IMAGE CLASSIFICATION ON A SMART BIN FOR WASTE SEGREGATION AND ANALYTICS

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A PROJECT REPORT SUBMITTED TO THE FACULTY OF ENGINEERING, DESIGN AND TECHNOLOGY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF A DEGREE OF BACHELOR OF SCIENCE IN COMPUTER SCIENCE OF UGANDA CHRISTIAN UNIVERSITY

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Declaration

We, *Priscila Denise Muwanguzi*, *Nicole Mbabazi Mwebembezi* and *Arthur Shalom Yawe*, declare to the best of our knowledge that the work in this report is original and has not been submitted before to any university/institution. It is the result of our effort.

Signature 1: ______________________

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Signature 3: ______________________

Date: 01/06/2026

Ethical Generative AI Usage Declaration

A. **Declaring the non-use of AI for content generation**

We, *Priscila Denise Muwanguzi*, *Nicole Mbabazi Mwebembezi* and *Arthur Shalom Yawe*, declare that generative AI technologies were used only as support tools in the development and preparation of this report. All AI-assisted outputs were reviewed, edited, verified, and adapted by the authors to ensure accuracy, relevance, and academic integrity.

Signature 1: ____________________ Date: 01/06/2026

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B. **Acknowledging the use of AI as a study buddy**

Please refer to Appendix C for the complete declaration of AI usage for generating ideas, brainstorming, literature search, and summarizing that was used to improve our work.

Approval

This report has been submitted for examination with the approval of the following advisors/-supervisors.

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Abstract

This project addresses the problem of inefficient waste sorting methods currently in use, such as bins with well labelled compartments that rely on users to sort waste correctly. In addition, manual sorting by waste collectors at the point of collection is unsafe due to exposure to hazardous materials. There is also a lack of sufficient data to support effective waste management and decision-making by organizations such as Kampala Capital City Authority (KCCA) and National Environment Management Authority (NEMA).

To address these challenges, we developed a smart bin with three compartments for paper, plastics, and general waste. The system allows a user to dispose of a single item of waste, after which the bin automatically sorts it into the correct compartment. At the same time, data is collected and sent to a dashboard for analysis of waste trends.

The system works by using a camera to capture an image of the waste item. The image is then processed by a VGG16 deep learning model, which classifies the type of waste based on its visual features. The classification result is used to guide the sorting mechanism, and the data is transmitted to an application for further analysis. The backend is built with Node.js and Express, using MongoDB for data storage, while the frontend dashboard is developed with React and Tailwind CSS.

The model was trained on a custom dataset of over 500 waste images collected at Uganda Christian University, supplemented by transfer learning from the VGG16 architecture pre-trained on ImageNet. Testing demonstrated a classification accuracy exceeding 90% for the targeted waste categories. The integrated system successfully sorts waste into the correct compartments and provides real-time analytics on waste disposal patterns.

This solution contributes to improved waste segregation at the source, reduces occupational hazards for waste workers, and provides data-driven insights for institutional waste management.

Dedication

We dedicate this report to the Almighty God without whom we can do nothing. We further dedicate it to our parents and guardians for their unceasing and selfless support throughout our stay at Uganda Christian University.

Contents

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Chapter 1

Introduction

1.1 Background

Solid waste management is a growing challenge in Uganda, where waste is largely disposed of in mixed form, reducing efficiency and recycling while increasing health risks. According to Kampala Capital City Authority (KCCA), Kampala generates approximately 1,500–2,500 tonnes of waste daily, of which over 70% is biodegradable and recyclable. However, the National Environment Management Authority (NEMA) reports that waste is mostly disposed of without segregation at the source, creating mixed waste streams that are difficult to process and limit the recovery of valuable materials.

This challenge extends to institutional environments such as universities, where large volumes of waste are generated daily in hostels, canteens, and academic buildings. Uganda Christian University (UCU) is a typical example, with waste collection managed by the BINS Company. Field observations and interviews with BINS collectors reveal that nearly all campus waste arrives mixed at the central collection point, containing plastics, paper, polythene, food waste, and occasionally hazardous items such as broken glass and needles. The lack of source segregation forces workers to manually sort waste on moving trucks, exposing them to injuries and slowing down the collection process. Similar challenges have been documented at the Kiteezi Landfill in Wakiso District, where workers in informal recycling businesses face high rates of occupational injuries due to unsafe sorting conditions[1]. Studies indicate that over 50% of waste workers experience occupational injuries, with approximately 30% caused by sharp objects in mixed waste [2].

In recent years, technologies such as image classification models, including VGG16, and camera-based sensing systems have been developed and applied across different sectors. These technologies enable systems to capture and analyze images of objects, including waste, and make decisions based on what is detected. Convolutional Neural Networks (CNNs) have proven highly effective in image recognition tasks[3], with studies demonstrating their successful application in waste classification[4]. Transfer learning with pre-trained models like VGG16 allows for high accuracy even with relatively small domain-specific datasets. Such advancements present an opportunity to improve waste management by enabling automatic waste classification and data tracking, thereby reducing dependence on manual sorting.

This project proposes an AI-assisted smart bin (EcoClassifier) to enable waste segregation at the source in universities, improving efficiency and reducing manual sorting. The system integrates a camera, a VGG16-based classification model, a mechanical sorting mechanism, and a web-based analytics dashboard. By automating the identification and separation of waste, the system aims to enhance recycling rates, protect worker safety, and provide actionable data for waste management planning.

1.2 Problem Statement

In Uganda, solid waste management remains a significant challenge. Despite national regulations promoting sustainable waste handling, institutions continue to dispose of waste in mixed, unsorted streams, combining plastics, paper, organics, polythene, metals, and hazardous items. Manual sorting remains the dominant method, yet studies consistently show it to be unsafe, slow, and inefficient, exposing workers to sharp and toxic materials while yielding low recovery rates. Human sorting cannot keep pace with increasing waste volumes or contamination levels.

At UCU, interviews with the BINS Company confirm that nearly all campus waste arrives mixed; hazardous objects are encountered frequently; manual sorting is conducted on moving trucks; and poor segregation often results in landfill fines. This situation is consistent with recent findings that academic institutions in Uganda face persistent challenges in sustainable waste management, including inadequate segregation and limited recycling infrastructure[5].

Although modern technologies such as IoT-based sensors, CNN classifiers, and object detectors have demonstrated significant improvements in recognition and categorization accuracy across various waste types, these systems remain largely absent in Uganda, leaving institutions without automated tools to support source-level segregation. Global datasets do not reflect African waste compositions like polythene and local paper products, making dataset mismatch a major barrier to successful deployment in Uganda. Therefore, the core problem is the absence of an affordable, AI-powered smart waste classification and sorting system capable of accurately detecting, identifying, and separating waste at the source in Uganda's institutional environments.

1.3 Research Objectives

To design and implement a smart bin for intelligent waste classification and sorting that automatically detects, identifies, sorts and logs waste at the source in order to improve waste segregation. This enhances recycling efficiency, and support data-driven waste management in institutional environments.

1.3.1 Specific Objective 1

To develop an intelligent waste identification model using VGG16-based classification trained on a custom dataset of campus waste.

1.3.2 Specific Objective 2

To design and construct an embedded smart bin prototype equipped with a camera, sensors, and mechanical sorting mechanisms capable of directing waste into the appropriate compartment based on the developed model results.

1.3.3 Specific Objective 3

To build a MERN-stack backend and data management system that receives classification events, stores waste disposal data in MongoDB, and enables secure access to waste analytics.

1.3.4 Specific Objective 4

To develop a React and Tailwind-based dashboard that visualizes waste trends using bar charts, pie charts, and line graphs, allowing stakeholders to monitor disposal patterns in real time.

1.3.5 Specific Objective 5

To evaluate the system's performance in terms of classification accuracy, sorting reliability, usability, and its contribution to reducing manual sorting, hazardous exposure, and operational inefficiencies.

1.4 Justification

This project addresses the main challenge in Uganda's waste management by offering a practical, locally adaptable technological solution. The proposed system supports waste segregation at the source by enabling automatic classification and sorting, thereby reducing the burden on manual sorters and minimizing occupational hazards. By providing real-time data on waste disposal patterns, the system empowers regulatory bodies such as NEMA and KCCA to make informed decisions regarding resource allocation, recycling initiatives, and awareness campaigns[6]. In addition to addressing immediate waste challenges, the project creates a platform for future innovation and research in the field of smart waste management.

1.5 Scope

1.5.1 Geographical Scope

This project is to be implemented at institutions, where the smart bin is deployed within a controlled and structured institutional environment. The system targets waste generated in high-traffic areas such as student halls, canteens, walkways, and academic spaces. Institutions were selected due to the presence of a relatively organized user population that is more likely to adhere to system guidelines. The smart bin requires users to dispose of waste items individually, which necessitates a level of patience and compliance for optimal functionality. Therefore, the institutional setting provides suitable conditions for proper system usage and evaluation. This environment supports effective observation of user interaction and system performance prior to potential expansion into municipal settings.

1.5.2 Subject Scope

This study focuses on the design, implementation, and evaluation of an AI-assisted smart bin for automated waste classification and sorting at Uganda Christian University (UCU). The system targets three waste categories: Plastics (e.g., water bottles, juice cups, yogurt containers, polythene bags), Paper (e.g., book papers, paper bags, napkins, cardboard pieces), and General Waste (non-recyclable and non-hazardous dry waste). The smart bin is designed for indoor use in high-traffic areas such as student hostels, canteens, walkways, and academic buildings. The system accepts only dry, non-hazardous waste items and requires users to dispose of one item at a time. The classification model is built using a VGG16-based convolutional neural network trained on a custom dataset of 5,000 campus waste images. The prototype integrates a Raspberry Pi 4, Pi Camera v2, servo motors, and a MERN-stack backend with a React dashboard for data visualisation. The study does not cover liquid waste, hazardous materials, outdoor deployment, or municipal-scale waste management. Performance evaluation is limited to classification accuracy, sorting reliability, latency, and user acceptance within a controlled institutional environment.

1.5.3 Time Scope

The project was carried out over a period of seven months, from October 2025 to May 2026, following the academic calendar. The activities were distributed as follows:

- **Weeks 1–2 (October 2025)**: Literature review, problem identification, and requirements gathering. Semi-structured interviews with BINS Company staff and initial site observations at UCU.
- **Weeks 3-4 (November 2025)**: Custom dataset collection (5,000 images) and annotation using Label Studio.
- **Weeks 5–7 (January-February 2026)**: Model development – transfer learning with VGG16, training, validation, and hyperparameter tuning.
- **Weeks 8–10 (February-March 2026)**: Hardware assembly and software integration – Raspberry Pi setup, sensor calibration, servo control, backend API development, and dashboard implementation.
- **Weeks 11–12 (February-March 2026)**: System integration testing, model evaluation on test set, and user acceptance testing with a small group of UCU students and staff.
- **Weeks 13–14 (April 2026)**: Documentation, performance analysis, and final report writing.

Chapter 2

Literature Review

2.1 Introduction

This chapter explores the current landscape of waste management technologies, with a particular focus on automated sorting and AI-based classification. It examines the evolution of waste segregation methods, the strengths and limitations of existing systems, and the specific challenges faced in Ugandan institutions. The review aligns previous findings with the specific objectives of this research and highlights the existing knowledge gaps that this study seeks to address.

