ASHESI UNIVERSITY COLLEGE

AQUILA – A SMART BIN DESIGNED FOR WASTE MANAGEMENT USING ARTIFICIAL INTELLIGENCE AND INTERNET OF THINGS (IOT)

CAPSTONE PROJECT

B.Sc. Computer Engineering

Kwaku Bobie Osei-Tutu

2021

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CAPSTONE PROJECT

Capstone Project submitted to the Department of Engineering, Ashesi University College in partial fulfilment of the requirements for the award of Bachelor of Science degree in Computer Engineering.

Kwaku Bobie Osei-Tutu

2021

DECLARATION

I hereby declare that this capstone is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature:

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Candidate's Name:

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Date: ……………………………………………………………………………………………

I hereby declare that preparation and presentation of this capstone were supervised in accordance with the guidelines on supervision of capstone laid down by Ashesi University College.

Supervisor's Signature:

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Supervisor's Name:

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Date: ……………………………………………………………………………………………

Acknowledgements

To my family and supervisor, Mr. Kofi Adu-Labi whose encouragement and academic advice helped me undertake and persevere throughout this project.

Abstract

This project elaborates on the design of a smart bin which incorporates Artificial Intelligence to promote source sorting of waste. Waste is a menace that has persisted in Ghana and in spite of the many efforts of the government and other private entities, there is still a lot that needs to be done to fully address this issue. One of the major proven causes of poor waste management is the inefficient sorting of waste at source (usually in households or offices) which results in a composite of waste of different waste types which makes the treatment of waste very difficult and inefficient. In this project, a bin capable of sorting waste at source and also deploying relevant waste data to a cloud server is developed.

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CHAPTER 1: Introduction

1.1 Background

Several attempts to ease the traditional way of doing things have led to a lot of innovations and inventions which have immensely improved productivity and efficiency in most fields. Data seems to be the new core of modern innovations, and this is what the new wave of technology; Internet of Things (IoT) and Artificial Intelligence (AI) ride on. This new wave, intended to make everyday gadgets, devices, and even cities ‘smart’ provides a generally positive outlook for the future ahead. This future is driven by the ease and efficiency of accomplishing tasks with little to no human intervention in the bid to create the most ideal world.

Among the various world challenges that combat this dream, poor waste management stands out unsurprisingly against the attempt at a sustainable life. The rise in urbanization and rapid population growth has consequentially had the ripple effect of a higher waste generation rate.

1.2 Problem Definition

The world generates 2.01 billion tonnes of municipal waste annually, with 33 percent of that not managed in an environmentally safe manner [1]. Global waste is projected to grow to 3.40 billion tonnes by 2050 because of the rapid growth of population which would also be accompanied by an anticipated rise in waste generation rates [1]. The average current rate of waste generation in Ghana lies at 0.47kg per person per day which translates to about 12,710 tons of waste per day [2]

The daily decisions on waste management influence productivity, community cleanliness, and overall health. Poor management of waste results in contamination of the ocean, flooding through clogging of drains, the spread of diseases through breeding, and even hinders economic development through diminished tourism. Municipal Waste Management (henceforth MWM) is the overwhelming responsibility of the local government bodies and despite their efforts, a lot more work must be done to ensure better waste management. MWM is quite expensive. In the Ghanaian budget for 2020, an amount of about Ghc143 million was allocated for waste management. Considering the pressing priorities of enhancing healthcare, education, and agriculture, this amount is quite substantive.

Unsatisfactory MWM systems in Ghana could be attributed to low waste collection coverage, frequent unavailable waste transport services, an inadequate number of suitable treatment plants, recycling, and disposable facilities. Among these problems, waste sorting seems to be one of the major issues which can be successfully tackled to obtain the optimal value from the waste generated. Waste sorting allows productive use of waste by promoting recycling and even energy production. It is also one of the most effective ways of reducing the rate of waste generation. Waste sorting at the level of recycling facilities is usually not optimized due to the difficulty of the machines to sort extremely compounded waste of different types. There are also very limited work hand-sorters in these factories can do in sorting out the waste before it gets into the machines.

1.3 Project Objectives

The project seeks to design and fabricate a smart waste bin for efficient sorting of in-house and in-office waste to promote optimal waste segregation. The smart waste bin should seamlessly and quickly be capable of sorting waste, detecting the waste-fill level, and transferring and storing waste data on the cloud with no human intervention. This data needs to be retrievable by users to allow them to optimize their waste disposal. The main technology the bin would be using is Artificial Intelligence (AI) for sorting the waste and Internet of Things (IoT) for data transfer and collection.

CHAPTER 2: Literature Review

2.1 Overview of the state of household waste sorting

Waste management in high-income countries is very effective and as such allows higher recycling rates. Middle-income and low-income countries in comparison have generally worse waste management practices [3]. Poor waste management leads to an increase in waste deposited in oceans and landfills. It starts from households and results in a distinctly escalated effect when the waste gets to landfills or oceans. Household waste sorting prevents the composition of different types of waste at a level impossible to sort. It allows more efficient waste segregation and processing at waste facilities which consequently ensures better recyclability. Household waste sorting usually is done in the form of having varied bins reserved for different kinds of waste. This process although effective tends to be quite time-consuming and sometimes not even very efficient.

2.2 Waste management in Ghana

Effective waste management practices allow the development of more sustainable cities. Some productive waste management techniques include the introduction of policies on waste, the increased skilled labour force in the waste management sector, and the use of effective technology in handling waste problems [4]. Ghana has implemented many waste management initiatives, including policy enactment, legal and institutional structures, environmental education, and awareness building, as well as waste recovery, recycling, and reuse projects and programs. Notwithstanding all these efforts, there are still many key issues in waste management that plague the country. According to the World Bank [5], the key issues surrounding solid waste management in Ghana are the lack of community awareness, absence of effective waste collection, segregation, and recycling systems, and limited disposal capacity.

2.3 The need for better waste sorting mechanisms

In improving waste management, one of the major solutions would be focused on the formation of effective waste collection, segregation, and recycling systems. This starts with waste separation at the source, also called source separation. Source separation is the process of separating different fractions of waste at the place it is generated, usually in homes, offices, etc. A global outlook of waste management indicates that cities that apply a waste sorting system at the source decreased the landfilling dramatically and increased the recycling rate [6]. In Ghana, sorting at source is almost inexistent with little to no source sorting at all. In the attempt to improve waste management, this practice has not been given the relevant importance and coverage it deserves.

2.4 Market Opportunities

Most waste management companies that exist in Ghana and perform sorting only do so at their waste centers. For companies like ZoomLion Ghana Limited that have recycling centers, they perform the sorting with machines and manual labour. This usually results in relatively inefficient recycling and thereby reduces the value obtained from the waste. The market for waste management is saturated with a focus placed on three major areas: waste transportation, collection, and recycling. Among these areas of focus, the project seeks to address better waste collection methods by promoting waste sorting at source as against the typical collection of different waste types compounded into one. It also intends to be a better alternative to manual waste picking which is currently the prevailing sorting option for source sorting.

There currently exists a Public-Private-Partnership (PPP) with the different Ghanaian municipalities and major waste management companies such as ZoomLion Ghana Limited, Safi Sana, and others. These companies are assessed by the different municipalities with different Key Performance Indicators (KPIs) to provide a general view of their performance.

