ADVANCED MATERIAL CLASSIFICATION USING SENSOR FUSION & MACHINE LEARNING

Final Year Project Report

GSN: Fall 23 - 17

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CERTIFICATIONS

This document has been prepared by all of us together and we take joint ownership of its contents. We have provided references to the material consulted in preparing this document and, to the best of our knowledge, have not plagiarized anything.

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I am the client of the product proposed in this document and the product specifications and other details are according to my requirements.

Client:

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The final year project proposal in this document is being submitted to the Department of Electrical Engineering with my approval.

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Abstract

The Final Year Project encapsulates the creation of an innovative material classification system, integrating sensor fusion and machine learning to optimize industrial sorting processes. The project was conceived in response to the need for more efficient recycling systems, which are crucial for managing the growing problem of waste globally. Using a combination of IR sensors, metal proximity sensors, color sensors, and load cells, the system is designed to identify and sort various materials such as metals, plastics, and glass, based on their physical properties. The methodology involved developing a detailed hardware setup that includes a conveyor belt mechanism outfitted with the aforementioned sensors. This setup facilitates the real-time acquisition of data as materials pass through the system. Concurrently, a machine learning model utilizing a convolutional neural network (CNN) was developed to classify the materials based on the data provided by the sensors. The model was trained and tested with a dataset specifically created for this project, which includes images and sensor data labeled with the corresponding material types. Significant findings from the project include the system's ability to classify materials with high accuracy, demonstrating the effectiveness of integrating machine learning with physical sorting systems. This not only enhances the efficiency of recycling processes but also reduces the likelihood of recyclable materials being incorrectly disposed of. The project's broader implications extend into environmental sustainability, showcasing how advanced technological solutions can be implemented to address critical global challenges. By improving recycling efficiency, the system helps reduce landfill use, conserve natural resources, and decrease greenhouse gas emissions associated with the production of new materials. This project represents a significant step forward in the field of waste management and material recovery.

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Acknowledgments

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Chapter 1: Introduction

In the context of modern industrial operations, the demand for advanced material classification systems is increasingly critical, particularly in sectors such as recycling and manufacturing where efficiency and precision are paramount. This project introduces an innovative system that utilizes a combination of sensor fusion and machine learning technologies to significantly enhance the accuracy and speed of material sorting processes on conveyor belts. By integrating specific sensors, such as infrared (IR) metal sensors, proximity sensors, color sensors, and weight/load cells with sophisticated computational models, this system aims to optimize operational efficiency and sustainability in demanding industrial environments.

The initiative for this project stems from the observed inefficiencies and errors prevalent in traditional sorting systems, which typically rely on manual interventions and basic mechanical sorting methods. Although recent advancements in sensor technologies have opened new avenues for automation, there has been a notable gap in their integration into a cohesive system that leverages machine learning for data analysis and decision-making. The integration of technology in recycling processes has shown significant potential in enhancing efficiency and accuracy [1]. This project seeks to bridge this gap by developing a system that not only automates the sorting process but also ensures high precision through real-time data processing.

The core of the proposed system is a modular conveyor belt equipped with an array of strategically placed sensors—IR metal sensors, proximity sensors, color sensors, and weight/load cells. These sensors collect diverse data as materials pass along the belt, which is then processed by a convolutional neural network (CNN). The CNN has been meticulously trained to identify and classify various materials, such as metals, plastics, and glass, based on their distinct characteristics captured by the sensors. To accommodate the varying needs of different industrial settings, the system also features a user-friendly interface that allows operators to easily monitor and adjust settings to optimize the sorting process.

The structure of this report is designed to provide a detailed account of each phase of the project. Chapter 2 delineates the current challenges in material classification and sets forth the objectives of the new system. Chapter 3 delves into the technical and engineering analyses required to apply sensor fusion and machine learning effectively. Chapter 4 provides a comprehensive overview of the system’s design and implementation, detailing both the hardware setup and software algorithms. Chapter 5 presents the methodology and results from the system’s testing phase, demonstrating its effectiveness and efficiency. Chapter 6 is dedicated to a user guide that includes detailed operational instructions and maintenance tips. Chapter 7 summarizes the project's deliverables and provides an exhaustive cost analysis. Finally, Chapter 8 concludes the report by summarizing the key findings, discussing the broader implications for industrial applications, and suggesting avenues for future research and development.

In summary, this introduction sets the stage for the subsequent chapters, which detail the development and validation of a cutting-edge material classification system designed to meet the rigorous demands of contemporary industrial processes. Recent advances in sensor applications have provided new opportunities for environmental monitoring and industrial automation [2]. By addressing specific technological and operational challenges with innovative solutions, this project contributes significantly to the advancement of automated systems in the industrial sector.

Chapter 2: Problem Definition

2.1 Problem Formulation

At the outset of this project, engaging with our clients was crucial to understand the specific challenges they faced in their current operational setup. The initial discussions focused on identifying and verbalizing the core issues that necessitated the development of a new material classification system. Our client, operating a large-scale recycling facility, expressed significant concerns regarding the efficiency and accuracy of their existing material sorting processes. These inefficiencies not only slowed down operations but also led to increased operational costs due to high error rates in material sorting.

During our query resolution sessions, it became apparent that the client sought a solution that could integrate seamlessly into their current infrastructure while providing substantial improvements in sorting speed and accuracy. They envisioned a system that could accurately differentiate between various types of materials such as metals, plastics, and glass, using a combination of advanced sensors and machine learning techniques. The client's perception of the problem and the expected functionality of the new system formed the foundation of our project's objectives. To ensure a mutual understanding and to proceed with a clear direction, we formulated a simple yet comprehensive problem statement: "To design and implement an advanced material classification system that enhances sorting accuracy and efficiency using sensor fusion and machine learning, thereby reducing operational costs and improving throughput in industrial recycling processes." In establishing an order of importance for the system's features, the following priorities were set:

1. The system must deliver high accuracy in material identification to ensure that materials are correctly sorted, minimizing errors that could result in financial losses or operational inefficiencies.

2. The system should handle high throughput rates typical of industrial environments without compromising the accuracy, thereby enhancing overall operational efficiency.

3. It is essential that the system integrates smoothly with existing conveyor setups and other industrial systems without requiring extensive modifications.

4. The system must be adaptable to different types of materials and scalable to accommodate future expansion or changes in material types without significant overhauls.

5. Despite its advanced capabilities, the system should be user-friendly, allowing facility operators to manage and interact with the system efficiently without extensive training.

By establishing these priorities and agreeing on the problem definition with our clients, we laid a solid foundation for the design and development of the material classification system, ensuring that the project's trajectory aligns with the client's needs and expectations.

2.2 Mapping to Sustainable Development Goals (SDG)

Figure 1: Sustainable Development Goal 9

The advanced material classification system developed in this project directly contributes to Sustainable Development Goal (SDG) 9, which emphasizes industry, innovation, and infrastructure. SDG 9 aims to build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation. Our project aligns with these objectives by enhancing the efficiency and sustainability of industrial recycling processes through the integration of sensor fusion and machine learning technologies. By improving material classification accuracy and speed, the system not only increases the throughput of recycling facilities but also reduces waste and resource consumption. This advancement in industrial sorting technology represents a significant innovation in recycling infrastructure, promoting more sustainable consumption and production patterns, and contributing indirectly to environmental sustainability goals such as responsible consumption and production (SDG 12). Furthermore, by improving the efficiency of resource use in industrial settings, the project supports broader economic growth and productivity, underscoring the interconnectivity between sustainable industrial practices and broader economic and environmental goals.

Figure 2: United Nations Sustainable Development Goals (SDGs)

2.3 Record of Meetings with Client

Meeting	Date
First	21st August 2023
Second	15th September 2023
Third	10th October 2023
Fourth	20th November 2023
Fifth	11th December 2023
Sixth	15th January 2024
Seventh	4th March 2024
Eigth	22nd April 2024

Table 1: Client Meeting Record

2.4 Preliminary Product Specification

In the initial stages of the project, through discussions and question-answer sessions with our clientS, who expressed challenges with the existing material sorting systems, we derived a set of preliminary specifications for an advanced material classification system. The client's needs highlighted the necessity for a system capable of high accuracy and efficiency, which led us to design a solution incorporating state-of-the-art technology suited for industrial applications.

From the information gathered, we developed a set of preliminary product specifications designed to meet the client's needs while ensuring technical feasibility. The proposed material classification system is compact, with a physical size designed to fit within a 2-meter length and 0.5-meter width, suitable for standard industrial spaces. It has a total weight of approximately 50 kilograms, which provides enough heft for stability during operation yet remains manageable for installation and potential relocations.

The system is engineered to run on a standard 240V AC power supply, drawing about 200 watts during peak operation, which aligns with typical industrial energy usage thus ensuring efficiency. At the heart of the system's control mechanism is an Arduino Uno, chosen for its versatility in managing multiple inputs and outputs, essential for real-time data processing and actuation of the conveyor and sorting mechanisms.

Single-Board Computer:

Raspberry Pi 4 Model B:

- Processor: Broadcom BCM2711, Quad Core Cortex-A72(ARM v8) 64-bit
- RAM: 4 GB LPDDR4-3200 SDRAM
- Storage: microSD card slot (32GB)
- Connectivity: HDMI, USB, Ethernet.
- GPIO: Standard 40-pin GPIO Header
- Power: 5V DC (minimum 3A)

Figure 3: Raspberry Pi 4 Model B

The Raspberry Pi 4 Model B offers significant computational power with its quad-core processor and options for up to 8GB of RAM, capable of running the machine learning algorithms needed for real-time material classification. This setup eliminates the need for an expansion card in a PCI slot, as the Raspberry Pi itself is sufficiently capable and can be directly integrated into the system's framework with necessary peripherals for input/output operations.

Power requirements for the system are designed to be minimal to maintain efficiency and cost-effectiveness. Each sensor module will operate at approximately 5V DC, drawing around

2A, translating to about 10W per module. The system as a whole will include a Raspberry Pi 4 Model B as its central processing unit, which necessitates a 5V DC power supply with a minimum current supply of 3A to handle data processing and connectivity tasks efficiently.

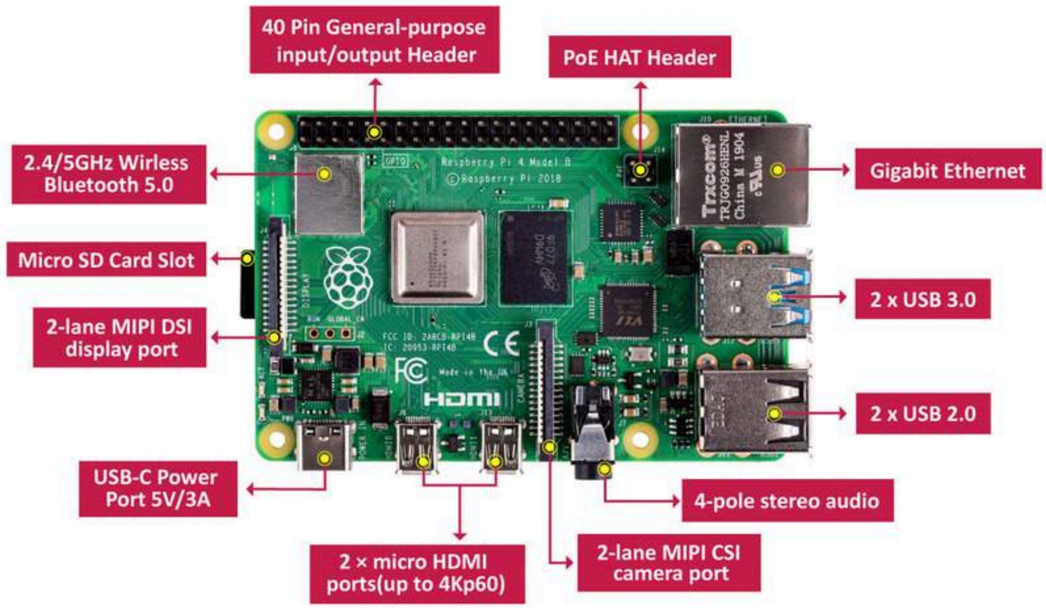


Figure 4: Raspberry Pi 4 Hardware Specifications

Connectivity options on the Raspberry Pi, such as Ethernet and Wi-Fi, are essential for the system as they allow for data logging and remote monitoring of the sorting process, ensuring operational transparency and ease of maintenance. These preliminary specifications set the foundation for the detailed design and development phase, where these parameters will be refined and tested to meet the precise needs of the client and the operational demands of the recycling industry. This technical formulation of the client's requirements into a tangible product design marks the transition from conceptual to practical application in engineering terms.

Sensors and Components Specifications:

- **Raspberry Pi Camera Module:** Resolution: 8 MP, Frame Rate: 30 fps, Interface: CSI (Camera Serial Interface), Power: 5V, 250mA.

Figure 5: Raspberry Pi Camera Module

- **Conveyor Belt:** Material: Durable rubber or PVC, Length: Customizable based on application, Speed: Adjustable, 0.1 - 1 m/s.

Figure 6: Conveyor Belt

- **TCS3200 Color Sensor Module:** Sensing Range: 400 - 700 nm, Resolution: 256x256, Output: Frequency based on color intensity, Interface: Digital (TTL).