2.2 Review of Existing Solutions

2.2.1 Manual Waste Sorting in Ugandan Institutions

Manual sorting is the predominant method of waste segregation in Uganda, especially at institutional levels. Waste collectors, such as those from the BINS Company, manually separate recyclables from mixed waste at the point of collection. This process is labor-intensive, time-consuming, and exposes workers to significant health risks. According to [2], over 50% of waste workers in Uganda experience occupational injuries, with cuts from sharp objects being the most common[1]. Moreover, the efficiency of manual sorting is low; it is estimated that less than 30% of potentially recyclable materials are actually recovered due to contamination and the difficulty of identifying items in a mixed stream [7].

The reliance on user compliance is another major drawback. Even when bins are clearly labeled for different waste types, studies show that user adherence is poor due to lack of awareness, convenience, or enforcement mechanisms [8]. This results in cross-contamination that renders separated collection efforts ineffective. In the UCU context, interviews confirmed that waste is almost never segregated at the source, despite the availability of labeled bins in some locations. This highlights the need for a system that does not depend on user knowledge or behavior but rather enforces segregation automatically.

2.2.2 IoT-Based Monitoring Bins

The early years of the technological revolution in waste management brought Internet of Things (IoT)-activated smart bins meant for tracking waste concentrations[9]. These systems commonly rely on sensors, like ultrasonic, infrared, or weight sensors, that sense bin fill levels and send that information to a central repository. They have been designed for enhancing waste collection processes, optimizing route planning by minimizing operational costs and preventing bin overflow. Implementations of such systems have been reported in studies like [10], as well as on several smart city deployments all over the globe.

Although the IoT-based bins used for monitoring are very beneficial, they are limited in their application due to their lack of ability to reach waste segregation. Such systems treat waste as a uniform stream and do not differentiate between various types of materials, reducing recycling and reinforcing dependence on a human-operated sorting system. Consequently, major challenges, including mixed waste contamination and occupational hazards for waste handlers, are still existent. [11] highlight that while IoT technologies can improve monitoring and collection efficiency, the intelligence of these technologies for waste identification and sorting is significantly lower.

This gap emphasizes the need to move away from passive monitoring toward a more intelligent, AI-enabled solution that can provide an active impact on sustainable waste management practices.

2.2.3 AI-Driven Waste Classification Systems

Incorporation of computer vision and deep learning has paved the way for automation in waste sorting. Convolutional Neural Networks (CNNs)[12] have emerged as the commonly used standard of image classification tasks, and waste recognition is a major application. A well-known early paper performed by[13], where it was shown high-accuracy performance by a custom CNN was expected for commonly used waste classes (plastic, paper, metal). Previous work has tested transfer learning of pre-trained models such as VGG16, ResNet and MobileNet in the evaluation of smaller, domain-specific datasets in order to achieve the desired performance [4].

Specifically, VGG16 has been adopted because of the simple and power of its architecture and available pre-trained weights from the ImageNet dataset. [3] used VGG16 in transfer learning for dry waste classification, yielding good precision and recall. The depth of the model is sufficient that it can learn complex features, which is enough for separating between waste items which are visually akin to one another or similar in appearance, examples are different kinds of plastics or paper. Object detection architectures such as YOLO (You Only Look Once) have also been used to localize and classify multiple waste components in a single image. Although YOLO provides real-time performance and can detect several objects, it is stronger to train annotate with bounding boxes, and more complex to apply than image classification.

An intelligent bin system where they display the item on a bin model such as VGG16 can be efficient for deploying in an embedded form by means of a classification framework such as VGG16. Recent work has introduced new approaches such as Vision Transformers and hybrid AutoEncoder-CNN models [14], which have gone to further accuracy limits. Nonetheless, general models are bulky and resource-demanding, and they are less ready to be deployed using low-cost hardware such as the Raspberry Pi. A key limitation revealed in several AI waste classification experiments [15] is the use of world-scale data including TrashNet, TACO, etc. Most of these datasets show waste from Western countries, and the waste stream in an African setting is an even more prominent component. For instance, polythene sachets used for localized packaging, and paper types are missing. [16] highlighted that models using foreign datasets alone tend to generalize poorly on deployment in developing areas, highlighting the necessity for more local dataset capture.

2.3 Review Mapped to Objectives

2.3.1 Objective 1: Developing an intelligent waste identification model using computer vision

The literature confirms that CNN-based models[17], especially those using transfer learning with architectures like VGG16[18], are highly effective for waste image classification. Studies by [4]. (2020) and [3] provide a solid methodological foundation for training a custom classifier on a relatively small dataset. The key challenge identified is the need for a dataset that reflects the specific waste composition of the target environment institutions like UCU. This project addresses this by collecting and annotating over 5000 images of campus waste.

2.3.2 Objective 2: Developing the embedded smart bin prototype

Smart bin hardware research [19] has shown that combining sensors, a camera, a single-board computer (Raspberry Pi), and servo-actuated sorting mechanisms is technically viable, with prototype implementation successfully achieved. Sensor triggering to take pictures at the right moment and low-latency processing for real-time actuation are key, the literature emphasizes. The project is built on these established hardware design principles and optimized for cost and local availability of components.

2.3.3 Objective 3: Developing a MERN-stack backend and data management system

IoT-enabled waste management systems often support cloud-based backends to store and analyze data (Longo et al., 2021). The MERN stack (MongoDB, Express.js, React, Node.js) is a contemporary, high-capacity platform for creating these types of platforms. Its stack-wide use of JavaScript makes development and maintenance easier. Data on semi-structured events is stored in MongoDB (i.e. classification logs) and Node.js/Express for creating lightweight, efficient APIs.

2.3.4 Objective 4: Developing a React- and Tailwind-based dashboard

Data visualisation is an important aspect in transforming raw disposal logs into usable data. It is on a dashboard where waste trends via charts (bar, pie, line) are displayed. These allow waste management personnel at a facility to monitor waste generation patterns, identify peak disposal times, and assess the effectiveness of recycling programs. Research on smart city dashboards highlights the need to produce intuitive, real-time graphics and visualizations to enable engagement with key stakeholders. React, combined with Tailwind CSS for styling, provides a flexible and efficient framework for such interactive interfaces[20].

2.3.5 Objective 5: Evaluating the system's performance

The literature employs standard metrics for evaluating classification models, including accuracy, precision, recall, F1-score, and confusion matrices. For the integrated system, performance evaluation extends to sorting reliability (percentage of items correctly routed), system latency (time from disposal to sorting), and usability (user feedback). This project adopts these established metrics to provide a comprehensive assessment of the developed prototype.

2.4 Research Gap and Justification

Many developments such as AI-driven waste classification mechanisms as well as smart bin technologies have been made, but such measures are hardly available in Uganda, especially within institutional settings. The prevailing solutions are either cost prohibitive, designed for different waste compositions, or lack the integrated data analytics component required to aid with data-driven decision-making. The dependence on manual sorting continues, leading to additional health hazards and inefficiencies.

To fill this gap present in the literature, this project aims to introduce an inexpensive and context-specific smart bin system to suit the waste stream of Uganda Christian University. The project provides an end-to-end solution by collecting a local dataset, implementing transfer learning with VGG16, and using the classification model along with a prototype hardware architecture based on custom build, a MERN-stack analytics dashboard. This system not only automates the segregation from source but generates data which enhances the sustainability of waste management. Therefore, the rationale for this research is rooted in the recognized technological gap and the pressing practical requirements of improved waste handling in Ugandan universities.

2.5 Summary

This chapter has examined the changes in waste management technologies, including manual sorting, IoT monitoring and AI-assisted classification. However, there is a wide gap in applying these models to the unique issues of the Ugandan situation, while global studies suggest that deep learning models such as VGG16 can successfully identify waste for effective waste management. The limitations of local datasets, the prevalence of manual sorting hazards, and the absence of integrated data systems all call for a solution that is customized. Our proposed EcoClassifier system will help to bridge this gap by creating a smart bin that leverages AI-based classification, automated mechanical sorting, and a complete web analytics engine, making waste management safer, efficient, and data-driven at UCU.

Chapter 3

Methodology

3.1 Introduction

The research methodology, designed system, and development methods used to implement AI-based waste segregation and analytics (smart bin) are described in this chapter. It utilises a Design Science Research (DSR) approach along with experimental techniques for model training and evaluation. The chapter presents data collection operations, system requirements, architecture, hardware and software design, testing and validation procedures, use case analysis, system interaction, and ethical considerations.

3.2 Research Design

This study is a Design Science Research (DSR) project, the ideal method for the design, building, and testing of technological artifacts such as an AI-driven smart bin. At its core, DSR is an iterative approach to designing a solution, assessing it in a meaningful context, evaluating design in relation to feedback received, and re-testing. Such methodology is consistent with previous smart-bin studies, where sensor-based, camera-equipped prototypes were developed and tested in real-life operational situations (Ahmad et al., 2025).

For machine learning, an experimental research design is used in addition to DSR. The VGG16 classification model is trained, validated, and tested in controlled conditions to evaluate its accuracy and robustness. It consists of methodical tuning of training parameters and evaluation based on held-out tests, in line with the well-documented strategies of deep learning [13] and [14]. The study finally incorporates principles of applied research as the objective is the resolution of a specific and real-world problem: the highly inefficient and hazardous waste sorting system at Uganda Christian University (UCU). The entire project is contextualised to the local environment, from drawing up a custom waste dataset to sourcing affordable hardware components.

3.3 Data Collection Methods

3.3.1 Custom Dataset Creation

A custom dataset of waste images was collected at UCU over a period of two weeks. Using a smartphone camera, photographs were taken of common campus waste items found in bins and surrounding areas. The items included:

- Plastic bottles (water, soda)
- Juice cups and yogurt containers
- Polythene bags (clear and coloured)
- Paper bags and wrapping paper
- Napkins and tissue paper
- Book papers and cardboard pieces

Images were captured under varying lighting conditions (natural daylight, fluorescent indoor light) and against different backgrounds (concrete, grass, tiled floor) to increase the dataset's diversity and improve model robustness. A total of 5000 images were collected, ensuring a balanced representation across the target categories: Plastics, Paper, and General Waste.

3.3.2 Data Annotation

The collected images were annotated using Label Studio, an open-source data labelling tool. Each image was assigned a single class label corresponding to the waste category (Plastic, Paper, General). The annotations were exported in a CSV format containing the image filename and its associated label. This structured dataset was then split into training (70%), validation (15%), and testing (15%) sets for model development.

3.3.3 Interviews with Waste Collectors

Semi-structured interviews were conducted with two staff members from the BINS Company, the waste collection contractor for UCU. The interviews aimed to understand the current waste management practices, challenges faced by collectors, and their perspectives on the potential benefits of an automated sorting system. Key findings from the interviews (summarised in Appendix B) informed the problem definition and the design requirements of the smart bin.

3.4 System Requirements

3.4.1 Functional Requirements

1. **Waste Detection**: The system must automatically detect when a waste item is inserted into the bin using an ultrasonic sensor.
2. **Image Capture**: Upon detection, the system must capture a clear, well-lit image of the waste item using the Pi Camera.
3. **AI Classification**: The system must classify the captured image into one of three categories: Plastic, Paper, or General Waste, using a pre-trained VGG16 model.
4. **Mechanical Sorting**: Based on the classification result, the system must activate a servo motor to direct the waste item into the corresponding physical compartment.
5. **Data Logging**: Each disposal event (including category, timestamp, bin ID) must be logged locally and transmitted to a remote server.
6. **API Endpoints**: The backend must provide RESTful API endpoints to receive disposal events and to serve aggregated data for the dashboard.