The major KPI this project focuses on is innovation and recycling which deducts a maximum of 10 points from the total points allocated for these companies [7]. Beyond the benefit of these companies improving their stance on the innovation and recycling scale, it also allows them to generate revenue. A company like Safi Sana, a Dutch company that designs and operates waste-to-energy factories in developing countries through incineration finds Ghana's residual waste consisting of 60% wet organic waste quite unattractive for their venture. This has led to the company concentrating on generating waste from faecal waste. According to this company, effective source sorting would create the needed fuel for incinerators. Zoomlion also processes waste directly at its waste recycling plant and sells the waste to developed countries in demand of processed waste for energy generation.

This project intends to provide companies such as these a better alternative for source sorting to improve their waste processing effectiveness as well as generate more revenue for them.

CHAPTER 3: Design

3.1 Requirements Specifications

Requirements and specifications well outlined provide a strong basis for good design and effective use cases. They also clearly lay out the standard for measuring the performance of the model and map out the functions and use cases of the product for specified target users. The major project requirements conform to the needs of users as well as the conditions and constraints the final product might undergo while still assuring optimal performance. This part of the project outlines two major sections; the user requirements and the system requirements which will serve as the yardstick for the effective design and assessment of the proposed solution.

3.1.1 User Requirements

User requirements spell out the functions the target user could expect the product to perform. These requirements also define the target users expected to interact with the product and the conditions the user could expect the product to work in.

The product would be used by any person capable of effectively disposing of waste by dropping one waste item at a time. The product would be expected to perform:

- The sorting of "in-house" or "in-office" waste items into three main categories: paper, plastic, and trash.
- Household waste data collection on a Web-based platform.
- Provision of waste-fill level in the bin.
- Storing of sorted waste into three compartments in the bin.

The product would be expected to work most effectively under the following conditions:

- Indoors, specifically in rooms where it would be free of harsh weather conditions.
- In rooms with moderate lighting conditions which would enhance the recognition of the waste.

3.1.2 System Requirements

Beyond the overall general features expected from a very reliable product such as durability, robustness, ease of use, and other relevant traits, technical requirements are needed to ensure the overall system works by a standard that is assessable and specific. These are outlined by the system requirements; they provide clarity on the qualities the product is intended to have as well as other support systems relevant to make the product fully functional. The main system requirements are as follows:

- The product must incorporate a means to ensure effective sorting of the waste into the categories and compartments specified.
- The product must have a robust power system to ensure constant functionality.
- The product must have a secure database for easy storage and retrieval of waste data
- The product must have a user-friendly manner to display different relevant information to the user.
- The product must be aesthetically pleasing, mobile, and have components that are easily accessible for repair and maintenance.
- The product should have a capacity of at least 25 L with a dimension of 500 mm for the height, and a base diameter of 350 mm.
- The product must be made of a material that is durable, affordable, and highly resistant to most chemicals.

3.2 Design Specifications

Design specifications explicitly state the essential information about the physical, technical, and functional requirements of the product. They provide details on how the product will look, the different systems it will be composed of as well as the justifications for the decisions. The design specifications of the product are going to be categorized into three: Product Design Specifications, System Design Architecture, and Design Components.

3.2.1 Product Design Specifications

The product design specifications outline the different solutions intended to meet the objectives outlined in the system requirements. They also provide justifications for the different design decisions based on data gathering and a decision model (in this case Pugh Matrices).

Pugh Matrix for Microcontroller

A microcontroller is needed for reading the sensor values and controlling the relevant actuators. It would also be the means of ensuring the bin operates autonomously after the firmware has been loaded onto it. There are four possible microcontrollers being considered for this task as shown in the matrix below. The Arduino Uno Board is very affordable and easy to program however it does not have wireless connectivity itself and would therefore require additional modules to allow this. The Freedom Development Board by ARM is another alternative, it is affordable, fast, and operates with a very low power however it also does not have wireless connectivity itself. The Raspberry Pi is robust and very reliable, but it is quite expensive. For this project, the ESP32 CAM was chosen because it is a microcontroller that has in-built wireless connectivity features, an integrated video camera, and a microSD card socket. It is cheap, easy to program, and of a relatively small size as compared to the other microcontrollers.

Microcontrollers	Cost	Wireless Connectivity	Configuration and Programming	Processing speed and memory	Total
weights	5	3	4	4	
Arduino	3	4	5	4	63
Freedom Board	5	4	3	5	69
Raspberry Pi	1	4	3	4	45
ESP32-CAM	5	5	5	3	72

Table 3.1: Pugh matrix for microcontrollers

Pugh Matrix for Sorting Algorithm

In ensuring that the waste sorting is done very effectively, computer vision would be employed. This would allow the bin to classify the different wastes into the categories provided before deciding on the compartment to place them in. The main sorting algorithms considered for the image classification are Support Vector Machines (SVM), Multilayer Perceptron (MLP), and Convolutional Neural Networks (CNN). SVMs can perform non-linear classification using the kernel trick however it has limited speed and size during training and testing of the algorithm. MLPs can learn non-linear models for image classification however it can have a non-convex loss function and tuning which does not enhance its accuracy. CNNs can perform non-linear image classification quickly and accurately even on large datasets. This project uses a CNN.

Sorting Algorithms	Accuracy	Speed	Computational Resources	Adaptability	Total
weights	5	4	3	4	
SVM	4	4	4	4	64
MLP	4	3	2	1	42
CNN	5	5	5	4	76

Table 3.2: Pugh Matrix for Algorithms

Pugh Matrix for Material

The material for the product needs to be durable, resistant to most chemicals, and rigid. The main consideration for this project is plastic. Two main thermoplastics are considered, Polypropylene (PP) and High-Density Polyethylene (HDPE). Both products are recyclable, malleable, and have low toxicity however HDPE is more rigid and denser than PP, it also has a higher resistance to chemicals than PP. This product would ideally need to be made with HDPE.

Material	Resistance to Chemicals	Rigidity	Density	Durability	Total
weights	5	3	4	5	
HDPE	5	5	4	5	81
PP	4	4	4	4	68

Table 3.3: Pugh Matrix for Material

Pugh Matrix for Power

The power of the bin is one of the most essential factors since this is mainly what would ensure its optimal operation. There are three main power considerations for the bin. Connection to the main power socket, a hybrid connection of solar power, and the main socket, and the use of batteries and a connection to the main socket. Since the product is intended to be used indoors, the solar option would be quite redundant, connecting the bin to only the main socket would also prevent it from working when there is a power cut. This project would use batteries and the connection to the main socket as the main power supply. Since the components have a low-power consumption rate and could effectively run on the batteries in the event of a power outage, this would be the most efficient alternative to resort to.

Power Supply	Dependability	Robustness	Ease of setup	Adaptability	Total
weights	5	4	3	4	
Main socket	3	4	2	1	41
Solar with the main socket	2	1	1	1	21
Batteries with the main socket	5	5	1	5	68

Table 3.4: Pugh Matrix for Power

Pugh Matrix for Proximity Sensor

Among the other functions the bin would be performing, one of the most critical would be sensing the level of the waste as well as how close a user's hand is to the bin to open it. There are two main options considered for this, an infrared (IR) proximity sensor and an ultrasonic sensor. The IR proximity sensor is cheap, has a wide detection angle of 45 degrees, and a fast response time. However, it is only able to detect a distance ranging from 1 mm to 100 mm. The ultrasonic sensor has a limited detection angle range of 10 – 15 degrees. It is however able to detect a distance up to 4 m. For this project, the ultrasonic sensor was chosen because of the higher distance detection range and availability.