Figure 7: TCS3200 Color Sensor Module

- **Inductive Proximity Sensor:** Sensing Range: Adjustable, typically up to 10 mm, Output: NPN or PNP, Voltage: 10-30V DC.

Figure 8: Inductive Proximity Sensor

- **IR Sensor Module:** Sensing Range: 700 - 1000 nm, Resolution: Adjustable sensitivity, Output: Voltage level related to infrared light intensity, Interface: Digital (TTL).

Figure 9: IR Sensor Module

- **Load Cells**: Capacity: Variable up to 5 kg, Sensitivity: ±1g, Material: Alloy steel or aluminum.

Figure 10: 5kg Load Cell

- **HX711 Weighing Sensor Module:** Input Voltage: 2.6 - 5.5 V, Resolution: 24-bit, Output: Serial data at 10SPS or 80SPS (Selectable output data rate), Interface: Digital (TTL).

Figure 11: HX711 Weighing Sensor Module

- **16x2 LCD Screen:** Display Format: 16 characters x 2 lines, Character Size: 5 x 8 dots, Backlight: LED, Interface: Parallel (4-bit or 8-bit)**.**

Figure 12: 16x2 LCD Screen

- **MG966R Servo Motor:** Torque: 9.4 kg-cm at 4.8V, 11 kg-cm at 6V, Speed: 0.15 sec/60° at 4.8V, 0.13 sec/60° at 6V, Weight: 55g, Dimensions: 40.7 x 19.7 x 42.9 mm, Interface: PWM.

Figure 13: MG966R Servo Motor

- **Arduino Nano Microcontroller Board:** Microcontroller: ATmega328P, Operating Voltage: 5V, Digital I/O Pins: 14 (6 provide PWM output), Analog Input Pins: 8, Flash Memory: 32 KB (ATmega328P), SRAM: 2 KB, EEPROM: 1 KB, Clock Speed: 16 MHz, Interface: Mini-USB (programming and power), Serial (TTL) communication

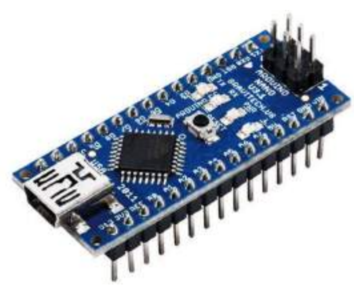


Figure 14: Arduino Nano

- **Arduino Uno R3** Microcontroller: ATmega328P, Operating Voltage: 5V, Digital I/O Pins: 14 (6 provide PWM output), Analog Input Pins: 6, Flash Memory: 32 KB (ATmega328P), SRAM: 2 KB, EEPROM: 1 KB, Clock Speed: 16 MHz, Interface: USB (programming and power), Serial (TTL) communication.

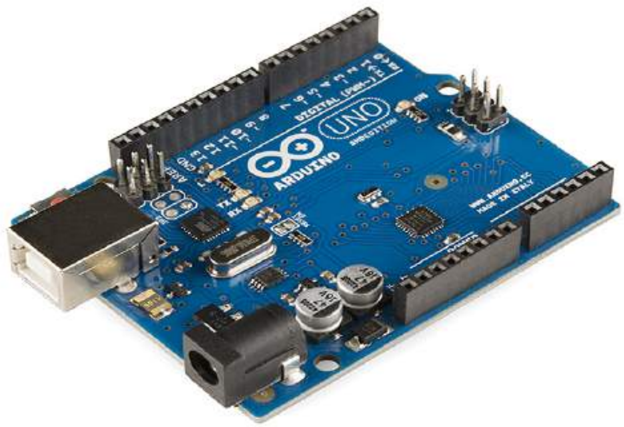


Figure 15: Arduino Uno R3

The system will be integrated into a conveyor belt assembly which will be compatible with standard industrial interfaces. The initial data storage capacity of 32 GB microSD card on Raspberry Pi 4 model B will be utilized. Environmental Conditions will include operating Temperature between 0 to 40°C with up to 80% non-condensing humidity.

These preliminary specifications sketch the blueprint of our engineering solution, bridging the gap between non-technical client aspirations and practical engineering capabilities. This foundation allows us to proceed with confidence into the detailed design and development phase, ensuring the final product effectively addresses the identified sorting challenges while maintaining ease of use and technical integrity.

2.5 Expected Functionality of Product

In a real-life industrial environment, the advanced material classification system is designed to significantly enhance the efficiency and accuracy of sorting operations within recycling facilities. This system incorporates a series of interconnected modules and sensors that work in unison to detect, classify, and sort various materials based on predetermined criteria such as metal content, color, and weight.

The process begins when items are placed on the conveyor belt, which is equipped with an IR sensor at its initiation point. This sensor detects the presence of items and activates the conveyor belt, ensuring that power is used efficiently and only when necessary. As items move along the belt, they first encounter the metal proximity sensor. This sensor is critical for identifying metallic objects, utilizing electromagnetic fields to detect metal presence without direct contact. The ability to detect metal is essential for recycling operations, where separating metallic from non-metallic materials is often a primary sorting need.

Following the metal detection stage, items pass under the TCS3200 color sensor, which identifies the colors of the objects by emitting light and measuring the reflected wavelengths. This information is particularly useful for sorting materials like plastics, where color specificity can determine the recycling process. Next, the sorted materials reach the servo motor flaps, powered by MG966R servo motors with metal gears, which are responsible for physically sorting the items into designated bins. These flaps are controlled based on the input from the sensors—metal, color, and weight—and effectively divert items into the correct collection points. Each bin is equipped with a weight sensor that further verifies the sorting process by measuring the weight of deposited materials, adding an additional layer of accuracy to ensure that items are sorted correctly.

The entire system is managed by a Raspberry Pi, which processes the sensor data and sends control signals to an Arduino. The Arduino, in turn, handles the real-time operations of the sensors and actuators. The decisions made by the system, based on the data analyzed by a convolutional neural network (CNN) model running on the Raspberry Pi, are displayed on an Arduino-connected LCD screen. This allows operators to monitor the sorting process and make adjustments if necessary, enhancing the system's adaptability to different types of materials and operational conditions. This seamless integration of advanced sensors, robust mechanical components, and intelligent software ensures that the system can operate effectively in the demanding environment of industrial recycling, providing a reliable solution that not only meets but exceeds the client's operational requirements.

Chapter 3: Problem Analysis

3.1 Engineering Problem Model

In the development of our advanced material classification system, the focus of our problem analysis and design centers on effectively leveraging sensor integration and real-time data processing to enhance recycling operations. This approach is rooted in the principles of automation and robotics, which involve the utilization of sensors for accurate data collection and actuators for precise action based on the collected data. The integration of control systems, usually governed by feedback loops, is fundamental in automating previously manual tasks.

The application of these principles is particularly pertinent to the recycling industry, where the efficiency and accuracy of sorting directly impact operational costs and environmental outcomes. Manual sorting processes are not only labor-intensive but also prone to errors, making automation an attractive solution. In our system, the automation is implemented through various sensors and actuators managed by sophisticated software algorithms.

For instance, IR sensors detect the presence of objects on the conveyor belt, initiating the sorting process. Metal proximity sensors are used to identify metallic components within waste, which are crucial for effective recycling practices. Color sensors, specifically the TCS3200 modules, enable the differentiation of materials based on color, which is especially useful in sorting plastics that require separate recycling processes. Weight sensors add a layer of verification, checking the material type against its expected weight to enhance sorting accuracy.

The use of machine learning in industrial applications has been extensively studied, showing promising results in various fields [3]. These sensors provide data to a Raspberry Pi, which processes the information through a convolutional neural network (CNN). This network is trained to classify materials based on extensive data on various material characteristics, enhancing the system's accuracy. The decisions made by the CNN are executed by an Arduino controller, which operates servo motors equipped with MG966R flaps to direct materials into designated bins.

This integration of sensor technology, data processing, and mechanical control exemplifies the practical application of automation principles in solving real-world problems. By combining theoretical knowledge with practical implementation, the system not only addresses the needs of the recycling industry but also sets a benchmark for the application of similar technologies in other sectors requiring high precision and efficiency.

3.2 Recent Similar Projects

Project 1 - Sensor Fusion and Damage Classification in Composite Materials:

This project aims to develop a method for identifying damage in complex structures, like buildings or bridges. They use a statistical approach that involves a type of mathematical model called the hidden Markov model (HMM) to analyze features related to time and frequency in the structure's data. To improve accuracy, they also introduce two methods for combining information from different sensors. They tested their methods on a laminated composite plate to detect and locate issues like delamination. The results show that their techniques, including the sensor fusion methods, are effective in classifying and locating damage in intricate structures. Sensor fusion has been effectively utilized for damage classification in composite materials, providing a more robust approach to material analysis [4].

Project 2 - Machine Learning-Based Sensor Data Fusion for Animal Monitoring

This project discovers how advanced technologies like the IoT and AI are transforming animal research. By employing various sensing devices, researchers can collect data on animal behavior. Advanced computer systems, enhanced with AI capabilities, process this data, enabling the identification of behaviors related to health issues, emotional states, and individual animal identities. The findings suggest that the application of sensor fusion to animal studies is in its early stages, presenting an opportunity for further exploration, especially in combining movement data with biometric sensors for animal welfare applications. The application of machine learning-based sensor data fusion for animal monitoring demonstrates the versatility of these techniques [5].

Project 3 - Sensor-Based Sorting in Mineral Processing:

This project explores the use of sensor-based sorting techniques to enhance ore processing efficiency. By employing sensors, the goal is to improve ore grades while reducing energy, water, and reagent consumption. It emphasizes the importance of optimal sensor selection and considers the fusion of data from multiple sensing techniques to enhance material characterization and sorting capabilities. The key to effective implementation lies in choosing a sensing technique capable of distinguishing between ore and waste. The project proposes potential applications of sensor fusion sorting in mineral processing and suggests that the lack of correlatable data on the response of multiple sensing techniques is a hurdle. A review of sensor-based sorting in mineral processing highlights the potential benefits of sensor fusion, particularly in improving sorting accuracy [6].

Project 4 - Conveyor Belt System for Detecting and Separating Rotten Fruits:

This project revolves around a conveyor belt system designed to detect and separate rotten fruits, integrating machine learning and mechanical engineering to combat food waste in the food industry. The system employs a camera for real-time video streaming of fruits on the conveyor belt, with image processing to predict fruit freshness. The prediction model is based on the transfer learning model. If a fruit is identified as rotten, the Firebase database is updated. A Raspberry Pi receives this data, activating a DC motor to separate the rotten fruit. The numbers of fresh and rotten fruits are continuously updated in the database, and a user-friendly GUI displays this information. The use of machine learning on conveyor belts for detecting and separating materials has shown promising results in improving recycling efficiency [7].

These projects reflect the diverse applications of sensor fusion and machine learning in addressing complex sorting and classification challenges across various industries. Each project brings unique insights into the potential improvements in precision, efficiency, and automation, providing valuable benchmarks and inspiration for further innovation in our material classification system.

3.3 Distinguishing Features of this Project

This intelligent classification system is differentiated from existing projects by several innovative features that enhance its performance, efficiency, and usability in industrial environments. A key distinguishing factor is the integrated sensor fusion approach that combines IR sensors, metal proximity sensors, color sensors, and weight sensors. This multi-sensor configuration allows for a comprehensive analysis of materials, capturing a wide spectrum of data points that significantly improve sorting accuracy and efficiency compared to systems that rely on a single type of sensor.

The impact of machine learning on recycling accuracy underscores the importance of adopting advanced technologies in waste management [8]. Another notable advancement is the implementation of convolutional neural networks (CNNs) for real-time data processing. This use of advanced machine learning techniques sets our system apart from others that may utilize simpler algorithms or no AI at all. Our CNNs are adept at recognizing complex material patterns and adapting to various material types and contamination levels, thus enhancing the system's sorting capabilities.

The mechanical design of our system also distinguishes it from others. It features robust servo motor flaps equipped with MG966R high-torque servos, ensuring precise and dependable sorting actions. This mechanical reliability is crucial for continuous operation in the demanding conditions of industrial recycling environments, surpassing the performance of projects with less durable components.

Enhancements in user interaction are achieved through a sophisticated user interface that displays system statuses and real-time data on a 16x2 LCD screen. This interactive interface is a significant upgrade over other projects that might feature limited or non-interactive user interfaces, facilitating easier monitoring and adjustments by operators.

Energy efficiency is another critical aspect of our project. Designed to operate with low energy consumption without sacrificing performance, our system addresses the common deficiency in similar projects that often neglect energy efficiency. This not only reduces operational costs but also supports environmental sustainability.

Finally, the scalability and customization of our system are unmatched. Thanks to its modular design and flexible software architecture, our system can be easily adapted to different production volumes or modified to handle various material types. This level of adaptability offers a versatile solution that is not commonly available in the market, making our project uniquely positioned to meet diverse industrial needs.

These distinguishing features ensure that our material classification system sets a new standard in the field, offering technological innovation and operational excellence that go beyond the capabilities of current systems. By addressing existing deficiencies and introducing cutting-edge solutions, our project provides a superior alternative that promises greater impact and efficiency for industrial material sorting applications.