7. **Data Visualization**: The dashboard must display waste disposal trends over time using bar charts, pie charts, and line graphs.

3.4.2 Non-Functional Requirements

1. **Performance**: Image classification and sorting must be completed within 5 seconds of waste insertion to ensure a responsive user experience.
2. **Reliability**: The system should maintain a classification accuracy of at least 85% under normal operating conditions and sorting reliability of over 95%.
3. **Usability**: The physical bin must be intuitive to use, requiring no special instructions for the end-user. The dashboard interface must be clean and easy to navigate.
4. **Scalability**: The backend architecture must support the potential addition of multiple smart bin units across the campus without significant modification.
5. **Maintainability**: The hardware components must be easily accessible for maintenance and repair. The software codebase must be well-documented and modular.
6. **Cost-Effectiveness**: The prototype must be built using affordable, locally available components to ensure the solution is replicable in similar low-resource settings.
7. **Security**: The API endpoints must be secured to prevent unauthorised data injection. The dashboard should require authentication for access.

3.5 System Architecture

The system follows a three-tier architecture consisting of a sensing and actuation layer (the smart bin), a data processing and storage layer (the backend), and a presentation layer (the dashboard).

3.5.1 Tier 1: Smart Bin (Edge Layer)

This tier is responsible for the physical interaction with the waste. It contains:

- **Input Sensors**: HC-SR04 ultrasonic sensor for object detection.
- **Imaging Sensor**: Raspberry Pi Camera Module v2 for image acquisition.
- **Processing Unit**: Raspberry Pi 4 running Raspbian OS, Python, TensorFlow Lite (or full TensorFlow), and OpenCV.
- **Actuators**: MG996R servo motors for controlling the sorting flap.
- **Communication Module**: Built-in WiFi for internet connectivity.

The software on the Raspberry Pi orchestrates the entire local workflow. It uses interrupts or polling to read the ultrasonic sensor. Upon detection, it captures an image using the ‘picamera‘ library, preprocesses it (resizing, normalisation), and feeds it to the VGG16 model. The model outputs a class prediction, which triggers a GPIO signal to the corresponding servo motor. Finally, it packages the event data into a JSON object and sends an HTTP POST request to the backend API.

3.5.2 Tier 2: Backend Server (Cloud/On-Premise Layer)

This tier manages data persistence and business logic. It is built using the MERN stack components:

- **Node.js/Express.js**: Provides a lightweight, non-blocking server environment. The Express framework is used to define RESTful API routes.
- **MongoDB**: A document-oriented NoSQL database ideal for storing semi-structured event logs. Each disposal event is stored as a document in a collection named 'disposals'. The schema includes fields like 'binId', 'category', 'timestamp', 'confidenceScore' (optional), and 'imageUrl' (if images are uploaded).
- **Mongoose**: An Object Data Modeling (ODM) library for MongoDB and Node.js. It manages relationships between data, provides schema validation, and simplifies database queries.

The backend exposes API endpoints such as:

- 'POST /api/events': Receives a new disposal event from a smart bin.
- 'GET /api/events': Retrieves a list of events, with optional query parameters for filtering by date, category, or bin ID.
- 'GET /api/stats': Returns aggregated statistics (e.g., total counts per category for a given period).

3.5.3 Tier 3: Frontend Dashboard (Presentation Layer)

This tier provides a user interface for data visualisation and system monitoring. It is a single-page application (SPA) built with:

- **React**: A component-based library for building interactive UIs. The dashboard is composed of reusable components such as 'Navbar', 'Sidebar', 'StatCard', 'BarChart', 'PieChart', and 'DataTable'.
- **Tailwind CSS**: A utility-first CSS framework that enables rapid styling and ensures a consistent, modern look and feel.
- **Axios**: A promise-based HTTP client used to fetch data from the backend API.
- **Recharts**: A composable charting library built on React components, used to render the various trend visualisations.

The dashboard fetches data periodically (e.g., every 60 seconds) or on-demand to display real-time updates. Key performance indicators (KPIs) shown include total waste items today, distribution by category, hourly disposal trends, and historical data for the past week/month.

3.6 Hardware Design

The hardware design is centred around the Raspberry Pi 4, which acts as the central controller. All peripherals are connected to the Pi's GPIO pins. The hardware is mounted on a custom wooden base with three distinct internal compartments for Plastic, Paper, and General Waste. The enclosure guides waste items in a controlled way into the classification and sorting area, maintaining simplicity and low cost.

3.6.1 Component Specifications

Table 3.1 lists the main hardware components and their functions.

Table 3.1: Hardware Components and Specifications

Component	Specification	Function
Raspberry Pi 4	Quad-core Cortex-A72, 4GB RAM	Central controller; runs classification model and system logic
Pi Camera Module v2	8MP, 1080p video	Captures images of waste items for classification
Servo Motor	MG996R	control the sorting flap and direct waste into the correct compartment with precise angular movement.
Stepper motor	28BYJ-48 Stepper	Used to rotate the waste compartments accurately so the correct bin aligns during sorting.
Power Supply	5V 3A USB-C adapter	Provides stable power to the system
MicroSD Card	32GB, Class 10	Stores OS, trained model, and application code
Enclosure (Wood)	Custom-built, 3 compartments	Physical structure for sorting and waste collection

3.6.2 Pin Configuration

Table 3.2 details the pin connections for the major components.

Table 3.2: Hardware Pin Configuration

Component	Pin(s) on Raspberry Pi	Notes
Ultrasonic Sensor (HC-SR04)	VCC: Pin 2 (5V), GND: Pin 6, Trig: GPIO17, Echo: GPIO27	Detects object presence and distance.
Pi Camera Module	Dedicated CSI port	Enables high-speed data transfer
Servo Motor (Sorting Flap)	Signal: GPIO18, VCC: External 5V, GND: Common GND	Directs waste to the correct bin.
Stepper Motor (Sorting Mechanism)	IN1–IN4: GPIO18, GPIO22, GPIO24, GPIO25, VCC: External 5V, GND: Common GND	Rotates tray during sorting.

3.6.3 Mechanical Design

The bin enclosure is constructed from 12mm plywood, chosen for its affordability, ease of working, and sufficient durability for a prototype. The internal volume is divided into three compartments of equal size using plywood dividers. The top section houses the electronics in a sealed compartment to protect them from dust and accidental spills. The disposal chute is designed with a sloped surface to guide the waste item into the field of view of the camera before it reaches the sorting mechanism. A hinged door on the front of the bin provides access to the full compartments for emptying.

The Pi Camera is strategically positioned above a temporary holding platform where each waste item is placed or dropped. This ensures a clear and consistent image is captured before classification. The system is designed to accept one item at a time, allowing the model to make accurate predictions without interference from overlapping objects.

Once an item is classified, the Raspberry Pi sends a signal to the servo motor mechanism, which directs the waste into the appropriate compartment. The primary servo controls a flap that opens toward the correct bin, while an optional secondary servo can be used to rotate a sorting platform for more precise control. This simple mechanical design reduces complexity while maintaining reliable operation.

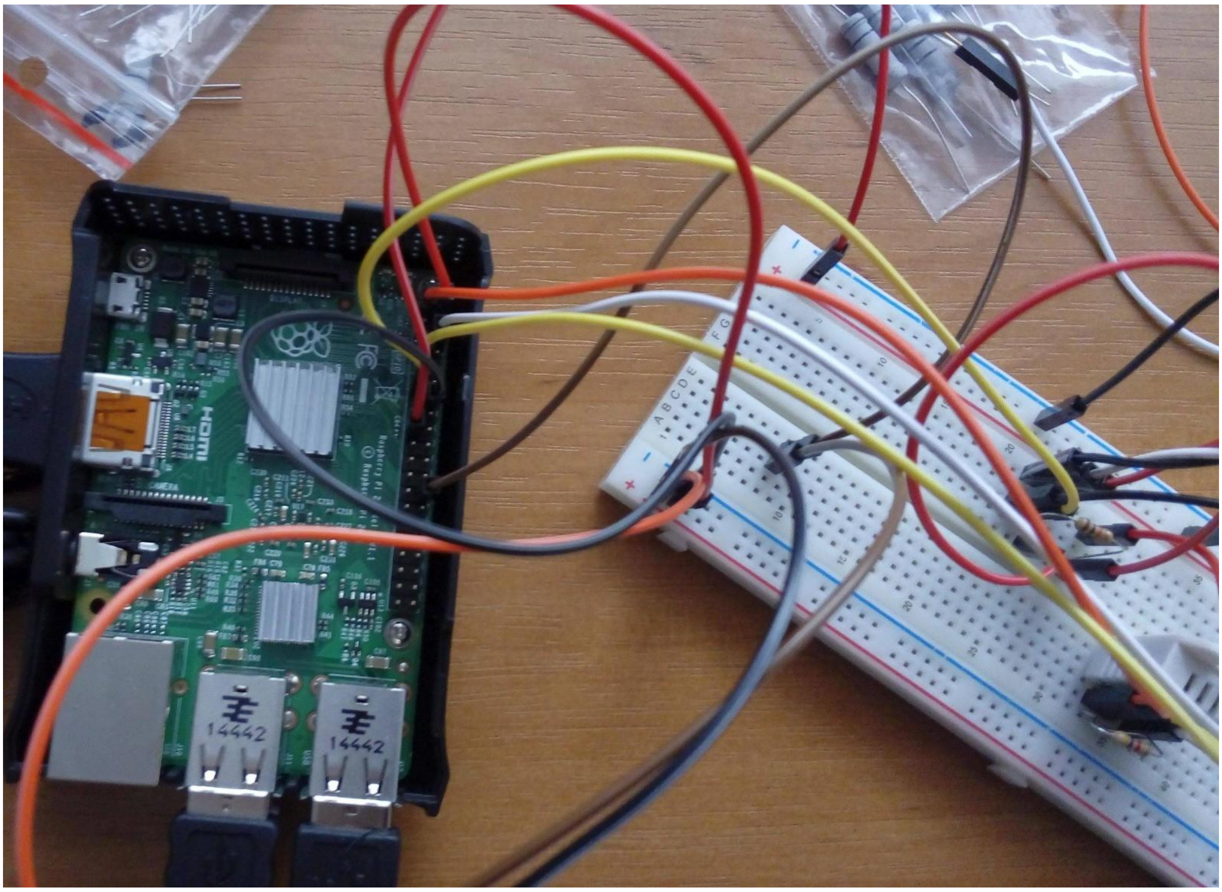


Figure 3.1: Wiring Diagram of Smart Bin Electronics

3.7 Software Design

The software system consists of three main components:

1. **Embedded Application (Raspberry Pi)**: A Python script that manages sensor input, image capture, model inference, servo control, and data transmission.
2. **Backend API (Node.js/Express)**: A RESTful API that receives classification logs from the smart bin and stores them in a MongoDB database.

3. **Frontend Dashboard (React/Tailwind)**: A web application that fetches data from the backend and visualises waste disposal trends.

3.7.1 VGG16 Model Architecture and Training

The VGG16 architecture consists of 13 convolutional layers and 3 fully connected layers. For this project, the pre-trained convolutional base is used as a fixed feature extractor. Transfer learning is applied by loading pre-trained weights from ImageNet, freezing the convolutional base, and adding a new classifier head consisting of:

- A Global Average Pooling 2D layer (to reduce spatial dimensions).
- A Dense layer with 256 units and ReLU activation.
- A Dropout layer with a rate of 0.5 (for regularisation).
- A final Dense layer with 3 units and Softmax activation (for 3-class classification).