Proximity Sensor	Accuracy	Range	Ease of use	Response time	Total
weights	5	5	3	4	
IR proximity sensor	5	3	5	5	75
Ultrasonic sensor	5	5	5	4	81

Table 3.5: Pugh Matrix for Proximity Sensor

Decision for Sorting Mechanism

The mechanism for sorting the waste into the different compartments is an essential part of the project. Since the design of the bin is cylindrical, there is a need for a sorting mechanism that can operate in the bin and respond to the ESP32-CAM module. Since this module is low-powered and cannot drive dc motors, the project resorts to the use of a servo motor. This would rotate at different angles after the waste is decided on, the rotation would drive different separators to ensure the waste is in the right compartment. This is based on the concept of revolving doors.

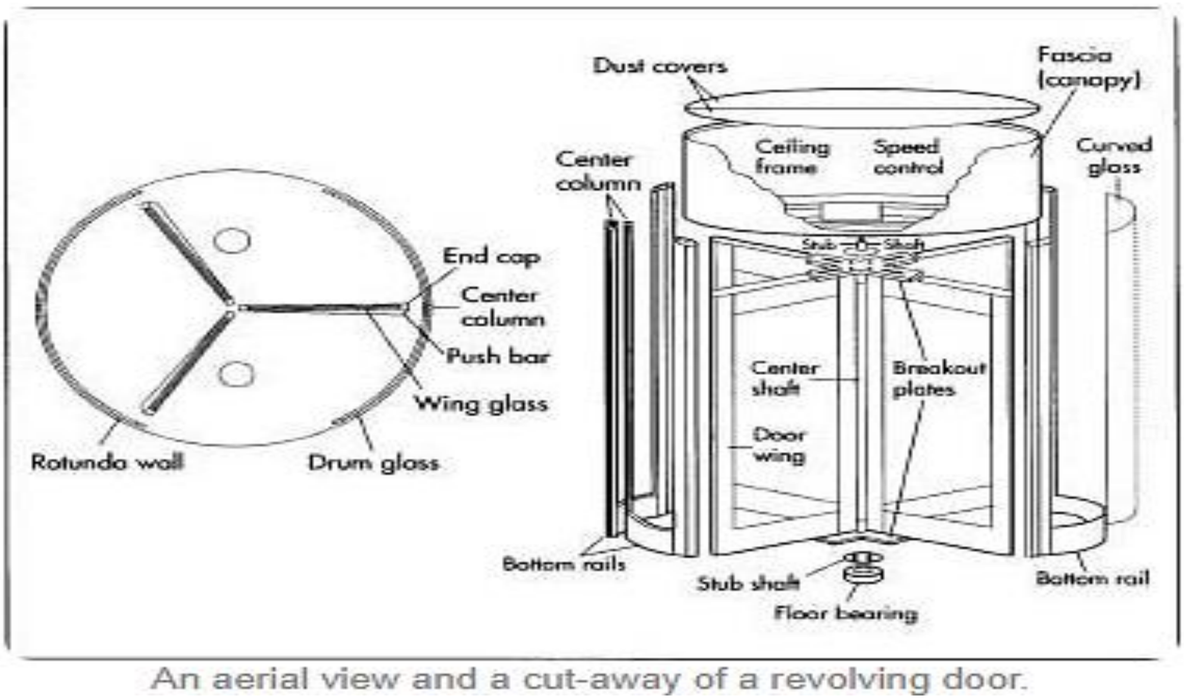


Figure 3.1: Revolving Door working concept

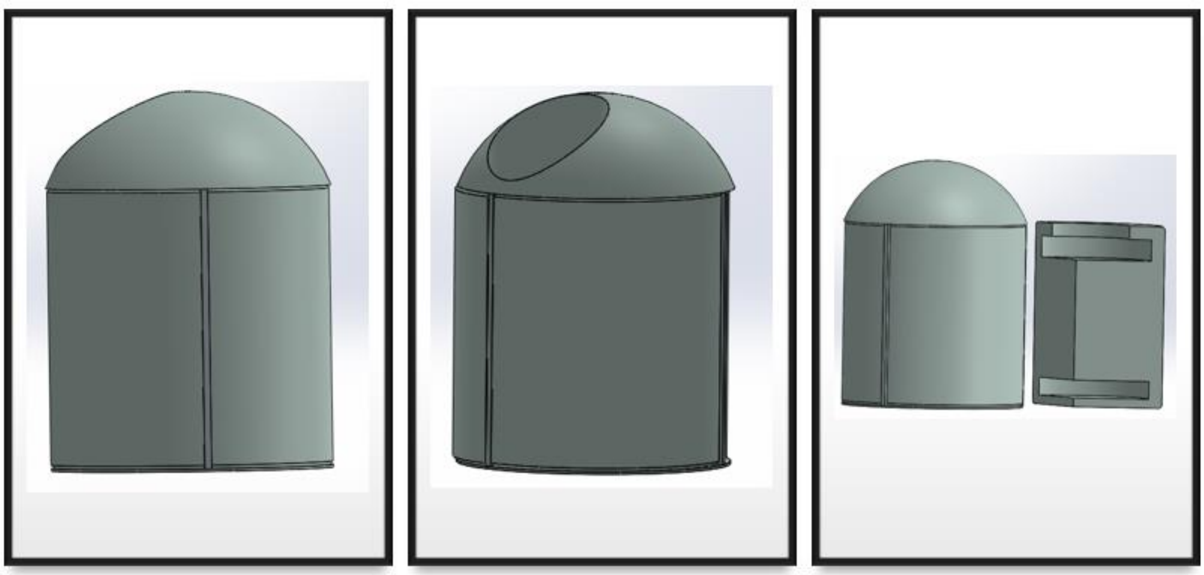


Figure 3.2: Design concept of SmartBin

Pugh Matrix for Data Transfer

The transfer of the data generated by the device is one of the key distinguishing factors of the project. The alternatives are Message Queue Telemetry Transport (MQTT), Hyper-Text Transfer Protocol (HTTP), and Constrained Application Protocol (CoAP). HTTP is a response-request protocol for client-server computing, it uses text message format by HTTP protocol to compose lengthy headers and messages, it is slow, has a low quality of service, and consumes a lot of power. CoAP is a client-server protocol that is not yet standardized. With CoAP, a client node can command another node by sending a CoAP packet. CoAP has a bigger header size than MQTT, fewer existing libraries and support and it does not provide any guarantee of delivery. For this project, MQTT was used because it is lightweight, fast, reliable, and ensures a guarantee of delivery since you can set the quality of service to the standard preferred [8].

Data Transfer Protocol	Dependability	Speed	Power Consumption	Weight	Total
weights	4	5	5	3	
HTTP	2	3	2	1	36
CoAP	3	4	5	5	72
MQTT	5	5	5	5	85

Table 3.6: Pugh Matrix for Data Transfer Protocol

The design specifications for the Smart Bin are as follows:

- The cost of the Smart Bin should not exceed Ghc250. This would be reasonable since an average 25 L step on litter bin costs Ghc200.
- The product should be safe and easy to use without any training at all.
- The product should have a capacity of at least 25 L with a dimension of 400 mm for the height, and a base diameter of 350 mm.
- The product should be made from High-Density Polyethylene (HDPE).