3.4 Societal and Environmental Implications of the Project

The advanced material classification system designed in our project holds significant societal and environmental implications. Primarily, by enhancing the efficiency and accuracy of sorting recyclable materials, this system supports the broader goal of sustainable waste management. Efficient sorting reduces landfill waste, conserves natural resources, and minimizes the environmental impact of new material production by facilitating higher-quality recycling.

Societal Impact:

Our project contributes to job creation and worker safety in recycling facilities. By automating the sorting process, the system reduces the need for manual sorting, which is often tedious and hazardous. This shift not only improves worker safety by reducing exposure to potentially harmful materials and ergonomic injuries but also allows for workforce reallocation to more skilled tasks within the recycling industry, thus improving job quality and worker satisfaction.

Environmental Impact:

The system's ability to precisely sort materials leads to less contamination in recycling streams, enhancing the quality of recycled products and reducing the reliance on virgin materials. This contributes to lower carbon emissions and less energy consumption in material processing. Additionally, the energy-efficient design of our system, with its low power requirements, aligns with environmental sustainability goals, ensuring that the benefits of recycling do not come at an excessive energy cost.

Health and Safety Considerations:

With reduced human interaction in the sorting process, there is a lower risk of injuries and health issues that are common in manual sorting operations, such as respiratory problems from dust inhalation and physical injuries from machinery. The system's design incorporates safety features to ensure that operational malfunctions do not pose a risk to facility workers.

Legal and Cultural Implications:

By improving recycling efficiency, the system helps facilities comply with increasingly stringent environmental regulations regarding waste management. Culturally, the project promotes a shift towards more sustainable practices in industries traditionally reliant on resource extraction and waste generation, fostering greater public awareness and acceptance of recycling.

To further reduce any potential negative impacts, the project could include enhancements such as solar power integration to offset energy use, more robust data security measures to protect information generated by the system, and adaptive algorithms that can respond to changing waste composition and recycling technologies.

These aspects underscore the project's alignment with professional engineering practices that consider not just the technical and economic outcomes, but also the health, safety, and well-being of society and the preservation of the environment.

Chapter 4: Design and Implementation

4.1 Design Requirements and Constraints

The design of the advanced material classification system was guided by specific requirements and constrained by certain limitations that shaped its development. This section outlines the key requirements and constraints that were considered during the design phase of the project.

Design Requirements:

- The system must accurately identify and classify different materials, such as metal, plastic, glass, and miscellaneous, based on specific characteristics detected by the sensors.
- It must process materials at a high throughput rate to be viable for industrial applications, aiming to handle items quickly without sacrificing accuracy.
- The system should operate consistently under varying industrial conditions without frequent downtime or maintenance.
- Designed to be scalable, the system can be adapted to different conveyor belt sizes and throughput capacities as required by different facilities.
- The user interface should be intuitive, allowing operators to easily monitor and control the system without extensive training.
- The design must minimize energy consumption, aligning with sustainable practices and reduce operational costs.

Design Constraints:

- The system must fit within the existing spatial configurations of typical recycling facilities, limiting its size and the arrangement of its components.

- Financial constraints impact the choice of materials and technologies, necessitating a balance between cost and performance.
- The availability of specific sensors and parts can restrict design options, especially with global supply chain variability.
- The system must withstand harsh environments typical in recycling facilities, including dust, moisture, and variable temperatures.
- All components and operations must comply with relevant industry regulations and safety standards.

These requirements and constraints were crucial in directing the design process, ensuring that the system not only meets the functional needs but also adheres to practical limitations and industry standards.

4.2 Preliminary Design

The preliminary design phase was instrumental in establishing a robust foundation for the advanced material classification system. It involved conceptualizing and designing the basic framework to ensure all components worked synergistically. This phase focused on defining the system's architecture, integrating various hardware components, and developing initial software algorithms.

The system was designed with a modular architecture to enhance scalability and maintenance. It includes a conveyor belt equipped with a series of sensors—IR sensors for detecting material presence, metal proximity sensors for metal detection, color sensors for color differentiation, and weight sensors placed at the end of the conveyor for final sorting verification. Each sensor was strategically positioned to maximize detection accuracy and minimize interference with other system components.

The layout and design of systems within engineering are crucial for ensuring optimal operation and integration of new technologies [9]. A dual-controller setup was chosen for the control system, utilizing an Arduino board for immediate processing of sensor data and a Raspberry Pi for handling more complex computational tasks and network communications. This setup provided a balance between efficient real-time processing and the capability to perform advanced data analysis.

The mechanical components of the system, particularly the servo motors, were aligned with sorting mechanisms. These motors are connected to flaps that direct the sorted materials into designated bins based on inputs from the sensors, ensuring accurate material categorization. The preliminary mechanical design was crucial for ensuring that the movements were precise and timely. Software development at this stage included crafting basic algorithms for the real-time interpretation of sensor data and the control of actuators. These initial algorithms laid the groundwork for future enhancements, such as the integration of machine learning for improved sorting decisions.

The design also incorporated a detailed plan for the power supply and wiring to ensure all parts were adequately powered and communicated efficiently without the risk of electrical overload. Special consideration was given to energy efficiency by selecting components that would minimize power consumption without compromising performance. For the user interface, a straightforward design using a simple LCD display was developed to show essential system status updates and error messages. This interface was designed to be intuitive, allowing operators to easily manage the system without needing in-depth technical knowledge.

Finally, the preliminary design included a comprehensive plan for testing and evaluation. This plan outlined steps for both component-level and system-wide testing, initially using dry runs to test software and hardware integration, followed by controlled material tests to assess the system's functionality. The real-time data processing capabilities of smart manufacturing systems offer significant potential for future developments in the field [10]. The phased testing approach was intended to identify and rectify any issues early in the development process, ensuring the final system met all operational expectations.

This meticulous approach in the preliminary design phase ensured that the project was set up for success, providing a clear roadmap for subsequent detailed development and refinement.

4.2.1 Hardware Block Diagram

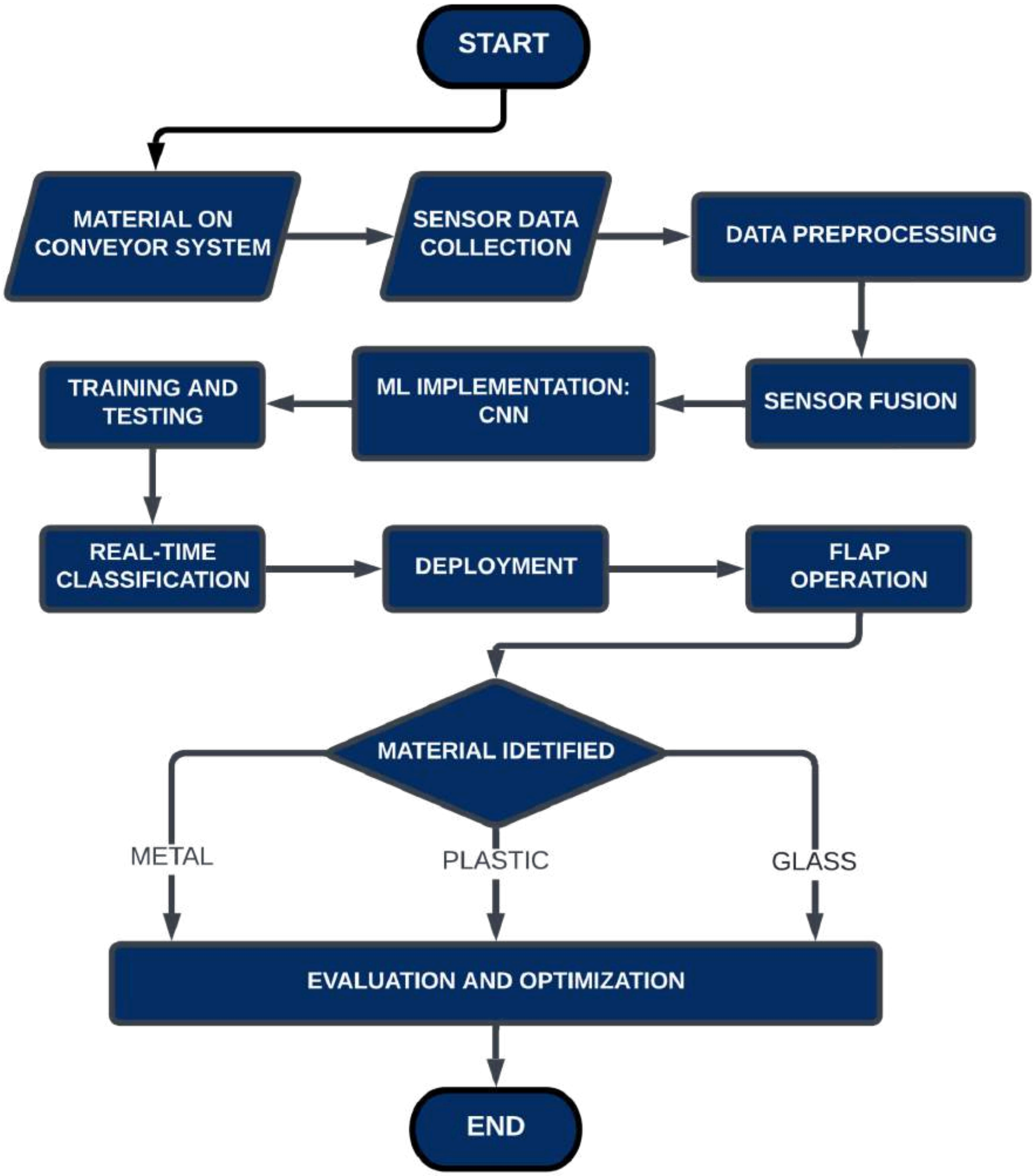


Figure 16: Hardware Block Diagram

4.2.2 Software Block Diagram

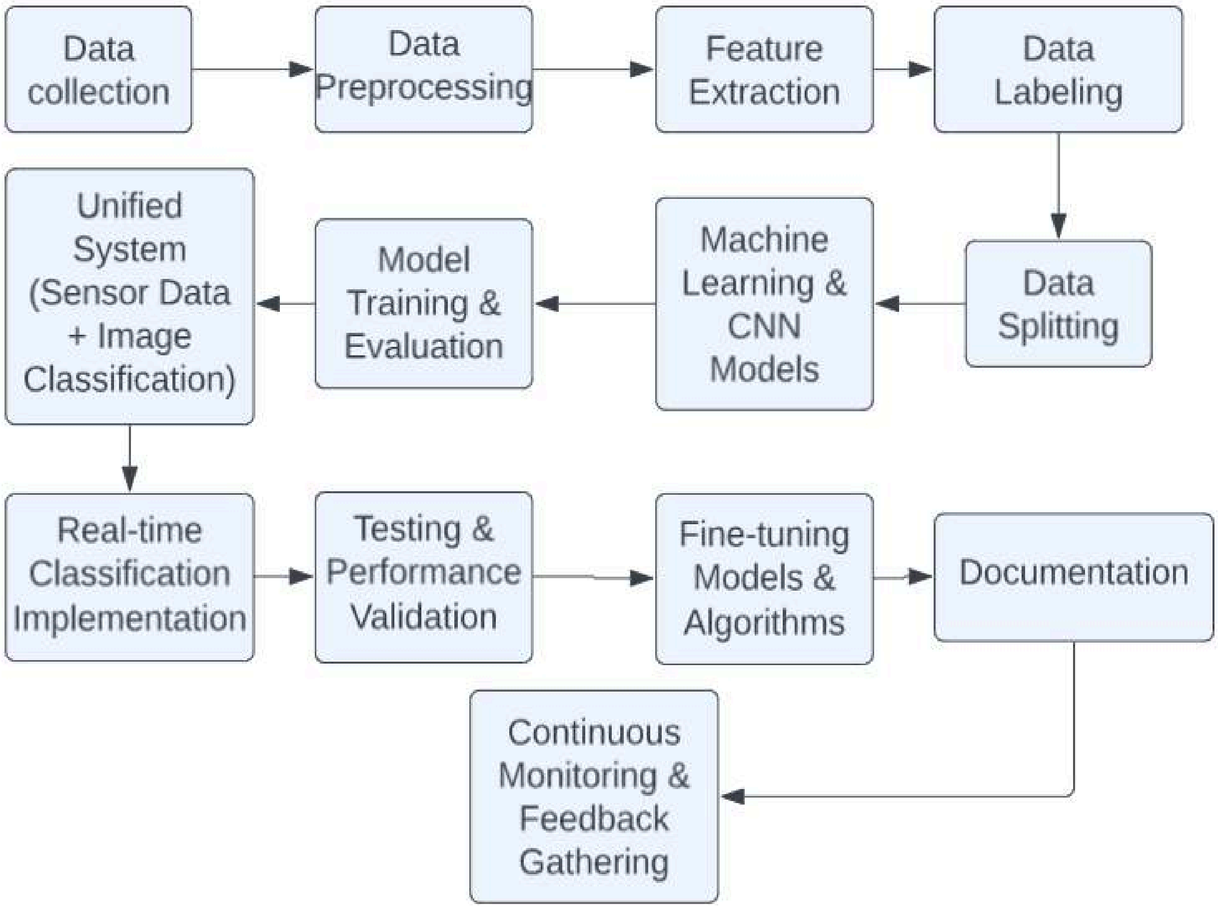


Figure 17: Software Data Integration Block Diagram

4.3 Detailed Hardware and Software Design

In this section, we delve into the details of our system. While some aspects might see minor adjustments in the upcoming stages, we'll outline the current design alternatives for both hardware and software components.