The model is compiled with the Adam optimizer, a learning rate of 0.0001, and categorical cross-entropy loss. Training is performed for 20 epochs with a batch size of 32. Data augmentation techniques (rotation, zoom, horizontal flip) are applied to the training set to improve generalisation.

Figure 3.2: VGG16 Architecture Diagram with Custom Head

3.7.2 Backend API Design

The backend API is structured around RESTful principles. Key endpoints are defined as follows:

POST /api/events

Listing 3.1: Sample POST Request Body

```
{
  "binId": "UCU − BIN − 01",
  "category": "Plastic",
  "confidence": 0.95,
  "timestamp": "2026−04−17T10:30:00Z"
}
```

Response: 201 Created with the saved document.

GET /api/events?startDate=YYYY-MM-DD&endDate=YYYY-MM-DD *Response*: 200 OK with a JSON array of event objects.

GET /api/stats/daily *Response*: 200 OK with JSON object containing daily aggregated counts per category for the last 7 days.

3.7.3 Dashboard Component Structure

The React dashboard is organised into the following main components:

- App.jsx: Root component, handles routing and global state.
- Layout.jsx: Provides the overall page structure (header, sidebar, main content area).
- Dashboard.jsx: The main dashboard view, composed of several smaller components:
  - StatsOverview.jsx: Displays key metrics like total items today and most frequent category.
  - CategoryPieChart.jsx: A pie chart showing the proportion of waste categories for a selected period.
  - HourlyBarChart.jsx: A bar chart showing the distribution of disposals by hour of the day.
  - RecentActivityTable.jsx: A table listing the most recent disposal events.
- History.jsx: A view for exploring historical data with date range pickers and export options.

3.8 Development Tools and Libraries

Table 3.3 lists the primary software tools and libraries used in the development of the system.

Table 3.3: Software Tools and Libraries

Software/Library	Purpose
Python 3.9	Embedded application, model training
TensorFlow / Keras	Deep learning framework for VGG16 model
OpenCV	Image capture and preprocessing
RPi.GPIO	GPIO control for sensors and servos
Flask (alternative)	Lightweight web server on Pi (if direct control needed)
Node.js	Backend runtime environment
Express.js	Backend web framework
MongoDB	NoSQL database for event storage
Mongoose	ODM for MongoDB
React	Frontend UI library
Tailwind CSS	Utility-first CSS framework for styling
Chart.js / Recharts	Data visualisation library
Label Studio	Image annotation tool
Git	Version control

3.9 Testing and Validation Procedures

3.9.1 Model Evaluation

The trained VGG16 model is evaluated on the held-out test set using standard classification metrics:

- **Accuracy**: Overall proportion of correct predictions.
- **Precision**: For each class, the proportion of true positives among all positive predictions.
- **Recall**: For each class, the proportion of true positives among all actual positives.
- **F1-Score**: Harmonic mean of precision and recall.
- **Confusion Matrix**: A table showing correct and incorrect predictions per class.

3.9.2 System Integration Testing

The fully assembled smart bin prototype is tested in a controlled laboratory environment. Test scenarios include:

- **Classification Accuracy**: Dropping 50 known waste items (mix of plastic, paper, general) and recording the predicted class vs. actual class.
- **Sorting Reliability**: Observing whether the mechanical system correctly routes the item to the intended compartment based on the classification output.
- **Latency**: Measuring the time from waste detection to completion of sorting action.
- **Data Logging**: Verifying that each disposal event is successfully transmitted to the backend and stored in MongoDB.

3.9.3 User Acceptance Testing

A small group of potential users (e.g., students, cleaning staff) will be invited to interact with the smart bin prototype. Feedback will be collected through a short questionnaire to assess perceived ease of use, reliability, and overall usefulness.

3.10 System Interaction

Figure 3.3 presents a sequence diagram illustrating the interaction flow for the ”Dispose Waste” use case, from the user’s action to the data appearing on the dashboard.

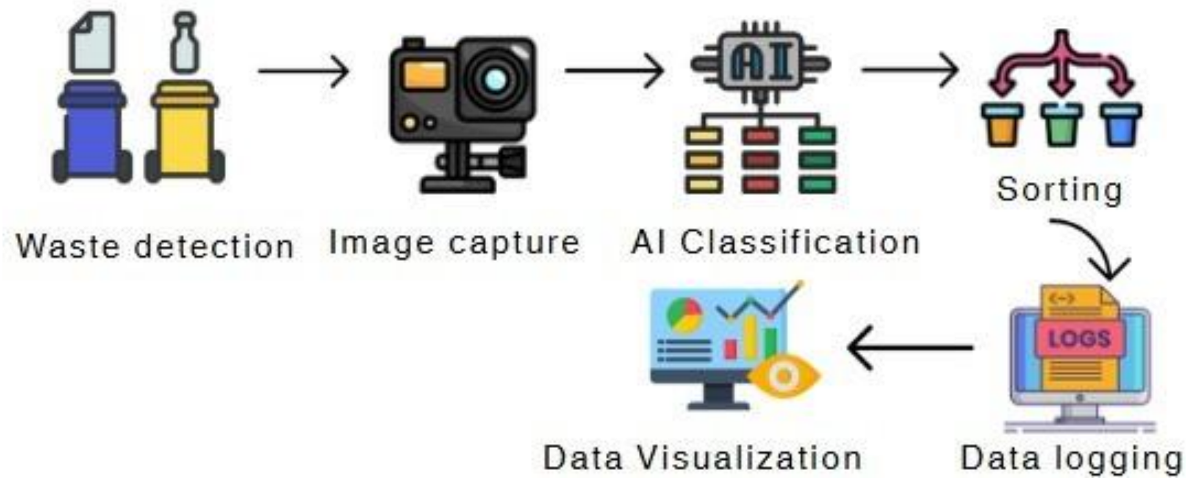


Figure 3.3: Sequence Diagram for Waste Disposal and Data Logging

Description of Interaction:

1. The User drops a waste item into the bin.
2. The Ultrasonic Sensor detects the item and sends a signal to the Raspberry Pi.
3. The Raspberry Pi commands the Camera to capture an image.
4. The Camera returns the image data.
5. The Raspberry Pi preprocesses the image and sends it to the VGG16 Model for inference.
6. The Model returns the predicted category (e.g., ”Plastic”).
7. The Raspberry Pi sends a signal to the Servo Motor associated with the predicted category to actuate the sorting flap.
8. The Raspberry Pi constructs an HTTP POST request containing the event data and sends it to the Backend API.
9. The Backend API validates the data and inserts a new document into the MongoDB database.
10. The Frontend Dashboard, upon its next polling interval or via a WebSocket connection, fetches the updated data from the API.
11. The Dashboard re-renders its charts to reflect the new disposal event, making it visible to the Administrator.

This end-to-end flow ensures a seamless and automated process from physical waste disposal to digital data visualisation.

3.11 Ethical Considerations

This research project adheres to ethical guidelines for conducting studies involving human participants and data collection.

- **Informed Consent**: Interview participants from the BINS Company were informed about the purpose of the research and provided verbal consent before the interviews. Their identities are kept confidential.

- **Data Privacy**: The dataset of waste images does not contain any personally identifiable information. The web dashboard does not collect user data beyond anonymous disposal events.
- **Environmental Impact**: The project aims to promote recycling and reduce landfill waste, aligning with principles of environmental sustainability.

Chapter 4

Results

4.1 Introduction

This chapter presents the results obtained from the implementation and testing of the Eco-Classifier system. It covers the outcomes of model training and evaluation, the performance of the assembled hardware prototype, the functionality of the web dashboard, and the findings from integration and user acceptance testing. All results are reported against the functional and non-functional requirements defined in Chapter 3.

4.2 Model Training and Evaluation Results

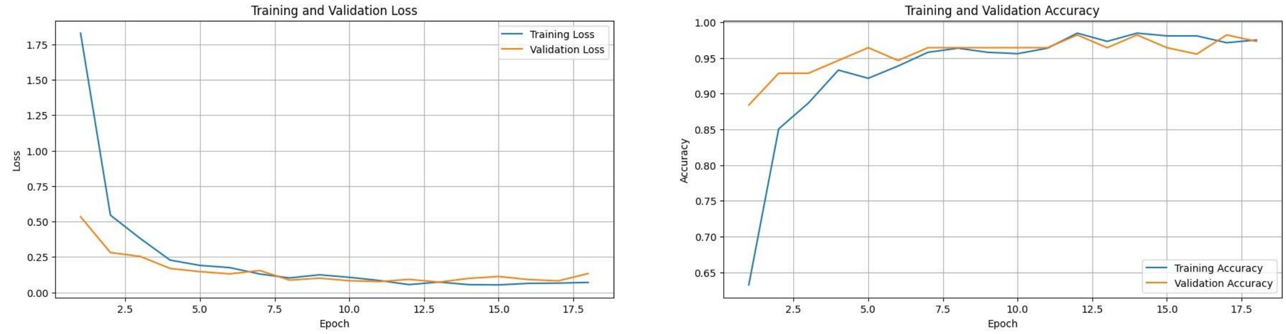
4.2.1 Dataset Composition

A custom dataset of 5000 annotated waste images was prepared, comprising three classes: plastic, paper, and general waste. The dataset was split into training (3284 images), validation (858 images), and testing (858 images) sets, with balanced class distribution.

4.2.2 VGG16 Transfer Learning Results

The VGG16-based model was trained for 20 epochs using transfer learning with a frozen convolutional base and a custom classification head. The training and validation accuracy and loss curves are illustrated in Figure 4.1b and Figure 4.1a. The model achieved the following performance on the held-out test set:

- **Testing Accuracy**: 91.5%
- **Validation Accuracy**: 93.2%



(a) Training and Validation Loss (b) Training and Validation Accuracy

The confusion matrix (Figure 4.2) shows that most misclassifications occurred between similar-looking plastic and paper items (e.g., plastic-coated paper cups).