- The product should be powered on a 220-240V main socket with a transformer and voltage regulator to step down the voltage to 3.3-5V. There should also be a battery that would power the product in moments of a power outage.
- The product should use a servo motor for sorting the waste into the different waste compartments.
- The product should have two ultrasonic sensors; one to send the user's hand close to the bin to enable it to open and another one to sense the waste level of the bin.
- The product should have an ESP32-CAM module to capture the images and control the sensors and actuators.
- The product should have detachable compartments to make components accessible and the compartment waste easily disposable.

3.2.2 System Design Architecture

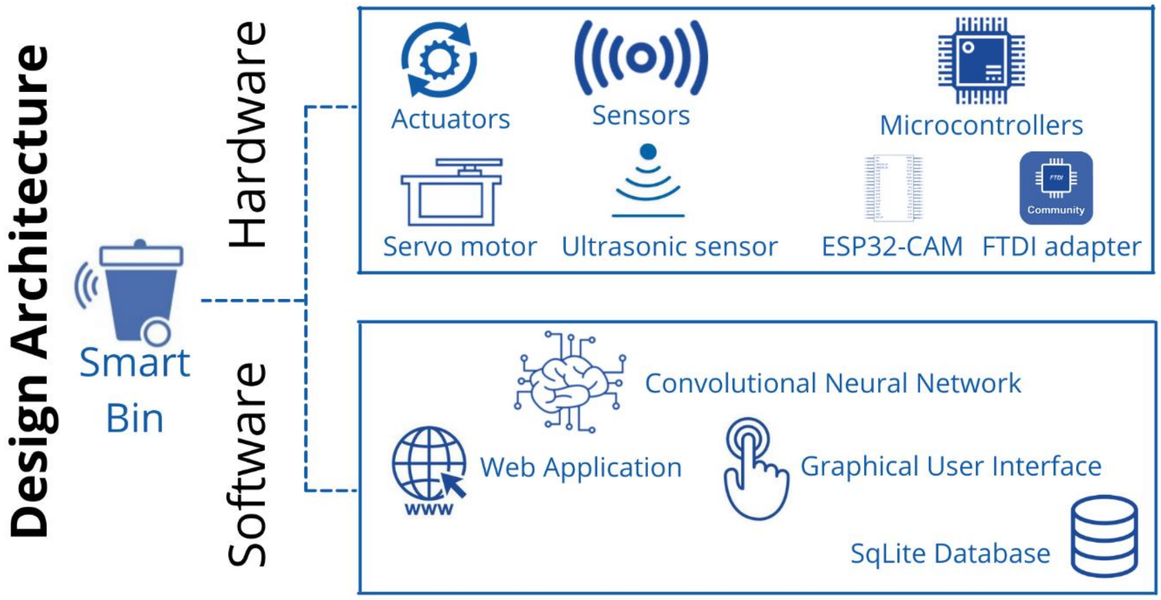


Figure 3.3: Design Architecture of Project

The Smart Bin has two main parts, the hardware system, and the software system. The hardware involves the use of actuators, sensors, and a microcontroller. The main actuator in the system is a servo motor which generates an amount of torque to place the waste item into the selected compartment. The main sensor in the system is an ultrasonic sensor that senses the level of waste in the bin. The development board in use is the ESP32-CAM, it is a low-cost development board with a WiFi camera. This allows it to be used for IP camera projects, it also has an SD card that allows a storage medium for the board. The software consists of a deep learning Convolutional Neural Network (CNN) model for handling the image processing. The results are then sent to a Web-based application that would harbour all the data. The platform would have an interactive Graphical User Interface (GUI) with a dashboard to display the amount of waste generated and other data on the waste that would be relevant to users. The data would be stored in a SqLite Database.

3.2.3 Design Components

The main design components of the system are the hardware and software components. For the hardware, there are two ultrasonic sensors, an ESP32-CAM module, a servo motor, and an FTDI adapter cable. The software components are the Convolutional Neural Network (CNN), the MQTT protocol, the Web Application, and the database.

Hardware Components

Ultrasonic level sensor

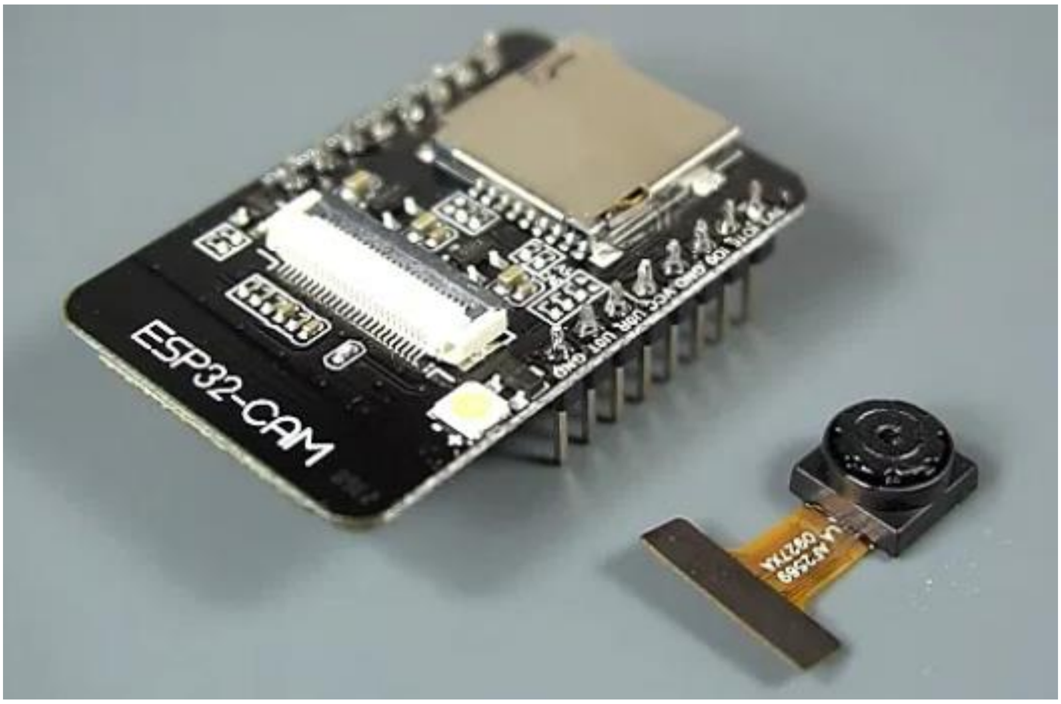
HC-SRO4 Ultrasonic sensor

Operating Voltage	DC 5V
Operating Current	15mA
Operating Frequency	40KHz
Max Range	4m
Min Range	2cm
Ranging Accuracy	3mm
Measuring Angle	15 degrees
Trigger Input Signal	10μS TTL pulse
Dimension	45 x 20 x 15mm

Table 3.7: Specifications for Ultrasonic Sensor

The distance is measured with the formula [distance = $\frac{speed\ of\ sound}{2} * time$]. The component is used for detecting the level of waste in the bin as well as the presence of a hand.