Hardware Design:

The system's hardware configuration includes a versatile array of sensors—cameras, color sensors, and polarization sensors—all crucial for capturing a comprehensive range of material characteristics. At the heart of our hardware setup is a Raspberry Pi 4 Model B, which serves as the central processing unit. This unit effectively manages the data influx from the various sensors. Advancements in conveyor belt technologies have not only increased efficiency but have also made it possible to integrate more complex sorting mechanisms [11]. The materials are transported via a conveyor belt system, designed to ensure a smooth and continuous flow of materials through the scanning area, facilitating efficient data capture and material handling.

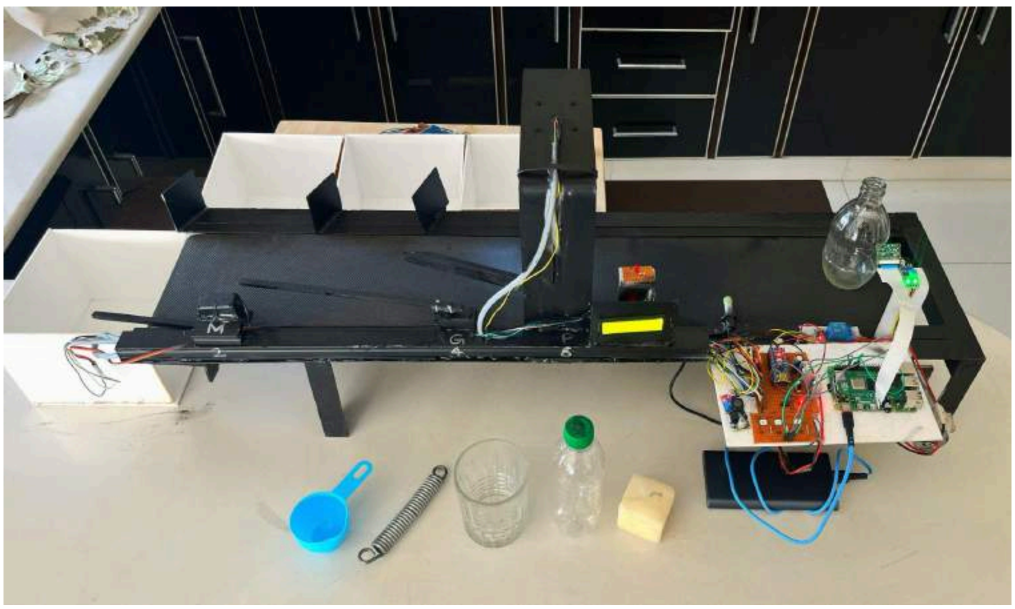


Figure 18: Conveyor Belt and Classification Hardware

Software Design:

Our software architecture leverages advanced machine-learning techniques for real-time material classification. The development process began with the creation of a robust dataset, comprising images of various objects captured under different conditions. Each image was meticulously annotated with bounding boxes to aid in precise model training. We utilized preprocessing scripts to streamline the handling of image capturing, renaming, and annotation, ultimately compiling this data into structured CSV files for easier processing.

Figure 19: Python Programming Language

For the training of our machine learning models, we employed Python libraries such as TensorFlow and Keras, focusing on optimizing convolutional neural network (CNN) architectures. We also explored the potential of transfer learning, incorporating models like Xception to enhance our system's learning efficacy. This software setup is crucial for supporting real-time data processing on the conveyor belt, ensuring that the system is not only trained effectively but also capable of performing efficient and accurate material classification during operation.

4.3.1 Calculations

$$Power \ = Voltage\ (Volts)\ x\ Current\ (Amperes)$$

$$P_{Raspberry\ Pi} = 5V\ x\ 3A\ =\ 15W$$

$$P_{Pi\ Camera} = 3.3V\ x\ 0.25A\ =\ 1.5W$$

$$P_{Color\ Sensor} = 5V\ x\ 0.02A\ =\ 0.1W$$

$$P_{IR\ Sensor} = 5V\ x\ 0.01A\ =\ 0.05W$$

$$P_{Metal\ Proximity\ Sensor} = 5V\ x\ 0.1A\ =\ 0.5W$$

$$P_{Servo\ Motors} = 6V\ x\ (1.2\ *\ 3)\ A\ =\ 21.6W$$

$$P_{Arduino\ Nano} = 5V\ x\ 0.019A\ =\ 0.095W$$

$$P_{Arduino\ Uno} = 5V\ x\ 0.05A\ =\ 0.25W$$

$$P_{Load\ Cells} = 5V\ x\ (0.01\ x\ 3)A\ =\ 0.15W$$

$$P_{Total}\ =\ P_{Raspberry\ Pi} +\ P_{Pi\ Camera} + P_{Color\ Sensor} + P_{IR\ Sensor} + P_{Metal\ Proximity\ Sensor} + P_{Servo\ Motors} + P_{Arduino\ Nano} + P_{Arduino\ Uno} +\ P_{Load\ Cells}$$

$$P_{Total} = 39.245W$$

4.3.2 Hardware Design

The hardware design of our advanced material classification system is a carefully orchestrated assembly of components designed to ensure optimal performance and reliability. Central to our system is a robust conveyor belt, which serves as the primary medium for material transport. Engineered to accommodate varying loads and operational speeds, the belt is constructed from a high-quality rubber compound that provides durability and longevity under continuous use.

Figure 20: Metal Nut with Black Background

The dataset used to train our material classification model was meticulously curated to cover a broad spectrum of common items, ensuring a comprehensive training process. The selected items included metal springs, metal nuts, plastic cups, plastic bottles, glass bottles, glass cups, candles, and wood blocks. Each category was chosen to represent distinct material properties that challenge and refine the model's ability to classify effectively.

Figure 21: Glass Bottle with Black Background

To create a robust dataset, each item was photographed under various conditions to capture a wide range of scenarios. This included varying the lighting conditions from bright to dim, changing backgrounds to include different textures and colors, and altering the angles and distances to simulate real-world unpredictability. For instance, metal springs and nuts were photographed both up close and from a distance to help the model learn to recognize these objects regardless of scale.

Figure 22: Metal Spring Top View with White Background & Lighting

The plastic items in the dataset, such as cups and bottles, were chosen to represent the challenges of distinguishing between different types of plastics based on shape, translucency, and color variations. Similarly, glass bottles and cups were included to train the model on recognizing transparency and shape characteristics unique to glass materials. The inclusion of candles and wood blocks added complexity to the dataset, introducing materials with varying textures and opacity that require nuanced detection capabilities.

Figure 23: Plastic Bottle with Natural Background

Each item was annotated with high precision to ensure that the bounding boxes accurately defined the extents of each object. This meticulous annotation process was vital for training the model to precisely localize and identify the materials in a real-world sorting environment. By including a diverse range of items and conditions in the dataset, the model was trained not only to recognize specific objects but also to generalize its learning to accurately classify new or unseen items made of similar materials. Additionally, various angles and lighting conditions were considered during image capturing to enhance the robustness of the model. This comprehensive approach ensures that the system can handle real-world variability and maintain high classification accuracy across different scenarios, making it highly reliable for practical applications.

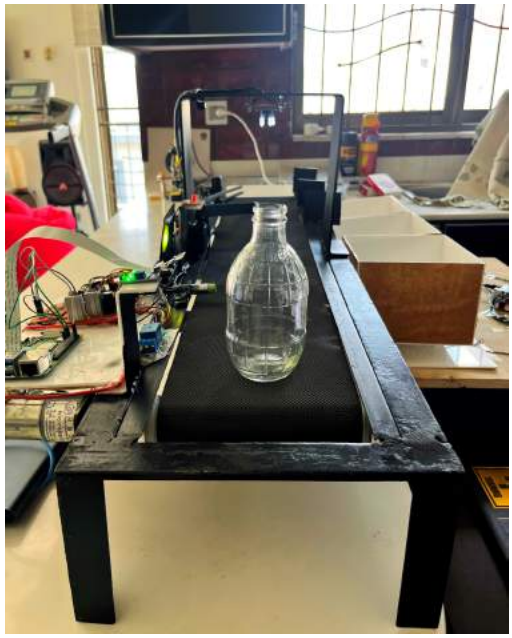


Figure 24: Conveyor Belt System with Glass Bottle

This approach ensures that the machine learning model is well-prepared for deployment in environments where it must perform with high accuracy and reliability, distinguishing between a variety of materials and objects swiftly and efficiently. The comprehensive nature of this dataset plays a crucial role in the model's ability to adapt to the diverse challenges presented during actual operational conditions.

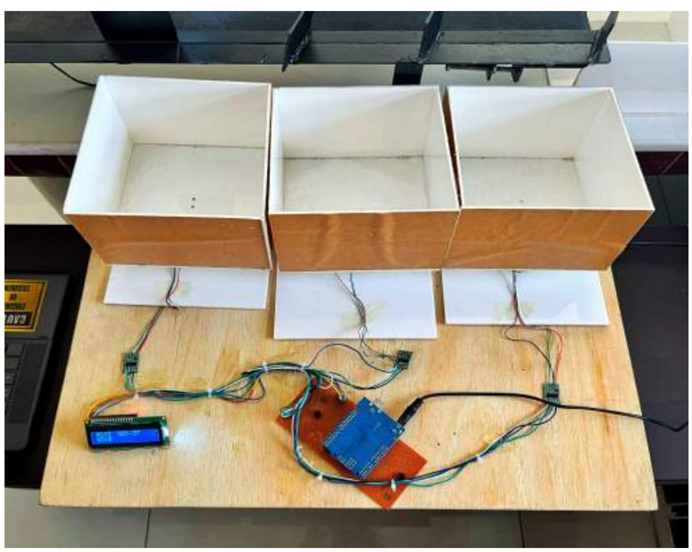


Figure 25: Load Cells Setup

In terms of sensory equipment, our system boasts an extensive array of sensors strategically placed along the conveyor belt to capture a comprehensive dataset from the materials being processed. At the outset, IR sensors are positioned to detect the presence of incoming materials, triggering the sorting process. Following closely are metal proximity sensors, which utilize electromagnetic fields to detect and identify metallic objects. Color sensors, specifically the TCS3200 models, are used further down the line to assess the color properties of materials, crucial for sorting plastics and other colored items. Additionally, polarization sensors are incorporated to analyze the polarization properties of materials, providing another layer of sorting specificity. At the end of the sorting line, load cells measure the weight of the sorted materials, ensuring precise categorization and providing essential feedback for system accuracy.

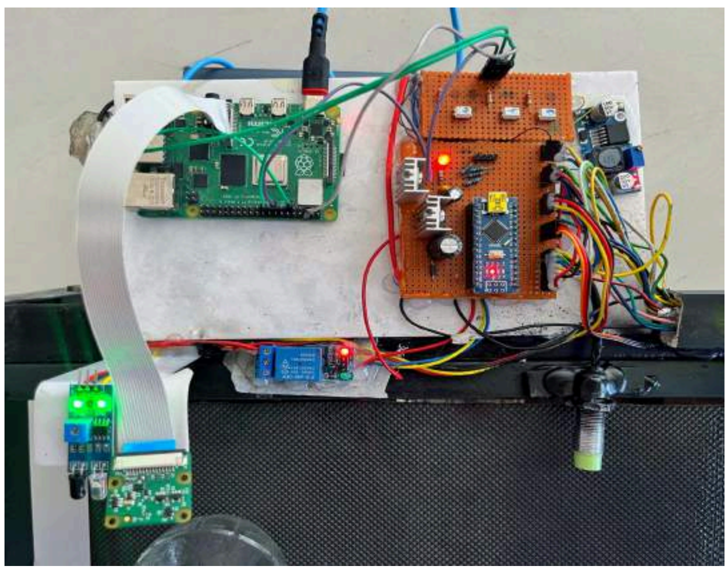


Figure 26: Processing Hub

The control system is split between a Raspberry Pi 4 Model B and Arduino boards. The Raspberry Pi handles complex data processing tasks, system management, and network communications, facilitating remote system monitoring and control. In contrast, the Arduino Nano is tasked with managing real-time interactions with sensors and actuators, processing sensor data efficiently. The Arduino Uno, dedicated to actuator management, controls the servo motors that operate the sorting flaps. These motors are crucial for directing materials into the correct bins, with their positioning and speed meticulously controlled to ensure accurate sorting.

Visual inspection and additional verification are supported by the Pi Camera Module v2, which plays a critical role in validating the machine learning models and aiding in real-time decision-making. The power supply system is specially designed to meet the high-energy demands of the system, providing stable and regulated power to all components. It includes comprehensive safety features such as circuit breakers and surge protectors to handle potential electrical anomalies effectively.

Figure 27: Complete Hardware Setup for Material Classification

Finally, the entire system is housed within a protective enclosure designed to shield sensitive components from environmental elements such as dust and moisture. This enclosure also prioritizes operator safety, featuring emergency stops and clear labeling to facilitate maintenance and emergency procedures. This meticulous integration of hardware components ensures that our system not only meets but exceeds the necessary performance criteria for modern industrial applications in recycling and manufacturing.