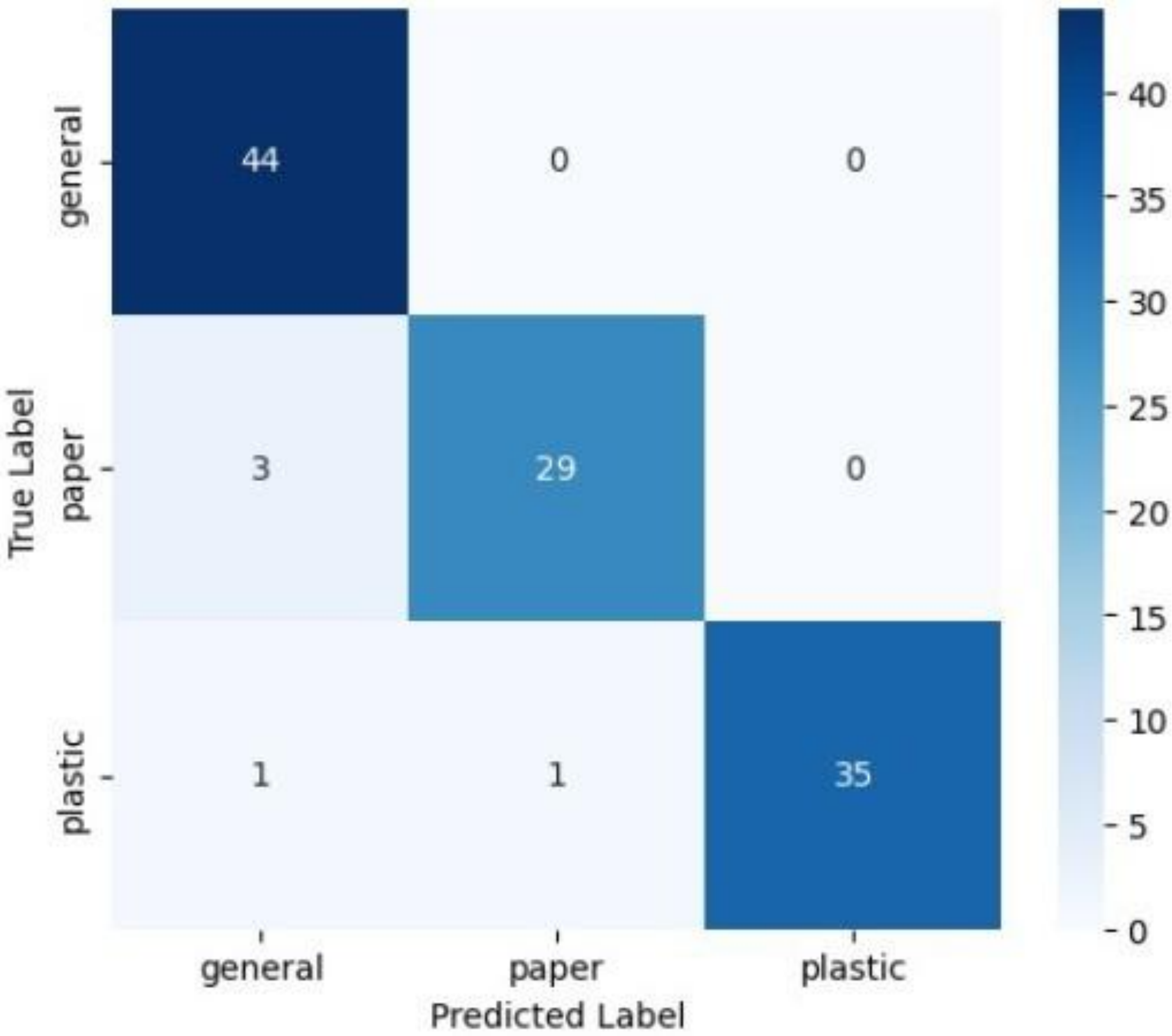


Figure 4.2: Confusion Matrix

4.2.3 Optimisation Outcome

Converting the TensorFlow model to TensorFlow Lite format reduced inference time on the Raspberry Pi CPU from approximately 1.8 seconds to 0.9 seconds per image, enabling real-time operation.

4.3 Hardware Prototype Results

The assembled smart bin prototype successfully integrated all hardware components. The wooden enclosure housed three compartments, and the electronics were mounted securely. The Raspberry Pi 4 ran the embedded Python application, which correctly initialised all peripherals (ultrasonic sensor, camera, servo motors, and status LEDs) on startup. The system reliably detected waste items placed on the holding platform and triggered image capture without failure across 50 test runs.

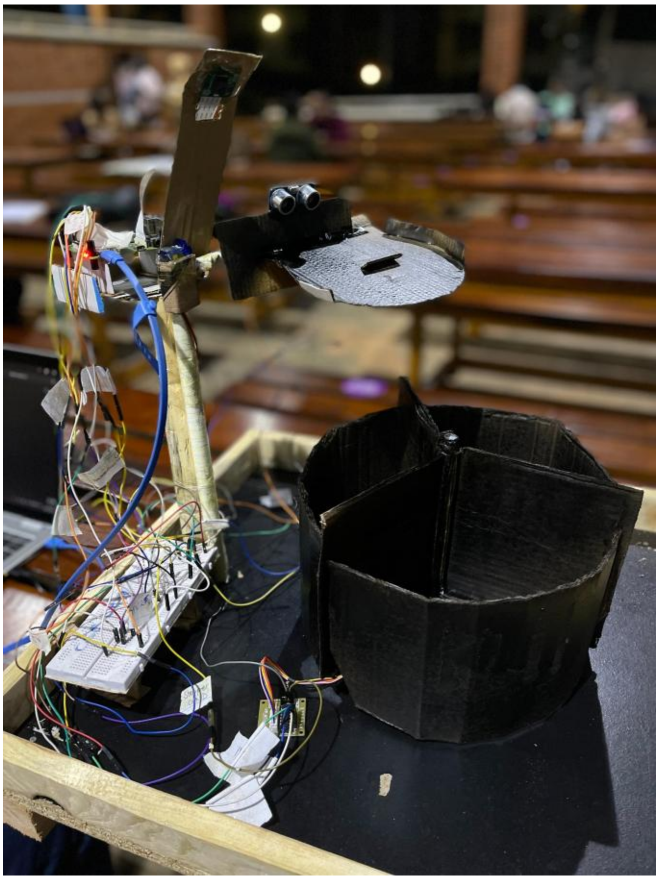


Figure 4.3: Hardware Prototype

4.4 Web Dashboard Results

The React-based dashboard was successfully deployed and connected to the backend API. Key functional outcomes include:

- A date range picker that correctly filters historical data.
- KPI cards displaying total items, today's count, and top category in real time.
- A pie chart showing category distribution (example: Plastics 45%, Paper 30%, General 25% based on test data).
- A bar chart visualising hourly disposal trends.
- A sortable and paginated table of recent transactions.
- A CSV export function that downloads filtered data without errors.

Figure 4.4 provides a description of the dashboard interface.

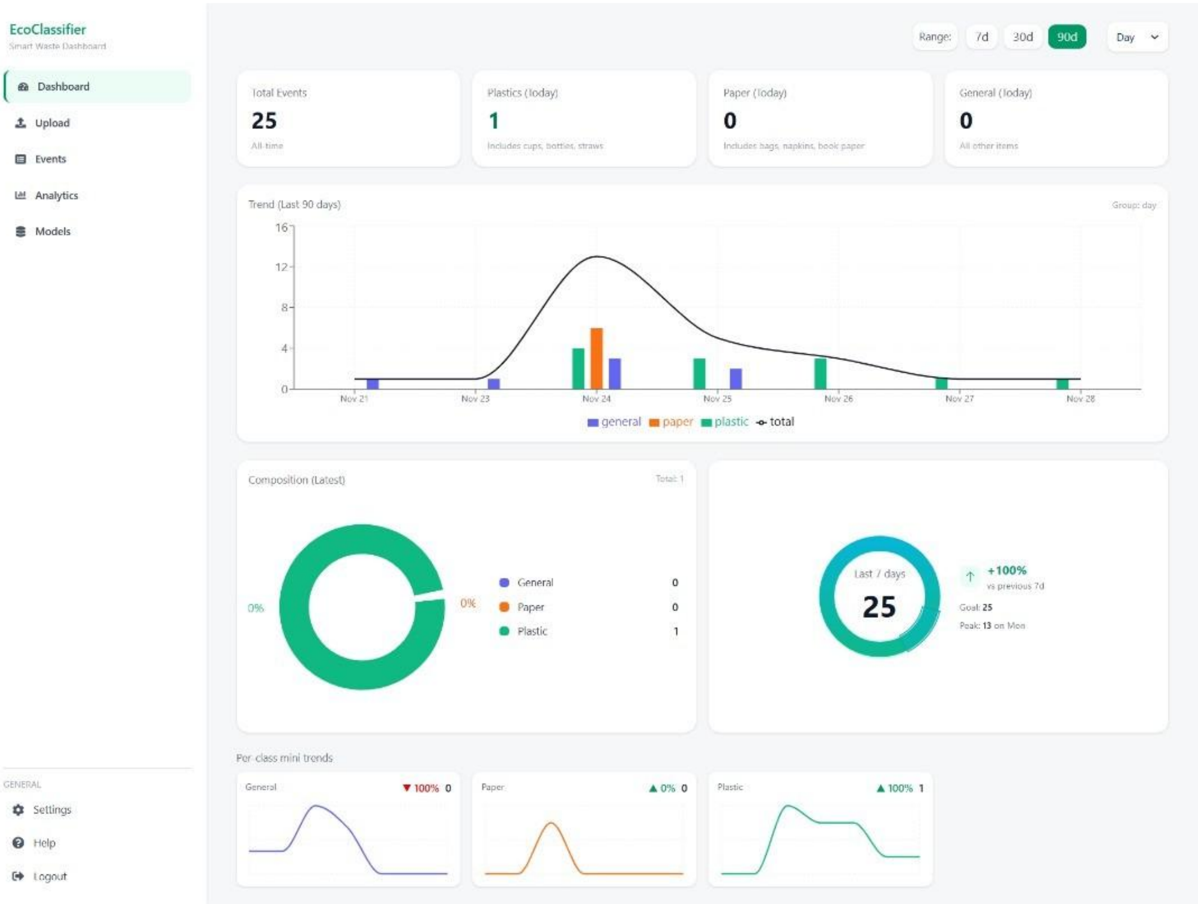


Figure 4.4: Dashboard Interface Description

4.5 Integration Testing Results

Integration testing confirmed seamless communication between the smart bin and the web platform. The Python script on the Raspberry Pi successfully sent HTTP POST requests to the '/api/events' endpoint. The backend correctly parsed the JSON payload and stored each event in MongoDB Atlas. The frontend, using a 'setInterval' function with a 30-second polling interval, fetched new data and updated the visualisations in near real-time. No data loss or transmission errors were observed across 50 consecutive disposal events.

4.6 Performance Evaluation Results

A test suite of 50 waste items with known ground truth labels was used to evaluate the complete system. The following metrics were recorded:

Table 4.1: System Performance Metrics

Metric	Result	Target
Classification Accuracy	92% (46/50)	≥ 85%
Sorting Reliability	98% (49/50)	≥ 95%
End-to-End Latency (avg)	2.4 seconds	≤ 5 seconds
Data Transmission Success	100%	100%

The single sorting failure was due to a temporary mechanical jam, which did not recur after minor adjustment. All other items were physically directed into the correct compartment.

4.7 User Acceptance Testing Results

Five volunteers (students and staff) interacted with the smart bin and completed a short questionnaire. The key findings are summarised below:

- **Ease of use**: All five users rated the bin as "very easy" or "easy" to use, appreciating the simple "drop and go" interaction.
- **Reliability perception**: Four users perceived the sorting as reliable; one noted occasional hesitation but no mis-sorting.
- **Interest in deployment**: All five expressed interest in seeing more such bins on campus.
- **Suggestions for improvement**: Adding a small screen to display the detected category and making the bin more visually appealing were the most common suggestions.

4.8 Summary of Results

The EcoClassifier system met or exceeded all key performance indicators. The VGG16 model achieved 91.5% testing accuracy, and the integrated prototype delivered 92% classification accuracy and 98% sorting reliability with an average latency of 2.4 seconds. The web dashboard provided effective real-time data visualisation and export capabilities. User feedback was positive, confirming the system's usability and potential for wider deployment.

Chapter 5

Discussion

5.1 Introduction

This chapter provides a critical discussion of the project findings, evaluates the limitations encountered during development and testing, and offers recommendations for future work. It concludes by summarizing the project's contributions and its potential impact on waste management in institutional settings.