WiFi module:



ESP32-CAM module

Operating Voltage	DC 5V
Operating Current	180mA
SPI Flash	Default 32Mbit
RAM	520KB SRAM + 4M PSRAM
Bluetooth	Bluetooth 4.2
WiFi	802.11 b/g/n
Support Interface	UART, SPI, I2C, PWM
Frequency range	2412 ~2448MHz
Dimension	27 x 40.5 x 4.5mm

Table 3.8: Specifications for ESP32-CAM module

The ESP32 CAM is a small camera module with the ESP32-S chip. It has a resolution of 2MP which is more than adequate for image processing. This is also compatible with Arduino IDE and Python which would be the main means of programming. The module also has an SD card slot which can provide some storage of the captured images. The module is equipped with a flash that could light up the subject in periods of low light. This module would be the main means of capturing the images of the waste and since it is compatible with Wi-Fi, it would send the data packets to the database via Message Queue Telemetry Transport (MQTT) system to a remote server.

Servo motor

MG996R Servo motor

Operating Voltage	DC 5V
Operating Current	2.5A
Stall Torque	9.4kg/cm
Maximum Stall Torque	11kg/cm
Operating Speed	0.17s/60°
Rotation	0°-180°
Weight of motor	55gm

Table 3.9: Specifications for MGPP6R Servo Motor

The servo motor uses a brushless dc motor to rotate the head at different angles after a desired angular input is provided. The servo motor is the main actuator for sorting the waste into different compartments in the bin. It would rotate at different angles to drive the waste to the preferred compartment.

FTDI adapter

FTDI adapter

The USB to UART serial adapter would be used to connect the ESP32-CAM to the computer and it would allow the download of the firmware to the ESP32-CAM module. This would be made possible through parallel to serial data conversion at the transmitter side and serial to parallel data conversion at the receiver end.

Software Components

Convolutional Neural Network (CNN)

CNNs allow images to be classified according to labels that are defined in a model [9]. These labels represent the different choices of classification the model needs to choose from. Labels can be binary, where the model predicts whether it is something or not. They can also be categorical where the model predicts from a different set of options. CNNs use the concept of convolution to determine different features of images which aid it in the classification process. The CNN takes an image as an input, convolves it with different filters, passes it to an activation function (usually Rectified Linear Unit), and then forms another matrix after picking the maximum values through a process called max pooling [10]. The CNN then flattens the matrices and passes it through a neural network to determine the label of the image. In the convolving process, a small matrix of numbers (filter or kernel) is passed over an input image to transform it based on the values of the filter. Feature maps are calculated by the following formula, where **f** denotes the input image, **h** denotes the filter and **m** and **n** are the rows and columns respectively.

$$G[m,n] = (f * h)[m,n] = \sum_j \sum_k h[j,k] f[m-j, n-k] \quad (1)$$

The processes involved in CNNs are illustrated in the figure below.

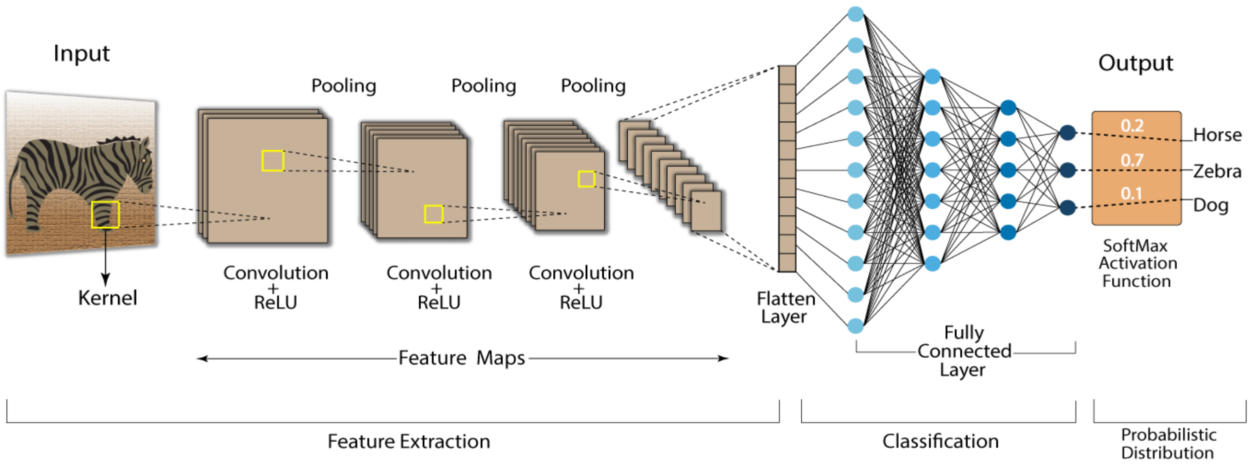


Figure 3.5: Convolutional Neural Network

Web Application

The Web Application for the project would be based on Flask which a Python-based framework. This was chosen because it provides a faster access time to the data it hosts on the Web Application; it also has compatible connectivity with the SqLite database. Flask also is compatible with MQTT. It is lightweight, modular and a good alternative to start with for prototypes.

Functionality breakdown

The bin would detect how close a user's hand is to the mouth of it and open on detection. The user would drop the waste item into the bin. The bin would use computer vision with the help of the ESP32-CAM module to detect which item was dropped in the bin. The servo motor would move at a certain angle to allow the bin to fall into a specific compartment based on the classification provided. This data is later sent to the cloud server and illustrated on the Web Application. These processes are illustrated in the flowchart below:

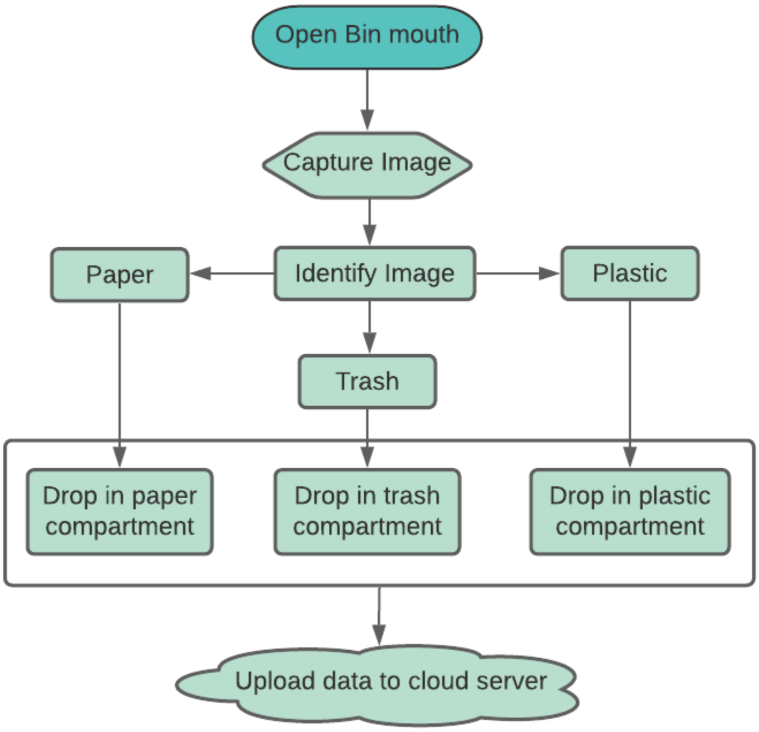


Figure 3.6: Flowchart of Bin operation

CHAPTER 4: Methodology

4.1 Implementation of Image Data Collection

The images used for the project were obtained from a dataset collected by Gary Thung and Mindy Yang [11]. This dataset consists of six categories of waste: glass, paper, cardboard, plastic, metal, trash. This project uses three categories: paper, plastic, and trash to further reduce the model to ensure easier deployment on a constrained device. Most of the images from the dataset were augmented images meaning, they had been adjusted according to different parameters like scale, rotation angle, and others which reduced its variance. In ensuring more variance in the model, more images were captured for the different categories specified. This allowed more variance in the dataset and ensured a balance in the number of images for all the categories. The phone used for capturing the images was an iPhone 6s which captured the images in a resolution of 750 x 1334 pixels. All the images were later resized to 64 x 64 pixels. The final image dataset used for the project consisted of 500 images from each of the three major categories resulting in a total of 1500 images used for the project.