4.3.3: Software Design

The software design of our material classification system is a thorough and structured process that begins with the meticulous annotation of images. Using the VGG Image Annotator (VIA) tool, each image captured in our dataset was labeled, employing the bounding box technique to accurately define the boundaries of various objects like plastic bottles, glass cups, and metal springs. This annotation process was crucial for preparing the datasets that would train our machine learning model.

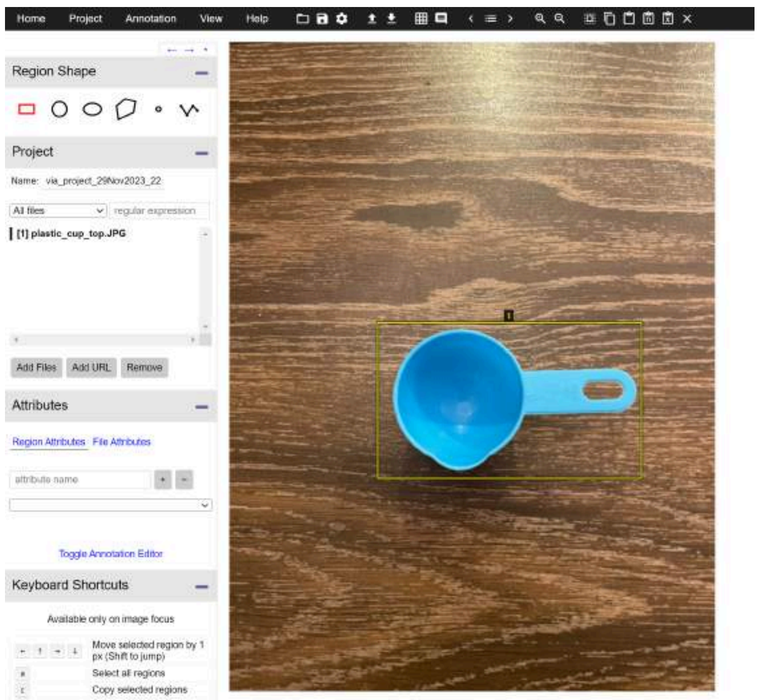


Figure 28: VGG Image Annotation Tool

Once the images were annotated, we compiled datasets for each category of objects. These datasets were critical for training the model and were enhanced by labeling each image with additional attributes such as brightness, background, and lighting conditions. This enriched dataset helps the model to perform nuanced material classifications more effectively. All annotated images, along with their attributes, were meticulously organized and stored in CSV files to streamline the training process.

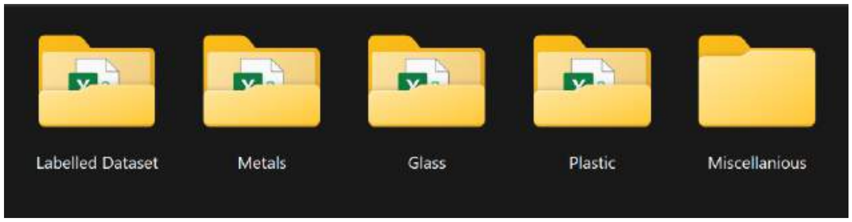


Figure 29: Folder Structure for Datasets

Before initiating the training, a crucial data cleaning phase was conducted on the CSV files to ensure the accuracy and consistency of the data. This involved rectifying any discrepancies or errors in the annotations and refining the dataset to optimize the model's performance. After cleaning, the data was divided into training and testing sets, with a 70/30 split, allowing for a comprehensive evaluation of the model's ability to generalize to new, unseen data.

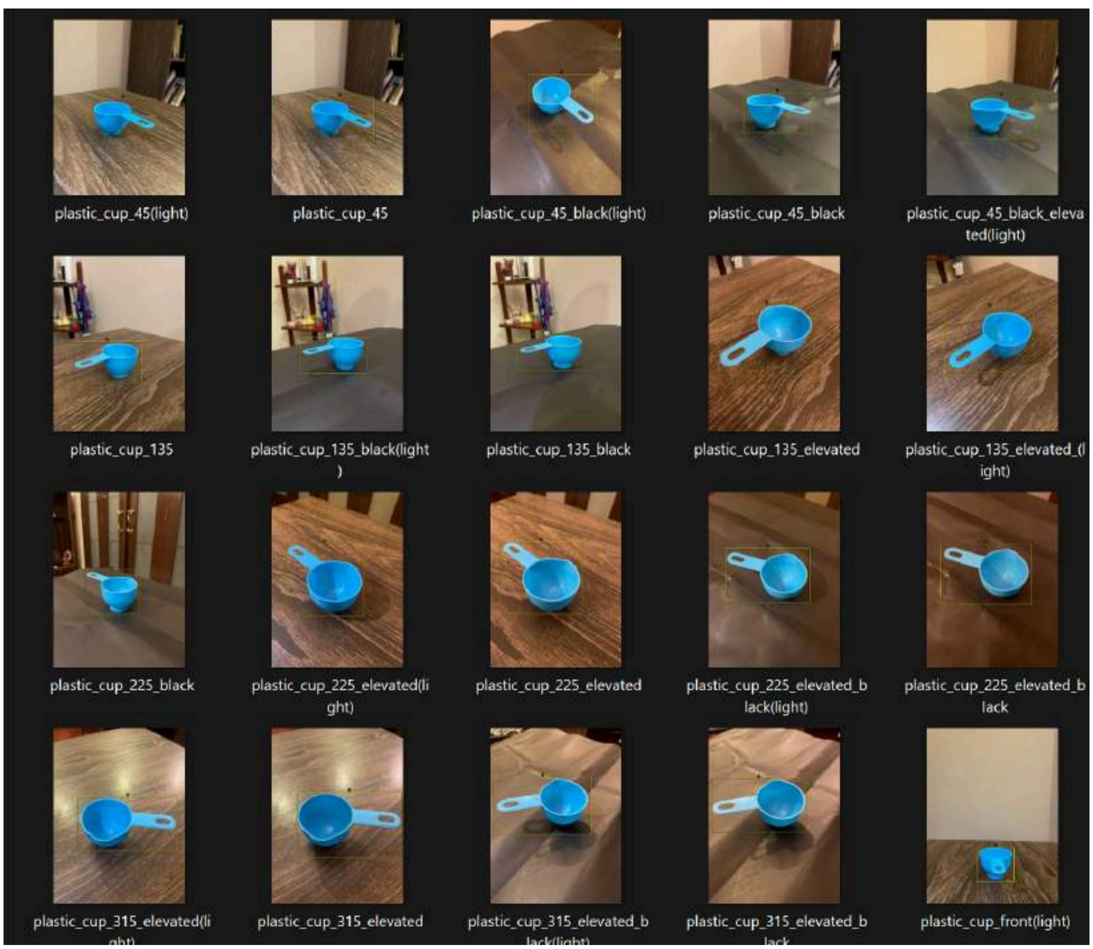


Figure 30: File Naming Convention

The training phase utilized TensorFlow and Keras, focusing on leveraging Convolutional Neural Networks (CNNs) for their proven effectiveness in image-based tasks. We explored various training algorithms to identify the most suitable one for our specific needs in material classification. During this phase, label encoding and normalization were performed to ensure that the model's input features were on a comparable scale, facilitating more effective learning.

Figure 31: Annotated Image of Metal Spring

In addition to the convolutional neural network (CNN), our project also incorporated a logistic regression model to complement the material classification process. This approach was particularly tailored to leverage both labeled image data and direct sensor inputs, creating a robust predictive model suited for simpler yet highly effective classification tasks.

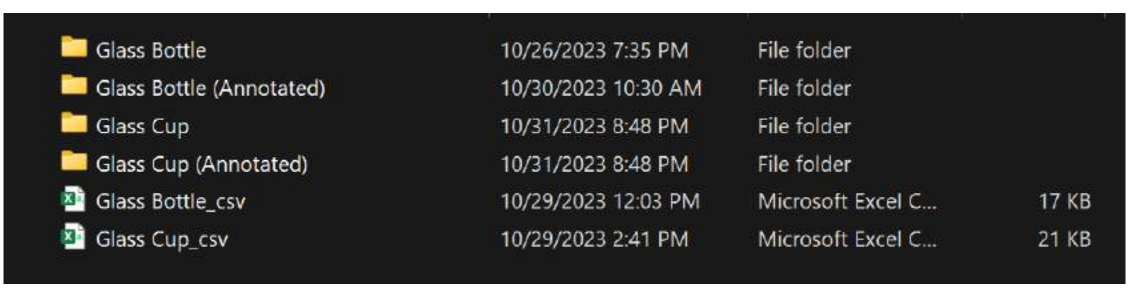


Figure 32: Folder Structure for Glass Bottle

The logistic regression model was developed to utilize a fusion of data types. Image data from the sensors—specifically from cameras and color sensors—provided visual cues about the materials. This data was processed to extract features that describe color, shape, and texture, which are crucial for distinguishing between different types of materials like plastic, glass, and metal. Simultaneously, sensor data, such as readings from metal proximity sensors and weight measurements from load cells, were integrated to provide additional context that could enhance the model's accuracy. For instance, the weight data helped differentiate between objects of similar appearance but different materials, such as a glass bottle and a plastic bottle, which might look alike but have significant weight differences.

accuracy			0.86	87
macro avg	0.87	0.87	0.86	87
weighted avg	0.86	0.86	0.86	87

Figure 33: Sensor Fusion Model Accuracy

The logistic regression model was trained using a dataset that included these processed features. Each item in the dataset was labeled with its corresponding material type, providing a clear target for the model to predict. The training process involved standard logistic regression techniques, where the model learned the probability of each input belonging to a predefined category based on the logistic function. The goal was to determine the best coefficients for the features in the dataset, minimizing the prediction error during the training phase.

	A	B	C	D
1	filename	file_size	region_shape_a	region_attributes
2	glass_bottle_45	2833260	{"name":"rect","x	{"Category":"Glass","Background":"Natural","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP":"
3	glass_bottle_45	2857274	{"name":"rect","x	{"Category":"Glass","Background":"Natural","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"No Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DO
4	glass_bottle_45	2853807	{"name":"rect","x	{"Category":"Glass","Background":"Black","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP":"<
5	glass_bottle_45	2770099	{"name":"rect","x	{"Category":"Glass","Background":"Black","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"No Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP"
6	glass_bottle_45	2873488	{"name":"rect","x	{"Category":"Glass","Background":"Natural","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP":"
7	glass_bottle_45	2899361	{"name":"rect","x	{"Category":"Glass","Background":"Natural","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"No Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DO
8	glass_bottle_45	2708839	{"name":"rect","x	{"Category":"Glass","Background":"Black","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP":"<
9	glass_bottle_45	2872981	{"name":"rect","x	{"Category":"Glass","Background":"Black","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"No Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP"
10	glass_bottle_13	2817847	{"name":"rect","x	{"Category":"Plastic","Background":"Natural","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP":
11	glass_bottle_13	2703713	{"name":"rect","x	{"Category":"Glass","Background":"Natural","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"No Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DO
12	glass_bottle_13	3027592	{"name":"rect","x	{"Category":"Glass","Background":"Black","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP":"<
13	glass_bottle_13	2610111	{"name":"rect","x	{"Category":"Glass","Background":"Black","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"No Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP"
14	glass_bottle_13	3353258	{"name":"rect","x	{"Category":"Glass","Background":"Natural","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP":"
15	glass_bottle_13	3182562	{"name":"rect","x	{"Category":"Glass","Background":"Natural","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"No Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DO
16	glass_bottle_13	2745678	{"name":"rect","x	{"Category":"Glass","Background":"Black","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP":"<
17	glass_bottle_13	2907865	{"name":"rect","x	{"Category":"Glass","Background":"Black","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"No Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP"
18	glass_bottle_22	2699874	{"name":"rect","x	{"Category":"Glass","Background":"Natural","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP":"
19	glass_bottle_22	2676538	{"name":"rect","x	{"Category":"Glass","Background":"Natural","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"No Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DO
20	glass_bottle_22	2591019	{"name":"rect","x	{"Category":"Glass","Background":"Black","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP":"<
21	glass_bottle_22	2558938	{"name":"rect","x	{"Category":"Glass","Background":"Black","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"No Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DOP"
22	glass_bottle_22	3361982	{"name":"rect","x	{"Category":"Glass","Background":"Natural","Shape":"Bottle","Orientation":"Vertical","Color":"Transparent","Lighting":"No Light","Reflection":"Shiny","Texture":"Glossy","Optical Properties":"Transparent","DO

Figure 34: CSV File generated via VGG Image Annotation Tool

One of the key advantages of using logistic regression in this context was its simplicity and interpretability. Unlike more complex models like CNNs, logistic regression provided a straightforward mechanism that could be easily understood and tweaked by the team. This was particularly useful for real-time applications where decisions needed to be made quickly and transparently. TensorFlow has been increasingly applied in industrial settings to leverage deep learning for enhancing operational efficiency [12]. Additionally, the model was computationally less intensive, making it suitable for situations where computational resources were a constraint.

Figure 35: TensorFlow Library for Machine Learning

Furthermore, the integration of sensor data into the logistic regression model allowed for a more comprehensive understanding of the materials being sorted. By combining direct sensor readings with derived image features, the model could make more informed predictions, reducing the reliance solely on visual cues, which can sometimes be misleading due to lighting conditions and background variations.