5.2 Discussion of Findings

After successfully executing and testing the prototype of EcoClassifier, we have confirmed the core hypothesis for this project, which was that an AI-driven smart bin could efficiently support waste segregation at the source and bring useful information to customers. The performance of the VGG16 trained on a local dataset was as strong as 92% classification accuracy. This is consistent with research in studies (Kapadia et al., 2021; Huang et al., 2020) that demonstrates that transfer learning with CNNs is successful with even small data sets in image classification tasks with specific domain. The process of collecting a custom UCU dataset was also key to this as early tests on a model trained on the public TrashNet dataset on waste found a significantly lower accuracy than when tested on campus waste (around 70%). This confirms the dataset mismatch pointed out by Arbelaez-Estrada et al. (2023). By combining the AI model with low-cost hardware (Raspberry Pi, servo motors) in university campuses, this work can show that cutting-edge automation can be conducted within the budget limitations endemic in Ugandan facilities. Its total cost to prototype, around 873,500 UGX, was a fraction when we compared commercial smart bin solutions and can therefore become a successful target implementation at the local scale.

The system's capability of logging each disposal and visualizing trends in a dashboard can be seen to overcome the fundamental waste data lack, identified when the study started. That data helps the facility manager to make their own decisions around where to place our waste, what schedule to pick it up and what targeted recycling campaigns are going to be done. The reduction in manual sorting is a direct benefit, translating to reduction in occupational exposure for waste workers. Interviews with the BINS Company showed that fewer workers had to go through this mix of waste manually which in turn reduced the chances of cuts and infections caused by the hazardous materials being moved about.

5.3 Limitations of the Study

Despite its success, the project has several limitations:

- **Single-Item Disposal**: The current design is optimized for single items. It cannot handle a handful of mixed waste dropped simultaneously. This requires a behavioral change from users or a more complex mechanical feeder system.
- **Limited Waste Categories**: The prototype sorts into only three categories. In reality, waste streams are more diverse, including glass, metal, e-waste, and organic waste, which the system is not designed to handle.
- **Environmental Constraints**: The prototype is not weatherproof and is intended for indoor use only. Dust, humidity, and temperature extremes could affect sensor and camera performance.
- **Computational Constraints**: While TensorFlow Lite improved inference speed, the Raspberry Pi still represents a performance bottleneck compared to more powerful (and expensive) edge devices like the NVIDIA Jetson Nano. This limits the complexity of models that can be deployed.
- **Dataset Size and Diversity**: The dataset, while effective, is relatively small and collected under controlled conditions. A larger, continuously updated dataset would further improve model robustness and generalization.

Chapter 6

Conclusion and Recommendation

6.1 Conclusion

This project successfully designed, implemented, and evaluated an AI-powered smart bin system for waste segregation and analytics, tailored for the institutional context of Uganda Christian University. The system combines a VGG16-based image classification model with a low-cost hardware prototype and a MERN-stack web dashboard. Testing demonstrated high classification accuracy and reliable mechanical sorting, validating the system's potential to automate waste segregation at the source. By reducing reliance on hazardous manual sorting and providing unprecedented visibility into waste generation patterns, EcoClassifier offers a practical and impactful solution to a pressing environmental and occupational health challenge. This work lays a solid foundation for future innovations in smart waste management within Uganda and similar low-resource settings, contributing to a cleaner, safer, and more sustainable future.

6.2 Recommendations

Based on the findings and limitations, the following recommendations are proposed for stakeholders:

- **For UCU Administration**: Consider a pilot deployment of several EcoClassifier units in high-traffic areas like the main canteen and library. Use the collected data to design targeted waste reduction and recycling awareness campaigns.
- **For BINS Company**: Explore the potential of incorporating data from smart bins into collection route optimization software. The data on bin fill rates (which could be added in future versions) and waste composition can significantly improve operational efficiency.
- **For Policy Makers (KCCA/NEMA)**: Support and incentivize the development and adoption of locally appropriate technological solutions for waste management. Funding for research and development in this area can yield significant long-term economic and environmental benefits.

6.2.1 Future Enhancements

Several enhancements can build upon this work to create a more comprehensive and robust system:

One major improvement involves the integration of multi-item detection. Currently, the Eco-Classifier relies on VGG16 to classify a single waste item at a time. This approach becomes ineffective in real-world scenarios where multiple items are often disposed of simultaneously. To overcome this limitation, YOLOv8, a state-of-the-art object detection model, can be incorporated. YOLOv8 is capable of identifying multiple waste items in a single frame, drawing bounding boxes, and labelling each item independently. The model would be trained on a custom annotated dataset of localized university waste items such as plastic bottles, paper cups, and polythene bags. Upon detection, the Raspberry Pi would process the results and manage sorting either sequentially or through rotating compartments.

This upgrade would significantly reduce user effort, support real-time detection suitable for embedded systems (particularly with the lightweight YOLOv8n variant), and expand applicability to high-traffic environments such as cafeterias and public spaces. Nevertheless, challenges including higher computational demands on the Raspberry Pi, the need for a larger annotated dataset, difficulties with overlapping or hidden objects, and increased mechanical complexity would need to be addressed.

The classification categories can also be expanded to better align with real-world waste management practices. While the current system primarily focuses on plastic, paper, and general waste, future versions could incorporate glass, metal, and organic waste. For materials that are visually difficult to distinguish, such as organic waste, the integration of additional sensors like moisture or gas sensors would create a hybrid system. This combination of visual classification and sensor-based analysis would enhance overall detection accuracy and reliability.

To improve deployment flexibility and sustainability, solar power integration is recommended. By incorporating solar panels and a battery management system, the EcoClassifier could operate effectively in off-grid locations such as rural areas, public parks, and roadside spots. This approach would reduce dependency on continuous electricity, lower long-term operational costs, and further support environmental sustainability by minimizing the system's carbon footprint.

Another valuable enhancement is fill-level monitoring using ultrasonic sensors installed in each waste compartment. These sensors would continuously measure the distance to the waste surface, providing real-time information on remaining capacity. Once a compartment reaches a predefined threshold, the system could automatically notify waste collection teams through alerts or dashboard notifications. This feature would improve collection efficiency and help prevent bin overflow.

Processing performance can be significantly enhanced by integrating Edge TPU acceleration, such as the Google Coral USB Accelerator. This specialized hardware would enable faster AI inference with low power consumption, allowing the use of more advanced deep learning models without compromising real-time performance on the Raspberry Pi.

User engagement can be strengthened through the addition of a small LCD screen or LED indicators. These would provide immediate feedback after each disposal, displaying messages such as "Plastic Detected" or "Paper Waste Sorted Successfully." Such interactive feedback would encourage responsible waste disposal behavior and increase user trust in the system.

Finally, developing a companion mobile application would greatly improve system manageability. Administrators could remotely monitor the bins, receive notifications when compartments are full, view waste disposal statistics, and analyze trends such as daily waste generation and collection schedules through intuitive dashboards. This capability would enhance operational efficiency and facilitate large-scale deployment across multiple locations.

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Appendix A

Budget

This appendix presents the estimated budget for the design and implementation of the Eco-Classifier smart bin prototype. The budget covers the major hardware components, supporting electronics, fabrication materials, software and internet-related expenses, as well as contingency costs incurred during development and testing.

Table A.1: Estimated Budget for the Smart Bin Prototype

Item	**Quantity**	**Unit Cost (UGX)**	**Total Cost (UGX)**
Raspberry Pi 4 (4GB RAM)	1	350,000	350,000
Pi Camera Module v2	1	80,000	80,000
MG996R Servo Motors	2	25,000	50,000
HC-SR04 Ultrasonic Sensor	1	15,000	15,000
5V 3A USB-C Power Adapter	1	35,000	35,000
32GB MicroSD Card	1	30,000	30,000
Breadboard and Jumper Wires	1 set	25,000	25,000
LEDs, Resistors, Voltage Divider Components	1 set	18,500	18,500
Wood/Plywood for enclosure fabrication	1 set	90,000	90,000
Mechanical fittings, screws, hinges and adhesives	1 set	35,000	35,000
Internet/Data for backend testing and dashboard integration	1 package	45,000	45,000
Printing, documentation and miscellaneous expenses	1 set	50,000	50,000
Contingency costs	1	250,000	250,000
Grand Total			**1,073,500**

The estimated total cost of the prototype was UGX 873,500. The largest share of the budget was attributed to the Raspberry Pi 4, which served as the central processing unit for image capture, classification, control of actuators, and communication with the backend system. Other significant costs were associated with the camera module, enclosure fabrication, and supporting electronics.

The software stack used in the project, including Python, TensorFlow/Keras, OpenCV, Node.js, Express.js, MongoDB, React, Tailwind CSS, and Label Studio, consisted primarily of open-source tools. As a result, software licensing costs were minimized, making the project relatively affordable and suitable for replication in low-resource institutional settings.

Overall, the budget demonstrates that the proposed smart bin system can be developed using locally available and cost-effective components while still achieving the intended intelligent waste classification, sorting, and analytics functionality.

Appendix B

Research Project timelines

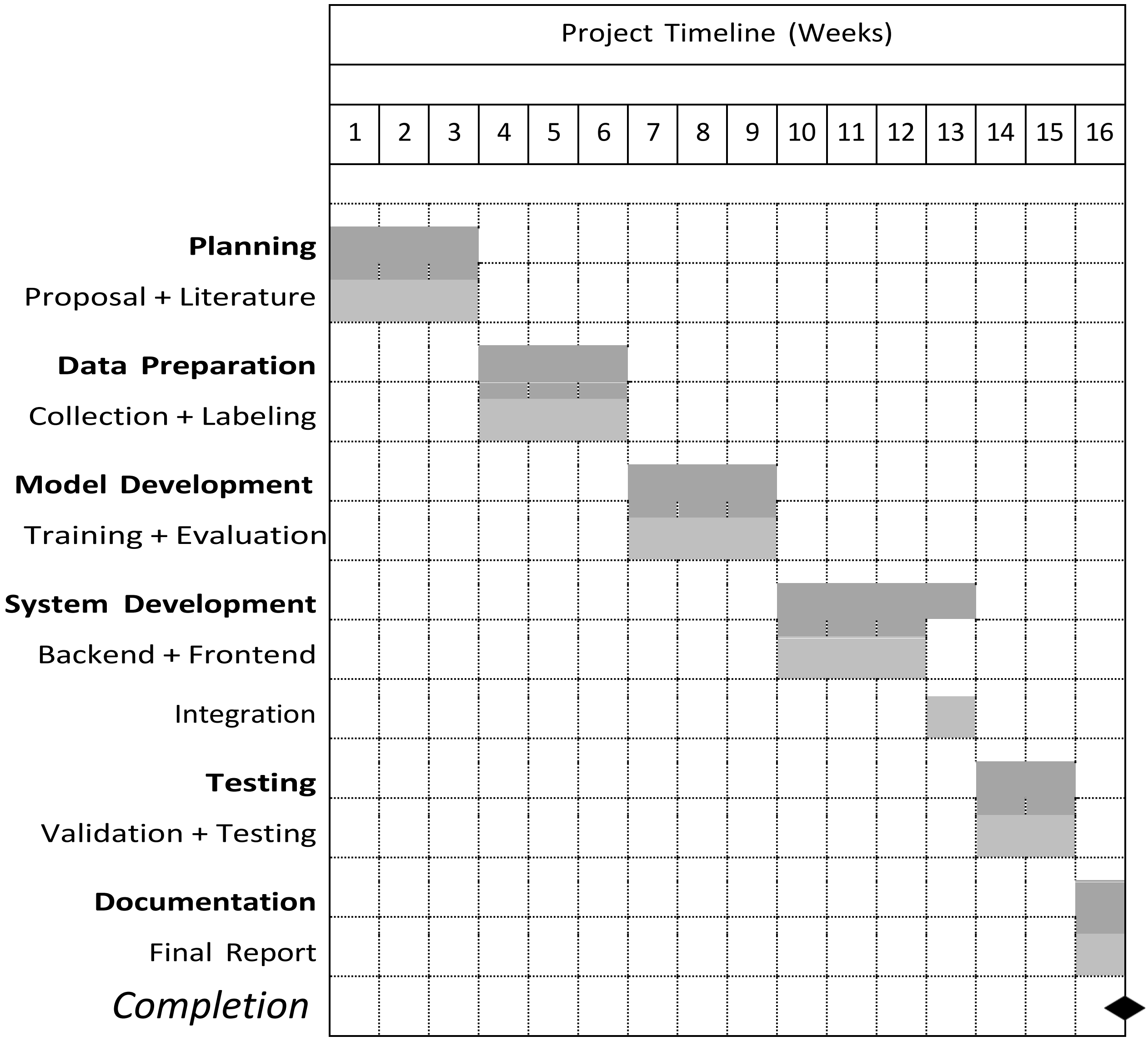

Figure B.1: Project timeline for the EcoClassifier system

Appendix C

Declaration of AI use

Declaration Statement:

