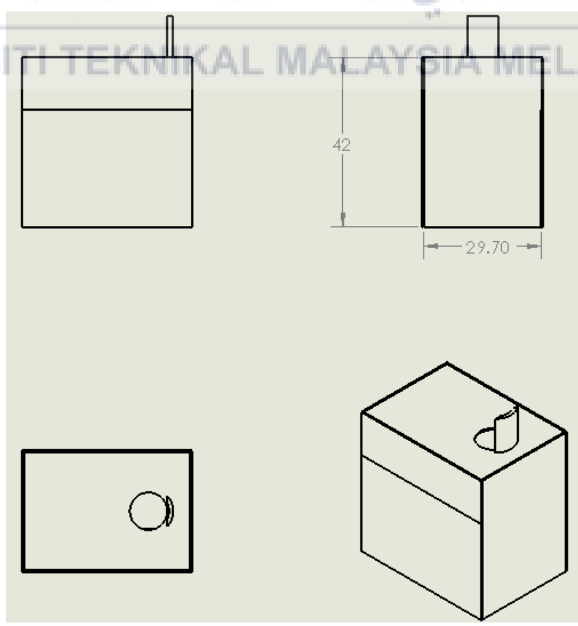
APPENDIX





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