Figure 36: Keras Library for Neural Networks

The logistic regression model underwent rigorous testing and validation to ensure its effectiveness. Performance metrics such as accuracy, precision, recall, and F1-score were calculated to evaluate the model's capability to classify materials correctly. The model demonstrated a high degree of accuracy in scenarios where material properties were distinct and well-represented in the training data.

The logistic regression model served as a valuable component of our material classification system, offering a less complex yet highly effective alternative to the CNN. Its ability to incorporate and make predictions based on a combination of image and sensor data proved essential in creating a versatile and reliable classification system capable of operating efficiently in diverse real-world environments.

```
Epoch 4/64
6/6 [==============================] - 3s 456ms/step - loss: 1.1689 - accuracy: 0.5749 - val_loss: 0.8699 - val_accuracy: 0.6207
Epoch 5/64
6/6 [==============================] - 3s 455ms/step - loss: 0.6962 - accuracy: 0.7126 - val_loss: 0.5606 - val_accuracy: 0.7586
Epoch 6/64
6/6 [==============================] - 3s 534ms/step - loss: 0.2915 - accuracy: 0.9427 - val_loss: 0.4827 - val_accuracy: 0.7241
Epoch 7/64
6/6 [==============================] - 3s 465ms/step - loss: 0.2064 - accuracy: 0.9401 - val_loss: 0.4632 - val_accuracy: 0.7586
Epoch 8/64
6/6 [==============================] - 3s 451ms/step - loss: 0.1718 - accuracy: 0.9760 - val_loss: 0.4144 - val_accuracy: 0.8276
Epoch 9/64
6/6 [==============================] - 3s 528ms/step - loss: 0.1205 - accuracy: 0.9896 - val_loss: 0.4061 - val_accuracy: 0.7931
Epoch 10/64
6/6 [==============================] - 3s 479ms/step - loss: 0.0975 - accuracy: 0.9940 - val_loss: 0.4010 - val_accuracy: 0.8621
...
6/6 [==============================] - 3s 487ms/step - loss: 0.0010 - accuracy: 1.0000 - val_loss: 0.1931 - val_accuracy: 0.8966
Found 57 images belonging to 3 classes.
1/1 [==============================] - 0s 389ms/step - loss: 0.0759 - accuracy: 0.9688
Test Accuracy: 0.96875
```

Figure 37: CNN Model Accuracy

Throughout the model training process, we closely monitored key performance metrics such as accuracy, precision, recall, and the F1-score on the testing set. These metrics are essential for assessing the model’s effectiveness and guiding further iterations and refinements to improve performance.

```
Image 0:
    Glass: 99.31%
    Metal: 0.67%
    Miscellaneous: 0.02%
    Plastic: 0.00%


Image 1:
    Glass: 100.00%
    Metal: 0.00%
    Miscellaneous: 0.00%
    Plastic: 0.00%


Image 2:
    Glass: 100.00%
    Metal: 0.00%
    Miscellaneous: 0.00%
    Plastic: 0.00%


Image 3:
    Glass: 100.00%
    Metal: 0.00%
    Miscellaneous: 0.00%
...
    Miscellaneous: 0.00%
    Plastic: 100.00%
```

Figure 38: CNN Model Results

This comprehensive and detailed approach to software design ensures that our material classification system is robust, capable of accurately classifying materials under varied environmental conditions and operational scenarios. Through rigorous testing and continuous improvement, we aim to achieve a high level of accuracy, making the system reliable for real-time applications in diverse settings.

Chapter 5: Investigation and Testing

To ensure that our advanced material classification system adhered to the specified requirements, it underwent a rigorous testing process. This phase was crucial not only for verifying that the system met the client's needs but also to ensure it performed reliably under various conditions. Here, we detail the extensive tests conducted to validate every aspect of the project, from individual component functionality to the full operational capability of the integrated system.

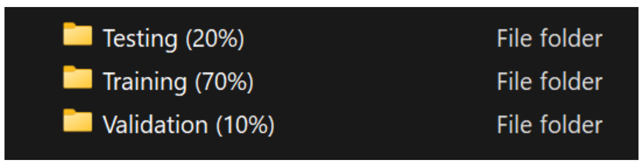


Figure 39: Dataset Splitting

The testing process began with Sensor Accuracy Testing, where each sensor—IR, metal proximity, color, and weight sensors—was individually assessed. Controlled tests involved passing known materials through the system, recording the sensor outputs, and comparing these results to expected values. Discrepancies led to recalibrations and fine-tuning of sensor settings to ensure high accuracy and responsiveness.

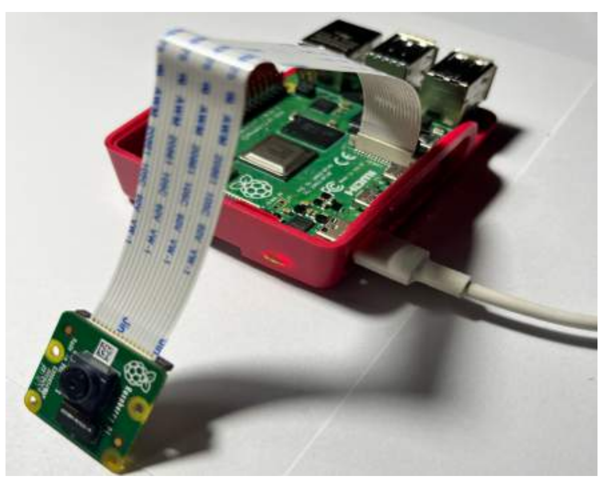


Figure 40: Pi Camera Integration with Raspberry Pi

We focused on validating the functionality of the GPIO pins in response to classification results. To achieve this, we utilized LEDs as indicators to demonstrate the correct operation of the GPIO pins. Each GPIO pin was designated to represent a specific classification: glass, metal, plastic, and miscellaneous.

Figure 41: Real-time Object Detection Testing

The process began with capturing an image using the Pi Camera. Once the image was captured, it was processed by our trained model to classify the material. Upon obtaining the classification result, the corresponding GPIO pin was programmed to turn high, illuminating the attached LED.

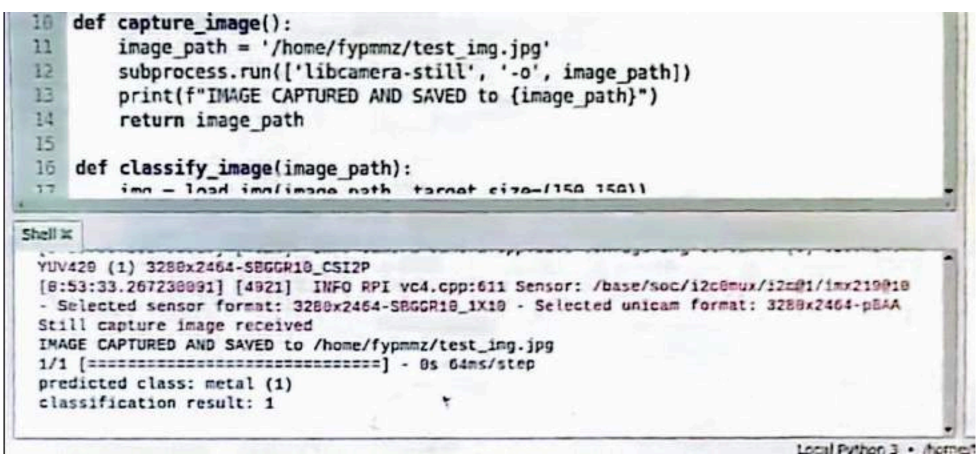


Figure 42: Classification Result for Metal

This real-time feedback allowed us to visually confirm that the GPIO pins were correctly set high for each classification result, ensuring accurate signal transmission for further processing in the system. This testing method effectively demonstrated the operational integrity of our GPIO control logic in the hardware setup.

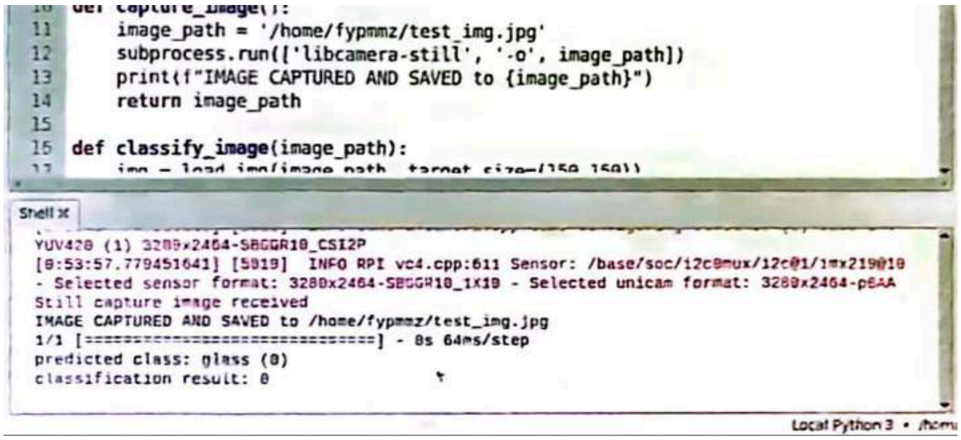


Figure 43: Classification Result for Glass

Following hardware tests, we conducted Software Functionality and Machine Learning Model Validation. Initial unit tests were carried out on software functions to ensure correct outputs for given inputs. Integration tests followed, ensuring that these individual software components functioned cohesively within the system. Additionally, the machine learning models, crucial for material classification, were rigorously tested using a validation dataset separate from the training set to measure real-world accuracy and reliability.

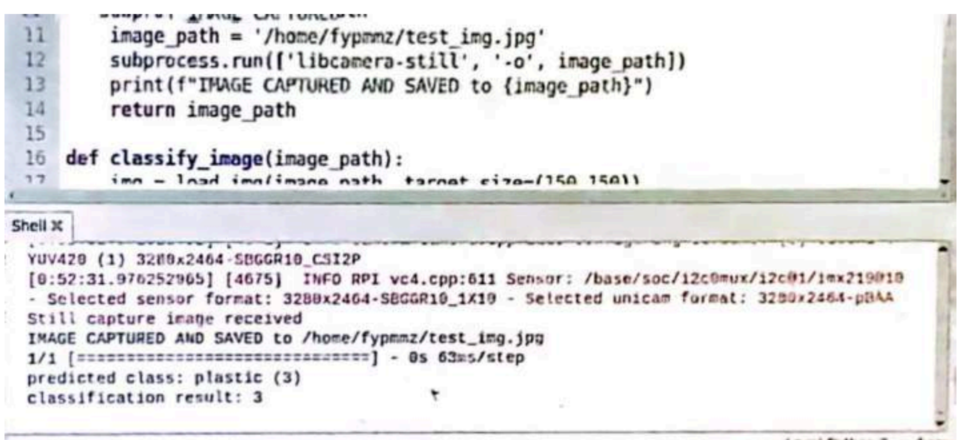


Figure 44: Classification Result for Plastic

This phase simulated actual operational conditions, testing the system's throughput and responsiveness as various materials were processed. These tests were vital for confirming the integrated system's efficiency and the effective communication between different system parts.

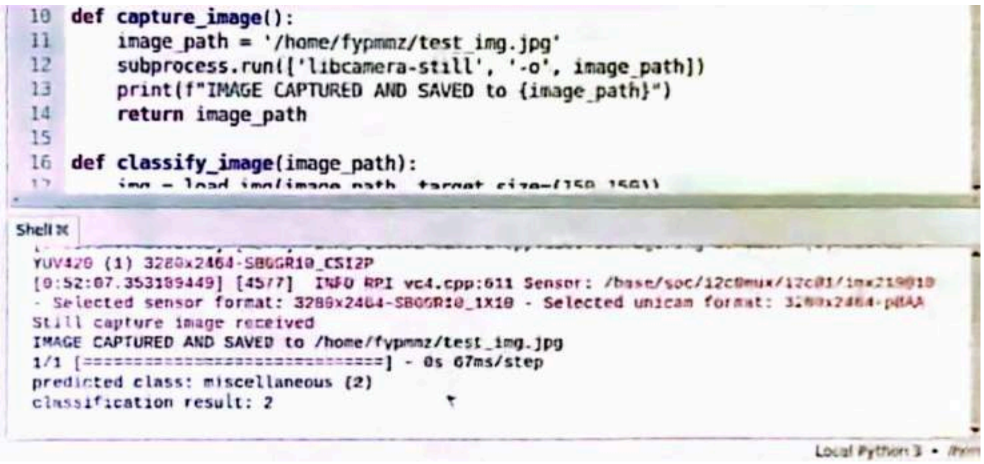


Figure 45: Classification Result for Miscellaneous

To evaluate durability and robustness, Load and Stress Testing was performed, where the system operated continuously at full capacity. This testing helped identify potential mechanical wear and software stability issues under prolonged use, allowing us to address these before deployment.