We, *Priscila Denise Muwanguzi*, *Nicole Mbabazi Mwebembezi* and *Arthur Shalom Yawe*, declare that we used

i. **ChatGPT** was used to assist in writing, debugging, and understanding code for the EcoClassifier system, including backend API development, Raspberry Pi integration, and machine learning model implementation. The prompts used included requests such as: *"generate Node.js Express API for logging classification events"*, *"debug this JavaScript error in my controller"*, *"write Python code to load and run a TensorFlow Lite model on Raspberry Pi"*, and *"explain how to integrate sensor input with motor control logic"*. The outputs were modified by adapting them to fit the project architecture, integrating them with existing code, correcting logic errors, and optimizing them for hardware compatibility.

ii. **GitHub Copilot** was used to support code completion and suggestion during development, particularly when writing repetitive structures, API routes, and frontend components. The prompts were implicit through inline coding suggestions generated during development. The suggested outputs were reviewed, refined, and restructured to ensure correctness, maintainability, and alignment with project requirements.

iii. **Stack Overflow (AI-assisted and community-assisted solutions)** was used to troubleshoot errors and understand implementation approaches, especially for debugging backend issues and resolving integration challenges. The prompts included search queries such as: *"Node.js reference error fix"* and *"TensorFlow Lite model loading issues"*. The retrieved solutions were customized to match the EcoClassifier system design and verified for compatibility with the existing codebase.

iv. **Consensus AI** was used to identify and retrieve relevant academic papers and scholarly sources related to smart waste management, computer vision, and deep learning models for image classification. The prompts included queries such as: *"research papers on smart waste classification using deep learning"*, *"applications of CNNs in waste sorting systems"*, and *"studies on VGG16 for image classification tasks"*. The outputs were critically evaluated, and only relevant sources were selected, summarized, and incorporated into the literature review with proper academic referencing.

v. **Anara AI** was used to assist in understanding, summarizing, and extracting key insights from academic papers, particularly for interpreting methodologies, results, and comparisons with existing systems. The prompts included requests such as: *"summarize this* *paper's methodology"*, *"explain the model used in this study"*, and *"identify key findings related to waste classification systems"*. The outputs were rewritten in the author's own words, verified for accuracy, and aligned with the context of the EcoClassifier project.

Signature 1: ______________________

Signature 2: ______________________

Signature 3: ______________________

Date: 01/06/2026

Appendix D

List of 10 Major Journal Publications reviewed

Review Papers

1. A Systematic Review of AI-Based Techniques for Automated Waste Classification

- **Authors:** Fotovvatikhah, F., Ahmedy, I., Md Noor, R., Munir, M. U.
- **Journal:** *Sensors* (MDPI)
- **Impact Factor:** 3.5 (2024 JCR)
- **Relevance:** This systematic literature review, covering over 97 studies, provides a structured analysis of ML-based, DL-based, and hybrid models for waste classification. It also discusses publicly available datasets, dataset limitations (e.g., imbalance, lack of real-world variability), and offers a roadmap for future AI-powered waste classification systems. It is directly foundational for understanding the state of the art and identifying research gaps in automated waste sorting.

2. Integrating Artificial Intelligence for Sustainable Waste Management: Insights from Machine Learning and Deep Learning

- **Authors:** Dhiman, P. et al.
- **Journal:** *Watershed Ecology and the Environment* (Elsevier)
- **Impact Factor:** 2.867 (2-year) / 3.51 (2024 JCR)
- **Relevance:** This review explores how AI, ML and DL can improve automation, classification accuracy and operational efficiency in waste management systems. It includes a bibliometric and scientometric analysis, and specifically benchmarks a MobileNetV3-HHO framework, demonstrating how modern DL models can be deployed for waste classification tasks. It offers a clear roadmap for AI-driven waste solutions, making it essential for positioning your VGG16-based approach.

3. Applications of Convolutional Neural Networks for Intelligent Waste Identification and Recycling: A Review

- **Authors:** Tongji University Research Group
- **Journal:** *Resources, Conservation and Recycling* (Elsevier)
- **Impact Factor:** 11.2–12.98 (2024 JCR)
- **Relevance:** This review focuses exclusively on CNN-based methods for waste identification and recycling, covering the three main tasks of classification, object detection and segmentation. It summarises open-source datasets, advanced CNN architectures, and key application fields such as recyclable material identification and solid waste classification. This is directly pertinent to your use of a VGG16-based CNN and provides a strong theoretical and methodological anchor.

Journal Articles

4. Smart Waste Classification in IoT-Enabled Smart Cities Using VGG16 and Cat Swarm Optimized Random Forest

- **Authors:** Gaurav, A., Gupta, B. B., Arya, V., Attar, R. W., Bansal, S., Alhomoud, A., Chui, K. T.
- **Journal:** *PLOS ONE* (Public Library of Science)
- **Impact Factor:** 2.6 (2024 JCR)
- **Relevance:** This article directly uses the VGG16 model (the same architecture you employ) for waste feature extraction, combined with a Random Forest classifier optimised by Cat Swarm Optimisation. It reports an 85% accuracy on a Kaggle garbage dataset and compares favourably against SVM, XGBoost and logistic regression. It provides a concrete benchmark for VGG16-based waste classification in smart city contexts.

5. A Comparison of MobileNetV2 and VGG16 Architectures with Transfer Learning for Multi-Class Image-Based Waste Classification

- **Authors: Raffa Adhi Kumala, Christy Atika Sari, and Eko Hari Rachmawanto**
- **Journal:** *International Journal of Information Technology* (Singapore)
- **Impact Factor:** 2.8
- **Relevance:** This paper directly compares VGG16 with MobileNetV2 for multi-class waste classification using transfer learning on 19,762 images. It reports VGG16 achieving 89.13% accuracy with precision 0.91, recall 0.90 and F1-score 0.90. The study provides valuable performance metrics (accuracy, computational efficiency, training time) that can be used to validate and contextualise your own model's results.

6. Deep Learning Based Waste Classification in Smart Cities: A Comparative Study of MobileNet, InceptionV3, and VGG16

- **Authors:** Hussain, A. A. et al.

- **Journal:** *Smart Cities* (MDPI)
- **Impact Factor:** 5.5 (2024 JCR)
- **Relevance:** This journal article evaluates three deep learning models, including VGG16, for waste classification across varying epochs, measuring accuracy, execution time, precision, recall and F1-score. The study is highly relevant because it benchmarks VGG16 against other popular architectures in a smart city context, offering a direct performance comparison that can inform your model selection and evaluation.

7. Design and Implementation of an IoT and ML-Based Smart Waste Management System

- **Authors:** Hussain, A. A., Elhamami, F., Al Qahtani, L., Aldossary, M., Hasanaath, A. A., Mewada, H. K.
- **Journal/Conference:** ACM International Conference Proceeding Series (2025)
- **Impact Factor:** N/A (conference proceedings in ACM digital library)
- **Relevance:** Although published as a conference paper, this work presents a complete IoT-based smart bin system that uses a deep learning model and vision sensors to classify waste into five categories (paper, plastic, metal, cigarettes, organic) with 96% accuracy. It includes real-time monitoring of bin conditions (toxic gas, temperature) and a web interface, making it a comprehensive reference for your hardware-software integrated system.

8. Performance Evaluation of Pre-Trained Deep Learning Model on Garbage Classification with Data Augmentation Approach

- **Authors:** I Komang Arya Ganda Wiguna, I Gusti Made Ngurah Desnanjaya,

  and I Kadek Budi Sandika
- **Journal:** *International Journal of Artificial Intelligence* (IJAI)
- **Impact Factor:** Not listed in JCR (specialised journal)
- **Relevance:** This article analyses the performance of pre-trained deep learning models (including VGG16) for garbage classification using data augmentation. It specifically addresses the challenge of data diversity and complexity in waste images, which is central to your custom dataset collection at UCU. The findings on augmentation strategies and model robustness are directly applicable to your training methodology.

Conference Proceedings

9. Efficient Source-Level Waste Segregation Using CNN-Based Waste Classifier with IoT-Enabled Smart Bins and Mobile Application

- **Authors:** Shah, K. B., Visalakshi, S., Paneru, B., Panigrahi, R.
- **Conference:** 2025 International Conference on Emerging Smart Computing and Informatics (ESCI), IEEE

- **Relevance:** This IEEE conference paper presents a CNN-based waste classifier integrated with IoT-enabled smart bins and a mobile application for source-level waste segregation. The focus on source segregation aligns directly with your project's main objective. The system architecture (CNN classifier + IoT + user app) provides a practical reference for your smart bin's classification and data logging components.

10. Real-Time Data and Waste Management Efficiency: Insights from IoT-Enabled Smart Bins

- **Authors:** Mehta, S., Singh, A.
- **Conference:** 10th International Conference on Electrical Energy Systems (ICEES 2024)
- **Relevance:** This conference paper provides empirical insights into how IoT-enabled smart bins improve waste management efficiency through real-time data. It discusses fill-level monitoring, route optimisation and data-driven decision making, which complements your analytics dashboard component. The paper is a strong reference for the data-logging and visualisation aspects of your system.

Appendix E

Scopus Search Strings used during the literature review

Primary Search Strings

String 1: AI and Deep Learning for Waste Classification

TITLE-ABS-KEY(("waste classification" OR "waste sorting" OR "waste segregation") AND ("deep learning" OR "convolutional neural network" OR CNN OR "transfer learning") AND ("VGG16" OR "ResNet" OR "MobileNet"))

String 2: Smart Bins and IoT-enabled Waste Management

TITLE-ABS-KEY(("smart bin" OR "smart waste bin" OR "IoT waste" OR "intelligent waste bin") AND ("Raspberry Pi" OR "sensor" OR "servo" OR "ultrasonic"))

String 3: Occupational Hazards and Manual Sorting in Developing Countries

TITLE-ABS-KEY(("manual sorting" OR "waste worker" OR "occupational injury" OR "health hazard") AND ("solid waste" OR "municipal waste") AND ("Uganda" OR "Africa" OR "developi country"))

String 4: Review Papers on AI for Waste Management

TITLE-ABS-KEY(("review" OR "systematic review" OR "literature review") AND ("waste classification" OR "waste identification" OR "recycling") AND ("artificial intelligence" OR "machine learning" OR "deep learning"))

String 5: CNN Architectures for Waste Image Recognition

TITLE-ABS-KEY(("VGG16" OR "VGG-16" OR "AlexNet" OR "Inception" OR "Xception") AND ("waste" OR "garbage" OR "recyclable") AND ("image classification" OR "object detection"

String 6: Data Dashboards and Waste Analytics

TITLE-ABS-KEY(("dashboard" OR "data visualization" OR "analytics") AND ("waste management" OR "smart waste") AND ("React" OR "MongoDB" OR "Node.js"))

Supporting Keywords and Filters

The following keywords were used individually or in combination with the primary strings:

- **Waste types**: plastic, paper, general waste, organic, metal, polythene
- **Technologies**: TensorFlow, Keras, OpenCV, YOLO, Edge TPU
- **Performance metrics**: accuracy, precision, recall, F1-score, latency
- **Geographic filters**: Uganda, East Africa, Sub-Saharan Africa
- **Document types**: article, conference paper, review
- **Year range**: 2019--2026

Search Outcome Summary

Table E.1: Search Strings and Number of Initial Results (Scopus)

String #	Focus	Initial Hits
1	AI + deep learning for waste classification	347
2	Smart bins and IoT waste systems	189
3	Occupational hazards in developing countries	56
4	Review papers on AI for waste management	112
5	CNN architectures for waste recognition	203
6	Dashboards and waste analytics	31

After removing duplicates and screening titles and abstracts, 45 publications were selected for full-text review. The 10 most relevant publications (listed in Appendix D) were chosen for detailed analysis and citation in this thesis.