4.2.1 Implementation of CNN model

The deep learning model used for the image classification was a CNN model. The model was implemented in TensorFlow with the Keras Library. The model was coded in Python and libraries such as OpenCV, and NumPy were used. The model was custom-defined. Different models were defined for comparison, including a transfer learning model: VGGNet. The major models used for comparison were the custom VGGNet (SmallVGGNet) with Stochastic Gradient Descent (SGD) as the main optimizer, a custom CNN model with Adaptive Movement Estimation (ADAM) optimizer with dropout, and one without any dropout. The performance of the algorithms over 100 epochs is shown in the figures below. The ADAM optimizer with no dropout was chosen due to its accuracy and size.

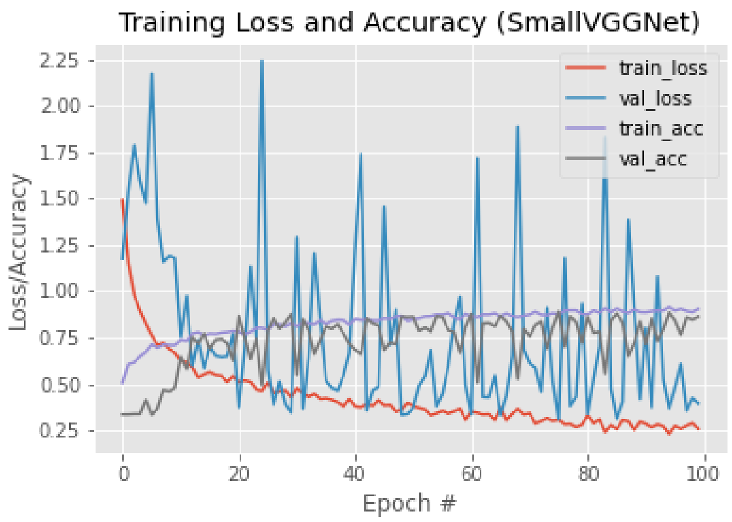


Figure 4.1: Performance of SmallVGGNet algorithm

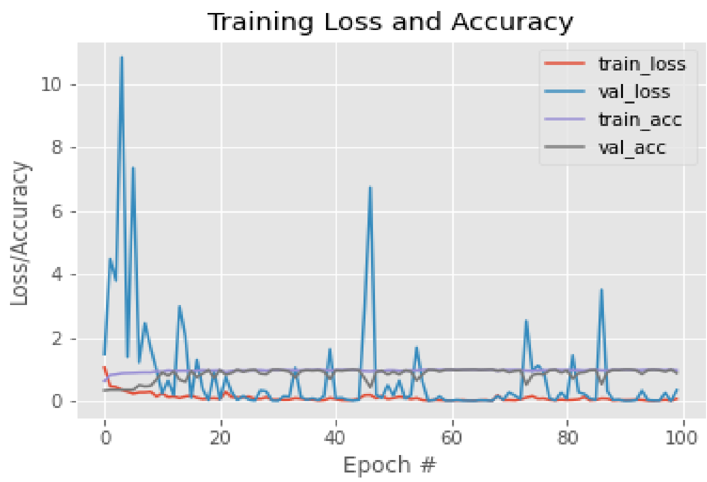


Figure 4.2: Performance of custom CNN with ADAM optimizer and dropout

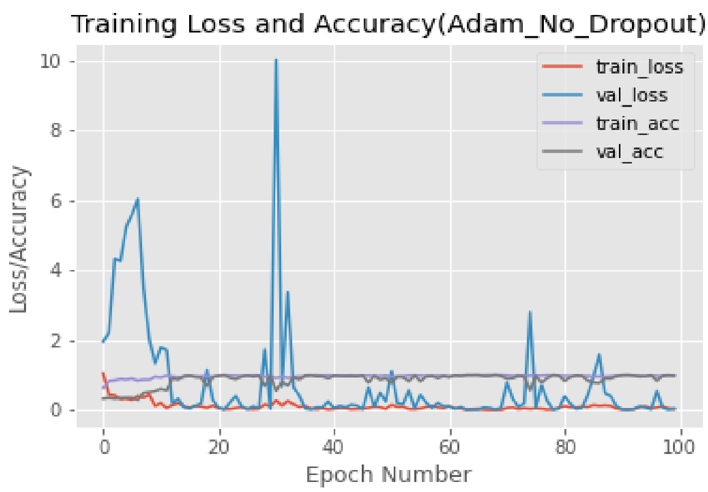


Figure 4.3: Performance of custom CNN with ADAM optimizer with no dropout

4.2.2 Optimization of CNN model

CNN models usually are optimized via the trial-and-error method for selecting a specific number of layers and neurons in each of the layers. This process can be tedious and extremely time-consuming since there are a lot of comparisons made after tuning the different parameters over different periods. Currently, this process has been eased with the introduction of an additional library to Keras; the Keras-Tuner. This Library allows the program to test the model with different parameters and finally select the optimal hyperparameters the model should be built with.

```
{'input_units': 32, 'n_layers': 6, 'conv_0_units': 96, 'conv_1_units': 160, 'conv_
Results summary
Results in 1617963833/untitled_project
Showing 10 best trials
Objective(name='val_accuracy', direction='max')
Trial summary
Hyperparameters:
input_units: 32
n_layers: 6
conv_0_units: 96
conv_1_units: 160
conv_2_units: 96
conv_3_units: 224
conv_4_units: 256
conv_5_units: 160
conv_6_units: 128
conv_7_units: 128
conv_8_units: 64
conv_9_units: 128
conv_10_units: 32
conv_11_units: 64
```

Figure 4.4: Screenshot of Hyperparameter Optimization

4.2.2 Size reduction of CNN model

The optimized model obtained needed further size reduction since it was going to be deployed on a constrained device. In IoT, constrained devices are devices, usually microcontrollers and sensors limited by its Central Processing Unit (CPU), Random Access Memory (RAM), power, and memory [12]. This led to a modification in the optimized CNN model selected. The images for the training of the model were further resized to 28 x 28 pixels and instead of the three channels (Red, Green, Blue), they were converted to one channel (greyscale). This allowed the model to be further optimized at a smaller size. To deploy a huge AI model on a constrained device, it needs to be adjusted for size, performance, and latency. For the project, TensorFlow Lite was used in reducing the model to a smaller size with little trade-off in the accuracy and performance of the model. Weight quantization is the process of reducing the decimal places of assigned weights to a model. This allows an additional reduction in the size of the models since less memory is required for storing the weights. After obtaining the optimized and reduced TensorFlow Lite model, additional size reduction was done through quantization.