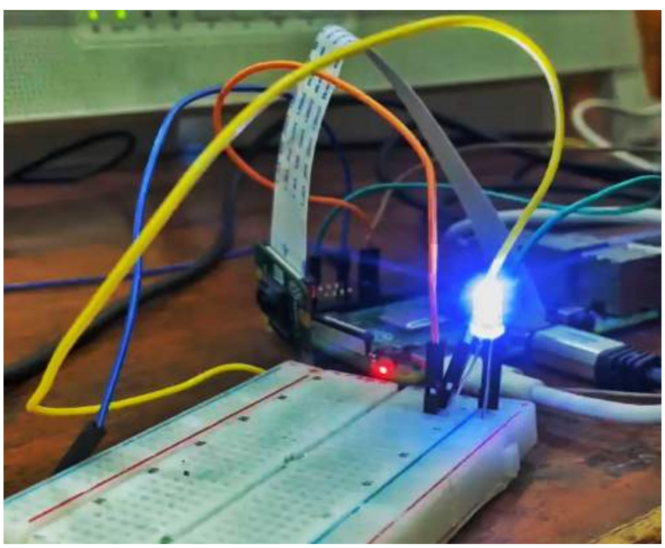


Figure 46: GPIO Pin Activation Testing

Finally, User Interface and Usability Testing ensured that the system was user-friendly and intuitive. Participants with no prior training interacted with the system, and their ability to operate it effectively was monitored. Feedback from these sessions was used to refine the user interface, simplifying system interactions and enhancing user satisfaction.Each test was meticulously documented, comparing the obtained results with the expected outcomes to ensure comprehensive coverage of all potential issues. This detailed testing not only demonstrated the system's operational readiness but also reinforced its reliability and effectiveness in meeting the rigorous demands of real-world material classification.

Chapter 6: User Guide

Following is the User Guide for our Advanced Material Classification System. This guide is designed to assist users of all technical backgrounds in safely and effectively operating the system. Whether you are a seasoned engineer or a newcomer to technical equipment, following these instructions will ensure that you can utilize our system with confidence and safety.

Getting Started:

1. Installation: Ensure that the system is installed on a stable, flat surface. All electrical connections should be made following the installation manual, with power supplies connected as specified to avoid any electrical mishaps. It is recommended to have a certified technician perform the initial setup.

2. Powering the System: Before turning on the machine, check that all emergency stops and safety barriers are in their correct positions. The main power switch is located on the control panel. Once the system is powered, allow it to perform a self-check before loading any materials.

Operation:

1. Loading Materials: Materials should be loaded onto the conveyor belt carefully. Ensure that the materials are evenly distributed and do not overload the conveyor to prevent jamming or damage to the sensors.

2. Starting the System: Use the start button on the main control panel to begin operations. The initial screen will guide you through a simple calibration check to ensure all sensors are functioning correctly.

3. Monitoring Operation: During operation, monitor the system through the user interface display. This display provides real-time feedback on system status, material sorting accuracy, and any errors or maintenance reminders.

Safety Precautions:

1. Emergency Stop: Familiarize yourself with the location of the emergency stop buttons. These are placed at accessible points around the machine and should be used to halt operations immediately if a safety concern arises.

2. Regular Maintenance Checks: Regular maintenance is crucial for safe operation. Check sensor alignments, conveyor belt tension, and motor function as per the maintenance schedule provided in the manual.

3. Handling Malfunctions: If the system reports a malfunction, follow the troubleshooting steps provided in the manual. Do not attempt to repair electrical components unless you are qualified. Contact support for any issues beyond basic troubleshooting.

Cleaning and Shutdown:

1. Cleaning Procedures: After operation, ensure the machine is cleaned according to the guidelines. This includes wiping down the sensors and conveyor belt and removing any debris that may have accumulated during operation.

2. Shutdown: To shut down the system, press the stop button on the control panel and then turn off the main power. Ensure the system is clean and that no materials are left on the conveyor belt before leaving the machine unattended.

User Support:

For additional support, contact our customer support team through the contact details provided. We are committed to ensuring that you have the best experience with our product and are available to assist with any queries or concerns.

By adhering to these guidelines, users can ensure that they operate the Advanced Material Classification System safely and effectively, maximizing its utility and lifespan. This guide should be kept accessible to all users and referred to whenever necessary to maintain the highest standards of operational safety and efficiency.

Chapter 7: Deliverables and Cost

7.1 Deliverables

As our Final Year Project comes to a conclusion, we have prepared a comprehensive list of deliverables that encompass all the hardware, software, and documentation components we have developed and refined. These deliverables are designed to provide the client with a complete and functional advanced material classification system, along with all necessary tools and information for operation and maintenance.

Hardware Deliverables:

- **Conveyor Belt System:** Includes the main conveyor belt equipped with an integrated motor and adjustable speed control.
- **Sensor Suite:** A set of sensors strategically positioned along the conveyor belt, including:
  - IR sensors for detecting material presence.
  - Metal proximity sensors for identifying metallic objects.
  - Color sensors (TCS3200) for distinguishing material colors.
  - Load cells for weighing materials after sorting.
- **Servo Motors:** Attached to flaps for sorting materials into designated bins based on sensor input.
- **Control Units:** Consisting of a Raspberry Pi 4 Model B and Arduino boards (Nano and Uno) for processing and control tasks.
- **Pi Camera Module v2:** Used for visual inspection and additional system verification.

Software Deliverables:

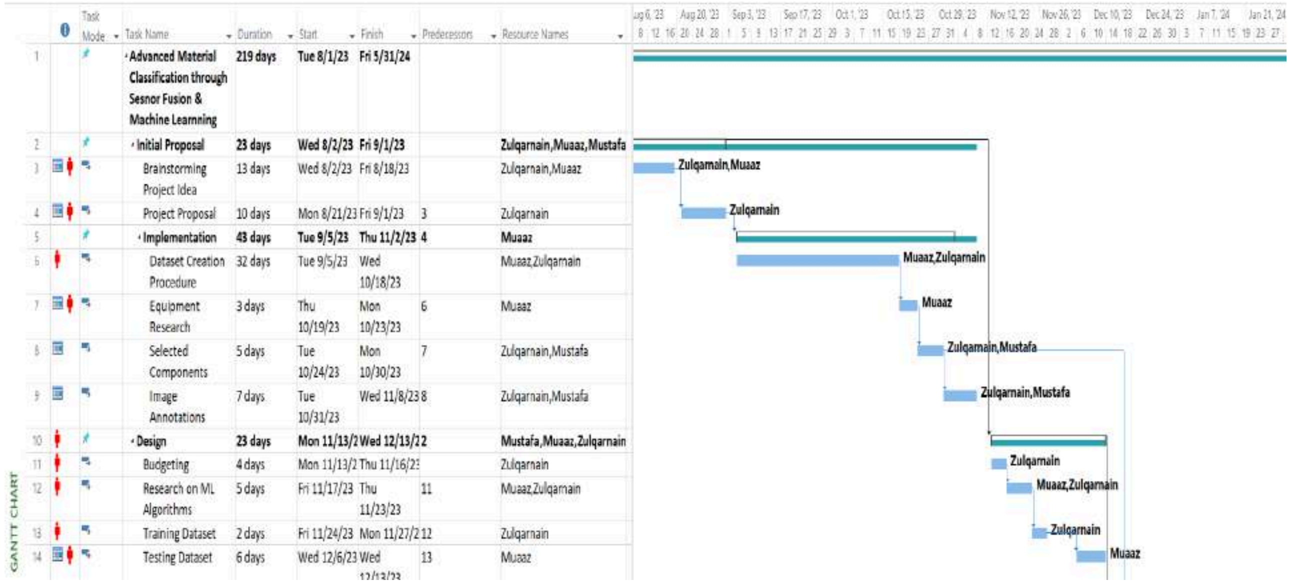
- **Control Software:** Developed in Python and C++, this software handles sensor data processing, actuator control, and system management.
- **Machine Learning Models:** Includes trained models for material classification, leveraging convolutional neural networks and logistic regression.
- **User Interface Software:** Provides a graphical interface on an attached display for system monitoring, error reporting, and manual control.

Documentation Deliverables:

- **User Manual:** A detailed guide on system setup, operation, troubleshooting, and maintenance.
- **Technical Specifications:** Documentation covering the detailed specifications of each component and their configurations.
- **Installation Guide:** Step-by-step instructions for installing and configuring the system hardware and software.
- **Maintenance Schedule:** A timetable for regular maintenance checks and procedures to ensure long-term system reliability.
- **System Schematics:** Electrical and mechanical schematics that provide a detailed overview of the system architecture.

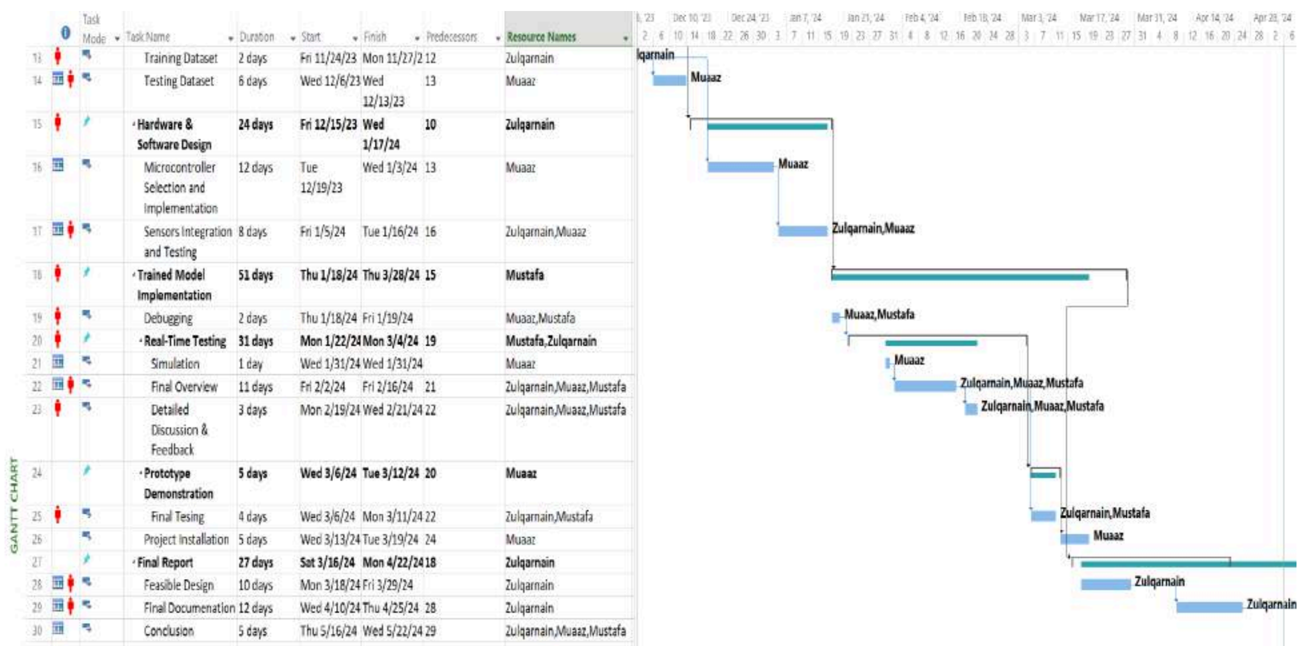
These deliverables are designed to ensure that the client receives a fully operational and maintainable system, equipped with all necessary tools and information for immediate deployment and long-term operation. Each component and document has been crafted to meet the highest standards of quality, ensuring that the system is both robust and user-friendly. As we hand over these deliverables, we are confident that they will meet the client's needs and exceed their expectations in managing and utilizing the advanced material classification system.