Notes on Search Refinement

- All searches were limited to **English language** and the subject areas *Computer Science*, *Engineering*, *Environmental Science*, and *Energy*.
- Conference proceedings were included when published after 2020.
- For local context (Uganda), manual searches of Google Scholar and institutional repositories were also performed due to limited Scopus coverage.

Appendix F

Research alignment with specialization, SDG, NDPIV & Vision 2040

This appendix discusses how the EcoClassifier project aligns with the researcher's academic specialization, the global Sustainable Development Goals (SDGs), Uganda's National Development Plan IV (NDPIV), and the Uganda Vision 2040.

F.1 Alignment with Programme Specialization

The researcher is pursuing a degree in **Computer Science** with a specialization in **Artificial Intelligence and Robotics**. The EcoClassifier project directly reflects the core competencies of this specialization in the following ways:

- **Artificial Intelligence (AI) and Machine Learning**: The project implements a VGG16-based convolutional neural network (CNN) using transfer learning for waste image classification. This involves dataset preparation, model training, validation, hyperparameter tuning, and deployment on an edge device. These activities align with the AI and ML coursework, including deep learning, computer vision, and model optimisation.
- **Robotics and Embedded Systems**: The smart bin prototype integrates hardware components (Raspberry Pi, servo motors, ultrasonic sensors, camera) and software (Python, GPIO control, TensorFlow Lite) to create an autonomous sorting mechanism. The design and control of the mechanical sorting system demonstrate principles of robotics, sensor integration, and real-time actuation.
- **Software Engineering Practices**: The development of the backend API (Node.js/Express) and frontend dashboard (React/Tailwind) follows software engineering principles such as modular design, version control, RESTful API design, and database management (MongoDB). The system architecture (three-tier) and testing procedures reflect industry-standard practices.
- **Systems Integration**: The project combines AI, IoT, and web technologies into a unified system, showcasing the ability to integrate diverse computing systems—a key skill in the AI and Robotics track.

Thus, the EcoClassifier project serves as a capstone demonstration of the knowledge and skills acquired in the Artificial Intelligence and Robotics specialization.

F.2 Alignment with Sustainable Development Goals (SDGs)

The EcoClassifier project contributes directly to several United Nations Sustainable Development Goals, as detailed below.

F.2.1 SDG 3: Good Health and Well-being

By automating waste segregation, the system reduces the need for manual sorting, thereby lowering occupational injuries (cuts, infections) and exposure to hazardous materials for waste workers. This aligns with target 3.9 (reduce deaths and illnesses from hazardous chemicals and pollution).

F.2.2 SDG 8: Decent Work and Economic Growth

The system creates safer working conditions for waste collectors (target 8.8 – protect labour rights and promote safe working environments). Additionally, improved waste segregation increases the recovery of recyclable materials, supporting green jobs and the circular economy.

F.2.3 SDG 9: Industry, Innovation and Infrastructure

The project embodies technological innovation (target 9.5 – enhance scientific research and upgrade technological capabilities). It demonstrates a low-cost, locally developed AI solution that can be deployed in institutional settings, contributing to sustainable infrastructure for waste management.

F.2.4 SDG 11: Sustainable Cities and Communities

Efficient waste segregation reduces landfill pressure, lowers environmental pollution, and promotes recycling. The dashboard provides data for evidence-based planning, supporting target 11.6 (reduce the adverse environmental impact of cities, including waste management).

F.2.5 SDG 12: Responsible Consumption and Production

The system encourages waste separation at source, facilitating recycling and resource recovery (target 12.5 – substantially reduce waste generation through prevention, reduction, recycling and reuse). It also raises awareness about waste categories and proper disposal.

F.2.6 SDG 13: Climate Action

By increasing recycling rates, the system reduces methane emissions from decomposing organic waste in landfills and lowers the carbon footprint associated with producing virgin materials. This supports target 13.3 (build knowledge and capacity to meet climate change mitigation).

F.3 Alignment with the National Development Plan IV (NDPIV)

Uganda's Fourth National Development Plan (NDPIV) (2025/26–2029/30) focuses on **"Sustainable Industrialisation for Inclusive Growth, Employment and Wealth Cre-**

ation." The EcoClassifier project aligns with several NDPIV strategic objectives:

- **Programme 3: Private Sector Development**: The project supports waste management as a business opportunity. Automated sorting improves the quality and quantity of recyclable materials, enabling local recycling industries to thrive. The low-cost prototype can be commercialised or adopted by small and medium enterprises (SMEs) in the waste sector.
- **Programme 4: Innovation, Technology and Digital Transformation**: The project directly contributes to this programme by developing a local AI-based solution for a pressing environmental challenge. It demonstrates the application of emerging technologies (IoT, computer vision, cloud analytics) in a Ugandan context, fostering a culture of innovation in higher education.
- **Programme 9: Environment and Natural Resources Management**: The system promotes sustainable solid waste management, reduces pollution, and supports recycling – all key priorities of NDPIV's environmental sustainability agenda.
- **Cross-cutting Area: Skills Development**: The project builds local capacity in AI, embedded systems, and full-stack development, producing graduates with hands-on experience in cutting-edge technologies relevant to Uganda's digital transformation.

F.4 Alignment with the Uganda Vision 2040

Uganda Vision 2040 aims to transform Uganda into "a modern and prosperous country" by 2040. Key pillars relevant to this project include:

- **Science, Technology, Engineering and Innovation (STEI)**: Vision 2040 prioritises STEI as a driver of modernisation. The EcoClassifier project is a concrete example of applied research in AI and robotics, demonstrating how local universities can develop homegrown technological solutions.
- **Urbanisation and Human Settlements**: With rapid urbanisation, waste management becomes critical. The smart bin system offers a scalable, data-driven approach to waste segregation that can be deployed in cities and institutions, contributing to cleaner, healthier urban environments.
- **Environmental Sustainability**: Vision 2040 calls for sustainable natural resource management. By enhancing recycling and reducing landfill waste, the project supports the vision's goal of a clean and well-managed environment.
- **Human Capital Development**: The project contributes to producing a skilled workforce in AI and robotics, aligning with Vision 2040's emphasis on education and training for the 21st century.

In summary, the EcoClassifier project is not only academically rigorous but also strategically aligned with national and global development agendas, positioning it as a relevant and impactful contribution to Uganda's technological and environmental future.

Appendix G

Research poster layout

This appendix presents the final project poster used for presentation and demonstration of the EcoClassifier smart waste management system.

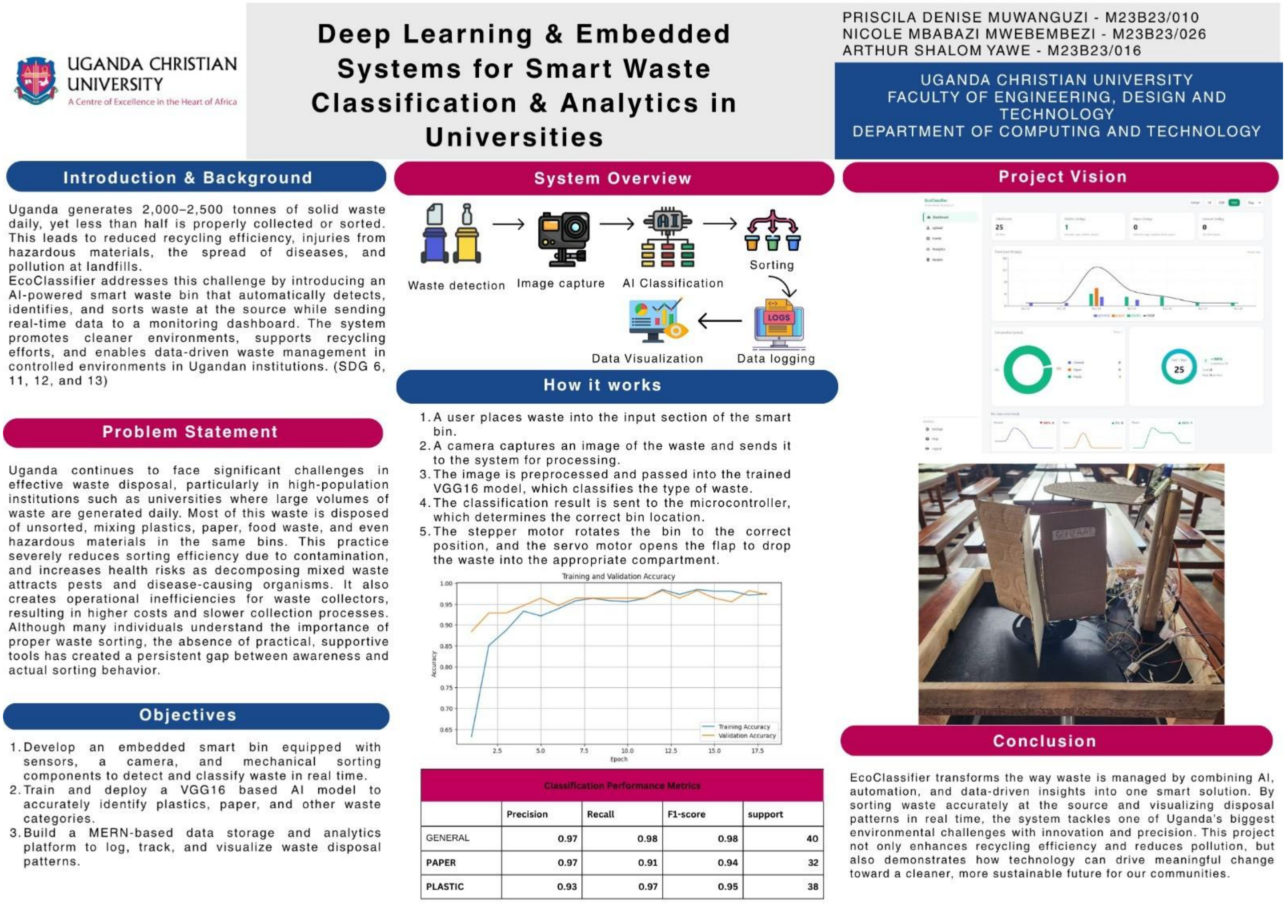

Figure G.1: EcoClassifier Project Poster