4.3 Deployment of CNN model on ESP32 Camera

The ESP32 camera module does not have a file system and hence the deployment of the model on it had to be in the form of an array of the weights of the model. To access these weights, the TensorFlow Lite model had to be converted to its C equivalent model. This was done using some commands available for Linux Ubuntu. The next steps involved the setting up of the Espressif IoT Development Framework (ESP-IDF). This provides a self-sufficient Standard Development Kit (SDK) for any generic application and supports programming languages such as C and C++ for IoT deployment. The setup involved the creation of a project with the ESP-IDF tools and the use of the tools to generate the adequate basic files to run the model on the ESP32 camera. Most of these files were C files that had to be customized for the model intended for use. The sufficient setup allowed additional modifications of some of the files to ensure the efficient deployment of the model on the ESP32 Camera.

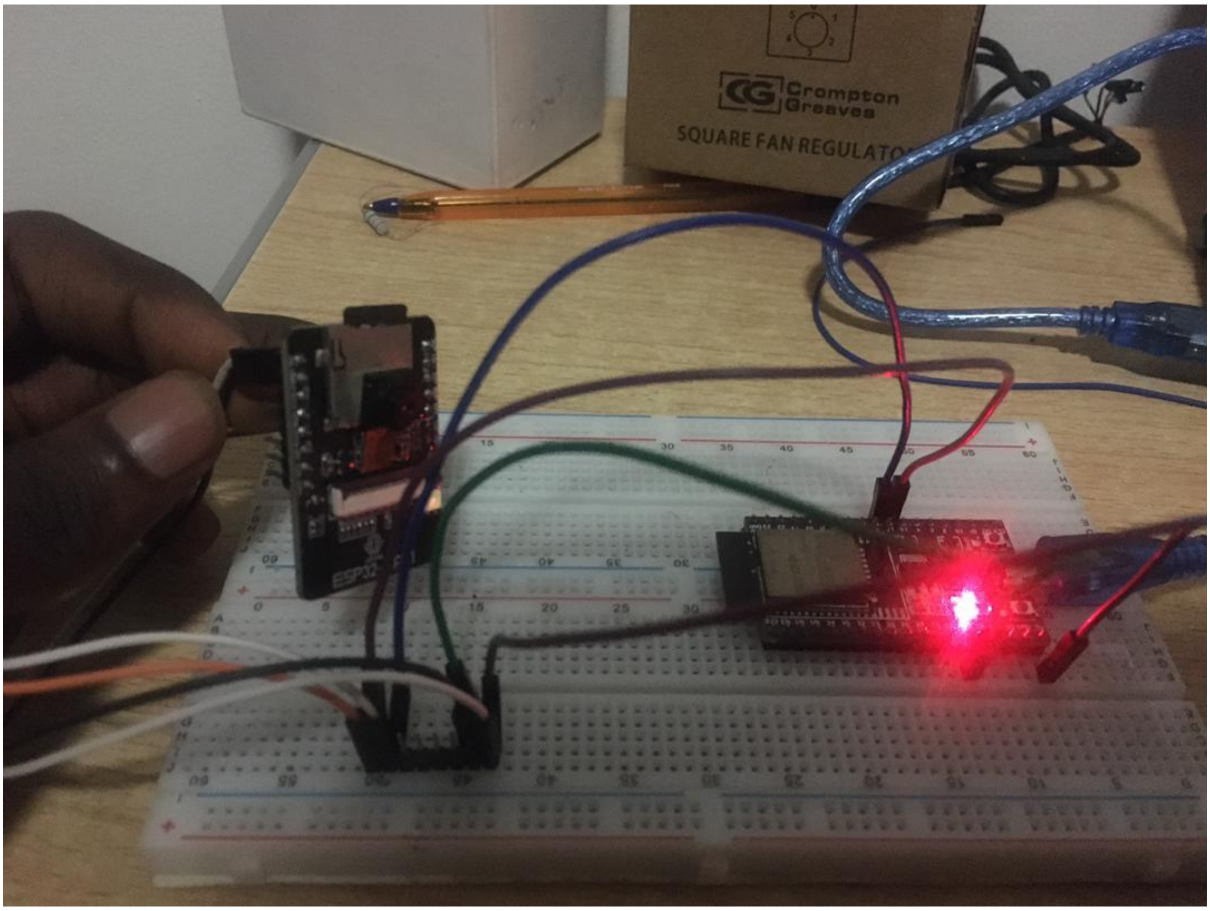


Figure 4.5: Connection of ESP32 Camera with USB UART medium

4.4 Control of sensors and actuators with ESP32 camera

The ESP32 Camera module can be used with ultrasonic sensors servo motors. There is however a limitation in the control of the actuators based on the size of the firmware intended to be uploaded on it. This usually leads to a trade-off in latency and extreme instances no response to the code at all. For this project, two channels on the ESP32 camera were used in controlling the servo motors. This was necessary because, the servo motors, could not efficiently operate on the same channel the images were being classified on. The ultrasonic sensor however could operate on the same channel used for the image classification.

4.5 Implementation of the MQTT and Web Application

The MQTT was implemented on Flask and the database used was the default Python database SqLite. The MQTT broker platform used for the project was Mosquitto MQTT and it was implemented with the Paho Python Client on Python 3.5. The Web Application used was Flask and was hosted on a localhost.

4.6 Supplying power to the ESP32 Camera and other modules

The ideal implementation of the power source would be by connecting the bin to the main power source and a battery for backup power supply. The 220 V AC power would be converted to a DC 5 V source via a transformer rectifier circuit. The rectifier would be used for converting from AC to DC and the transformer would be used to reduce the voltage to 5 V. For this project, however, the 5 V DC is obtained directly and used to power the ESP32 Camera and other modules.

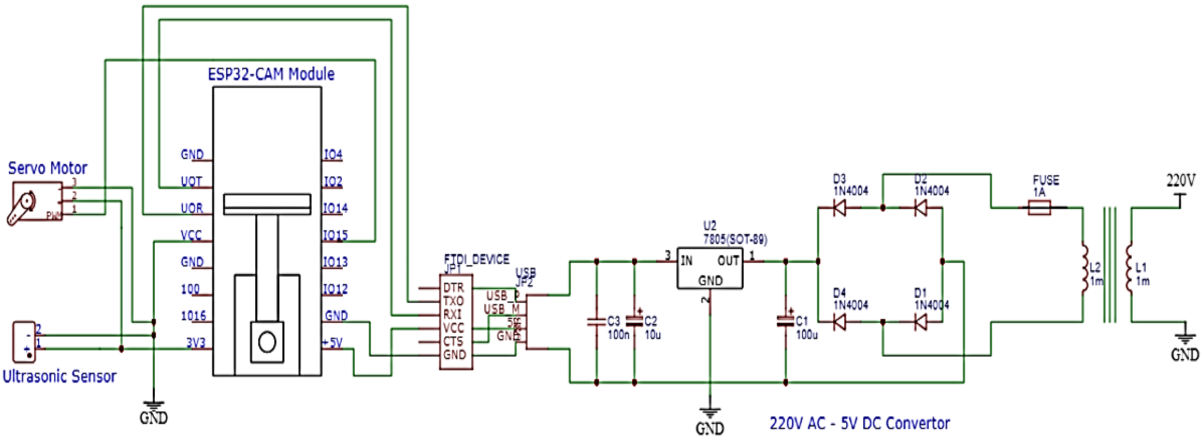


Figure 4.6: Schematic Diagram for Hardware Components

CHAPTER 5: Results

5.1 Size Reduction of CNN model

The initial file size of the CNN model was 54 MB. Reducing the image size to 24 x 24 pixels and changing the number of channels to one (greyscale) further reduced the model to 904 KB. Converting the model to a TensorFlow Lite model additionally reduced it to 234 KB. The final model size was reduced to 122 KB after quantization. This size was however increased once more after the model was converted to its basic C file with the weights assigned in an array. This led to the final model size for deployment at 704 KB.

CNN model	Accuracy	Size	Image Dimensions
Optimized model	93 percent	54 MB	64 x 64 x 3
Reduced model	80 percent	904 KB	24 x 24 x 1

Table 5.1: CNN model comparisons

5.2 Performance of CNN models

The performance of the CNN model after training was quite impressive. It achieved an accuracy of about 93 percent which translated to a lot of accurate predictions. This accuracy nevertheless was for the optimized CNN model before reduction. This model despite being quite accurate did struggle to correctly classify some waste images. These were mainly images that contained a combination of a particular type of waste (usually paper). These misclassifications could be highly attributed to the training data the model utilized. All the training data were single images of a particular waste type. It could therefore be inferred that identification of the different objects of a particular waste type in a single image was an activity the model struggled with. Although this was the case, the model was still able to correctly classify some images that had a collection of a particular waste type although it was done with limited accuracy. The reduced model also performed classifications fairly although through the size reduction it had reduced in accuracy to about 80 percent. It also shared the struggle of rightly classifying an image containing a collection of a particular waste type. This is owed to the fact that this model was obtained from the optimized model and hence would also share in its limitations though at a higher degree.

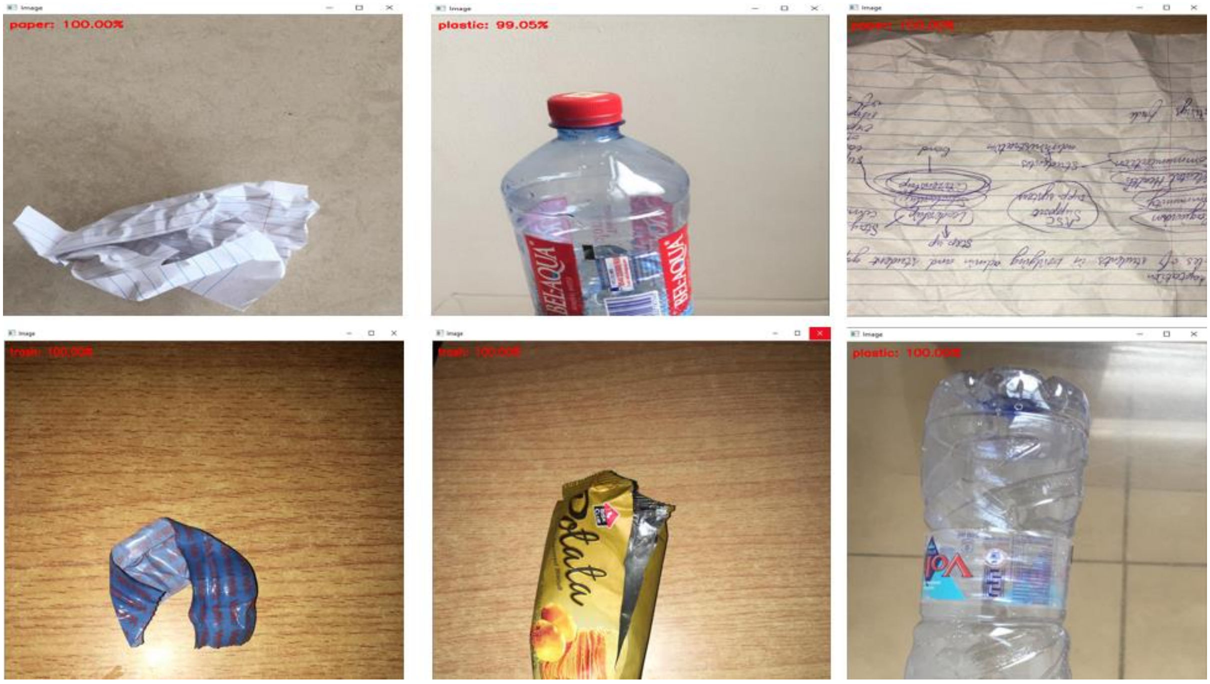


Figure 5.1: Accurate Classifications by Optimized CNN Model

Figure 5.2: Accurate Classifications by Reduced CNN Model

Figure 5.3: Accurate Classifications of Collective Images by Reduced CNN Model

Figure 5.4: Wrong Classifications by Reduced CNN Model

CHAPTER 6: Limitations and Conclusion

6.1 Discussion

The optimized CNN model was successfully implemented and tested with 45 waste images, it achieved high accuracy for both images on the internet and other images captured with the iPhone. The optimized CNN model was further effectively reduced to a lower size for deployment on a constrained device. The Web Application was also successfully created with Flask and the SqLite Database as well.

6.2 Limitations

There were several challenges and limitations of the project. The major challenge of the project was efficiently deploying the model on the constrained device. This was extremely hard to do due to the RAM limitation on the ESP32 AI-Thinker Camera module. Although the design of the project was meticulously done, not all the parts of the project could be effectively prototyped. For instance, even though the bin was designed with clear specifications on SolidWorks, it was not built due to the limited resource access. In addition to this, the ESP32 AI-Thinker Camera module had high latency, especially when used with the servo motor. It was extremely difficult to get the CNN model to work in real-time because the images used for the prediction had to first be retrieved from the SD card, before the image classification. The model also could not automatically detect the waste and classify it simply because it was based on a CNN model for image classification. It was therefore required that the image be captured remotely before the classification was done. Finally, the source of power for the project was solely a 5 V DC source with no backup power since the focus of the prototype was on the effective functioning of the bin first before the resolution of power cuts.

6.3 Future Work

The latency of the bin could be reduced by having another microcontroller (preferably another ESP32) controlling the movement of the actuators and the use of the other sensors. This other microcontroller could also be used for real-time waste sorting since it could be trained with a more effective deep learning model for real-time object classification. This can be achieved with a masked R-CNN model which would even detect the object even when the ESP32 Camera starts a video stream. Ideally, the design should be implemented as an integrated unit to further iterate on improving the product. There could also be the outsourcing of the image processing to TensorFlow.js via the microprocessor to ensure better accuracy and lower latency. There should also be better human-to-computer interaction to allow different options for different mode selections. For instance, if there was an option for outsourcing the image classification, this could reduce the latency when a lot of waste needs to be classified. Additionally, there could be an option for the human to sort the waste personally in cases where the person knows the kind of waste intended to be disposed of and has time to put it in the right compartment. These could ensure that the battery of the bin is better conserved and would allow the bin to be more versatile.

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