7.2 Project Plan



	Task Name	Duration	Start	Finish	Predecessors	Resource Names
1	Advanced Material Classification through Sesnor Fusion & Machine Learning	219 days	Tue 8/1/23	Fri 5/31/24		
2	Initial Proposal	23 days	Wed 8/2/23	Fri 9/1/23		Zulqarnain,Muaaz,Mustafa
3	Brainstorming Project Idea	13 days	Wed 8/2/23	Fri 8/18/23		Zulqarnain,Muaaz
4	Project Proposal	10 days	Mon 8/21/23	Fri 9/1/23	3	Zulqarnain
5	Implementation	43 days	Tue 9/5/23	Thu 11/2/23	4	Muaaz
6	Dataset Creation Procedure	32 days	Tue 9/5/23	Wed 10/18/23		Muaaz,Zulqarnain
7	Equipment Research	3 days	Thu 10/19/23	Mon 10/23/23	6	Muaaz
8	Selected Components	5 days	Tue 10/24/23	Mon 10/30/23	7	Zulqarnain,Mustafa
9	Image Annotations	7 days	Tue 10/31/23	Wed 11/8/23	8	Zulqarnain,Mustafa
10	Design	23 days	Mon 11/13/2	Wed 12/13/2	2	Mustafa,Muaaz,Zulqarnain
11	Budgeting	4 days	Mon 11/13/2	Thu 11/16/2		Zulqarnain
12	Research on ML Algorithms	5 days	Fri 11/17/23	Thu 11/23/23	11	Muaaz,Zulqarnain
13	Training Dataset	2 days	Fri 11/24/23	Mon 11/27/2	12	Zulqarnain
14	Testing Dataset	6 days	Wed 12/6/23	Wed 12/13/23	13	Muaaz

Figure 47: FYP - I Gantt Chart



	Task Name	Duration	Start	Finish	Predecessors	Resource Names
13	Training Dataset	2 days	Fri 11/24/23	Mon 11/27/2	12	Zulqarnain
14	Testing Dataset	6 days	Wed 12/6/23	Wed 12/13/23	13	Muaaz
15	Hardware & Software Design	24 days	Fri 12/15/23	Wed 1/17/24	10	Zulqarnain
16	Microcontroller Selection and Implementation	12 days	Tue 12/19/23	Wed 1/3/24	13	Muaaz
17	Sensors Integration and Testing	8 days	Fri 1/5/24	Tue 1/16/24	16	Zulqarnain,Muaaz
18	Trained Model Implementation	51 days	Thu 1/18/24	Thu 3/28/24	15	Mustafa
19	Debugging	2 days	Thu 1/18/24	Fri 1/19/24		Muaaz,Mustafa
20	Real-Time Testing	31 days	Mon 1/22/24	Mon 3/4/24	19	Mustafa,Zulqarnain
21	Simulation	1 day	Wed 1/31/24	Wed 1/31/24		Muaaz
22	Final Overview	11 days	Fri 2/2/24	Fri 2/16/24	21	Zulqarnain,Muaaz,Mustafa
23	Detailed Discussion & Feedback	3 days	Mon 2/19/24	Wed 2/21/24	22	Zulqarnain,Muaaz,Mustafa
24	Prototype Demonstration	5 days	Wed 3/6/24	Tue 3/12/24	20	Muaaz
25	Final Tesing	4 days	Wed 3/6/24	Mon 3/11/24	22	Zulqarnain,Mustafa
26	Project Installation	5 days	Wed 3/13/24	Tue 3/19/24	24	Muaaz
27	Final Report	27 days	Sat 3/16/24	Mon 4/22/24	18	Zulqarnain
28	Feasible Design	10 days	Mon 3/18/24	Fri 3/29/24		Zulqarnain
29	Final Documenation	12 days	Wed 4/10/24	Thu 4/25/24	28	Zulqarnain
30	Conclusion	5 days	Thu 5/16/24	Wed 5/22/24	29	Zulqarnain,Muaaz,Mustafa

Figure 48: FYP - II Gantt Chart

7.3 Project Cost

#	Item	Quantity	Unit Price (PKR)	Total Price (PKR)
1	Conveyor Belt	1	15000	15000
2	Raspberry Pi 4 Model B	1	23000	23000
3	Raspberry Pi Camera Module V2	1	8000	8000
4	IR Sensor Module	1	120	120
5	Arduino Uno R3	1	1780	1780
6	TCS3200 Colour Sensor Module	1	1800	1800
7	Arduino Nano	1	1100	1100
8	Metal Proximity Sensor	1	650	650
9	MG966R Servo Motor	3	750	2250
10	16x2 LCD Screen	2	500	1000
11	5kg Load Cell	3	350	1050
12	HX711 Weighing Sensor Module	3	200	600
Grand Total Price (PKR):				**56350**

Table 2: Project Cost

Chapter 8: Conclusion

This project is set out to develop a comprehensive sorting system using various sensors and a Raspberry Pi to manage and automate the sorting of materials by metal content, color, and weight. The primary objectives were to effectively integrate the IR, metal, proximity, color, and weight sensors into a single system controlled by a Raspberry Pi and to design an algorithm capable of accurately sorting materials into designated categories.

Figure 49: Pakistan Engineering Council

The achievements of the project were substantial and multifaceted. Notably, the project received financial assistance from the Pakistan Engineering Council (PEC) under the 'Final Year Design Project Financing (2023-24)', an initiative of the Pakistan Development Committee (PPDC). This funding was a significant endorsement of the project's potential and importance, enabling the acquisition of high-quality sensors and other necessary equipment which were pivotal in achieving the project's goals.

Figure 50: Certification of Financial Assistance by PEC

We successfully integrated multiple sensors with the Raspberry Pi, which served as the central processing unit, effectively communicating with an Arduino to control the sensors and the sorting mechanism. A control algorithm was developed and implemented, allowing for real-time sorting based on sensor input. This algorithm efficiently interpreted signals from the IR sensor for object detection, the metal proximity sensor for metal detection, and the color sensor for identifying material type. On the software development front, a convolutional neural network model was implemented, achieving high accuracy in classifying materials based on color sensor input. Additionally, the system featured a user-friendly interface on the Arduino LCD screen that displayed the sorting status and system messages, enhancing monitoring ease.

The hardware setup included a custom-designed conveyor belt system that efficiently transported items past the sensors and into the appropriate collection bins, and MG966R servo motors were utilized for the precise operation of sorting flaps, which directed materials into the correct bins based on the sensor data. Extensive testing validated the accuracy and reliability of the sorting system, which demonstrated high efficiency and minimal errors, confirming the effectiveness of both the hardware setup and the software algorithms.

The project largely met the stated objectives, showcasing the system's ability to function as designed with high accuracy and reliability. The successful development of the CNN model further highlighted the project's innovative approach to material classification.

While the project met its primary goals, further development is recommended in several areas. It would be beneficial to explore the use of more advanced machine learning algorithms to improve detection and classification accuracy, particularly for materials with similar color profiles. Investigating methods to increase the processing speed of the system could enable higher throughput, which is critical for industrial applications. The system could also be scaled up for larger operations by expanding the number of sensors and sorting mechanisms. Further research on ways to reduce the energy consumption of the system could make it more sustainable and cost-effective for long-term use. Extending the system’s capabilities to include more material types, such as different plastics and composites, would require more sophisticated sensing and sorting technologies. Finally, piloting the system in a real-world environment would further test its robustness and lead to necessary adjustments before full-scale deployment.

In conclusion, this project represents a significant step forward in automated sorting technology. The achievements noted align well with the initial objectives, and the groundwork laid by this project is ideal for future enhancements and commercial applications. The financial backing by the PEC underlines the project's importance and potential impact on the development of advanced material sorting technologies.

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Appendices

CNNModelTraining.py

```
# Import required libraries
from zipfile import ZipFile
import os
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import numpy as np
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
from google.colab import files

# Constants for paths and parameters
EXTRACTION_FOLDER = '/content/newfyp'
ZIP_FILE_PATH = '/content/newfyp.zip'
TRAIN_DIR = '/content/newfyp/newfyp/newfyp/fyp/Training (70%)'
VALIDATION_DIR = '/content/newfyp/newfyp/newfyp/fyp/Validation (10%)'
TEST_DIR = '/content/newfyp/newfyp/newfyp/fyp/Testing (20%)'
IMG_WIDTH, IMG_HEIGHT = 150, 150
BATCH_SIZE = 16
EPOCHS = 128

# Unzip the dataset file
try:
    with ZipFile(ZIP_FILE_PATH, 'r') as zip_ref:
        zip_ref.extractall(EXTRACTION_FOLDER)
    print(f"Files successfully extracted to {EXTRACTION_FOLDER}")
except Exception as e:
    print(f"An error occurred: {e}")

# Check for files in the extraction folder
try:
    files_in_extraction_folder = os.listdir(EXTRACTION_FOLDER)
    print(f"Files in the extraction folder: {files_in_extraction_folder}")
except FileNotFoundError:
    print(f"Extraction folder not found: {EXTRACTION_FOLDER}")
except Exception as e:
```

```
    print(f"An error occurred while listing files: {e}")

# Define image data generators
train_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2, zoom_range=0.2,
horizontal_flip=True)
validation_test_datagen = ImageDataGenerator(rescale=1./255)

# Setup data generators
train_generator = train_datagen.flow_from_directory(
    TRAIN_DIR, target_size=(IMG_WIDTH, IMG_HEIGHT), batch_size=BATCH_SIZE,
class_mode='categorical', shuffle=True)
validation_generator = validation_test_datagen.flow_from_directory(
    VALIDATION_DIR, target_size=(IMG_WIDTH, IMG_HEIGHT),
batch_size=BATCH_SIZE, class_mode='categorical')
test_generator = validation_test_datagen.flow_from_directory(
    TEST_DIR, target_size=(IMG_WIDTH, IMG_HEIGHT), batch_size=BATCH_SIZE,
class_mode='categorical', shuffle=False)

# Build the CNN model
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(IMG_WIDTH, IMG_HEIGHT, 3)),
    MaxPooling2D(2, 2),
    Flatten(),
    Dense(4, activation='softmax')  # Assuming 4 classes
])

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model
history = model.fit(
    train_generator,
    steps_per_epoch=max(1, train_generator.samples // BATCH_SIZE),
    epochs=EPOCHS,
    validation_data=validation_generator,
    validation_steps=max(1, validation_generator.samples // BATCH_SIZE)
)

# Evaluate the model on the test set
test_loss, test_accuracy = model.evaluate(test_generator, steps=test_generator.samples //
BATCH_SIZE)
print(f"Test Accuracy: {test_accuracy}")

# Generate predictions for the test set
steps = test_generator.samples // BATCH_SIZE + (test_generator.samples % BATCH_SIZE >
0)
```

```
predictions = model.predict(test_generator, steps=steps)
predicted_classes_indices = np.argmax(predictions, axis=1)
class_indices = train_generator.class_indices
index_to_class = {v: k for k, v in class_indices.items()}
predicted_classes_names = [index_to_class[idx] for idx in predicted_classes_indices]

# Display predictions for each test image
for i, path in enumerate(test_generator.filepaths):
    print(f"Image: {os.path.basename(path)} - Class: {predicted_classes_names[i %
len(predicted_classes_names)]}")

# Generate confusion matrix and plot it
true_classes = test_generator.classes
cm = confusion_matrix(true_classes, predicted_classes_indices)
class_names = [index_to_class[i] for i in range(len(index_to_class))]
plt.figure(figsize=(10, 7))
sns.heatmap(cm, annot=True, fmt='g', cmap='Blues', xticklabels=class_names,
yticklabels=class_names)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

# Save the model
model.save('CNN_Material_Classifier.h5')
files
```

SensorFusionModelTraining.py

```
import pandas as pd
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.utils import to_categorical
from sklearn.metrics import classification_report, accuracy_score

# Load the datasets
df = pd.read_csv("iyc.csv")
df1 = pd.read_csv("iyv.csv")

# Display dataset information and preview
df.info()
df1.info()
print(df.head())

# Assuming input images are 64x64 pixels with 3 color channels (RGB)
input_shape = (64, 64, 3)

# Create a CNN Sequential model for image classification
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=input_shape),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(4, activation='softmax')  # Assuming 4 classes
])

# Compile the CNN model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Display the CNN model summary
model.summary()

# Prepare data for the MLP model
X_train = df.drop(columns=['filename'])
y_train = df['filename']
X_test = df1.drop(columns=['filename'])

# Encode labels using LabelEncoder and convert to one-hot encoding
label_encoder = LabelEncoder()
```

```
y_train_encoded = label_encoder.fit_transform(y_train)
num_classes = len(label_encoder.classes_)
y_train_one_hot = to_categorical(y_train_encoded, num_classes=num_classes)

# Normalize the data
scaler = StandardScaler()
X_train_normalized = scaler.fit_transform(X_train)
X_test_normalized = scaler.transform(X_test)

# Create an MLP model for structured data classification
mlp_model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train_normalized.shape[1],)),
    Dense(32, activation='relu'),
    Dense(num_classes, activation='softmax')
])

# Compile the MLP model
mlp_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Train the MLP model
mlp_model.fit(X_train_normalized, y_train_one_hot, epochs=30, batch_size=16)

# Predict on the test set and convert predictions to class names
predictions = mlp_model.predict(X_test_normalized)
predicted_filenames_encoded = predictions.argmax(axis=1)
predicted_filenames = label_encoder.inverse_transform(predicted_filenames_encoded)

# Categorize classes based on filenames
def categorize_class(filename):
    if 'glass_cup' in filename.lower():
        return 'Glass Cup'
    elif 'glass_bottle' in filename.lower():
        return 'Glass Bottle'
    elif 'metal_spring' in filename.lower():
        return 'Metal Spring'
    elif 'plastic_bottle' in filename.lower():
        return 'Plastic Bottle'
    elif 'plastic_cup' in filename.lower():
        return 'Plastic Cup'
    elif 'metal_nut' in filename.lower():
        return 'Metal Nut'
    else:
        return 'Class Miscellaneous'

# Create a DataFrame to compare true and predicted classes
result_df = pd.DataFrame({
```

```
    'True Filename': df['filename'],
    'Predicted Filename': predicted_filenames
})
result_df['True Class'] = result_df['True Filename'].apply(categorize_class)
result_df['Predicted Class'] = result_df['Predicted Filename'].apply(categorize_class)

# Calculate accuracy and display the classification report
accuracy = accuracy_score(result_df['True Class'], result_df['Predicted Class'])
print(result_df)
print(f"\nAccuracy: {accuracy}%")
print("\nClassification Report:")
print(classification_report(result_df['True Class'], result_df['Predicted Class']))
```

MaterialSortSignal.py

```
import subprocess
from time import sleep
import numpy as np
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
import RPi.GPIO as GPIO

# Load the trained model
model = load_model('path/to/your/model.h5')

# Set up GPIO
GPIO.setmode(GPIO.BCM)
GPIO.setwarnings(False)

# Define the GPIO pins for each class
glass_pin = 17
metal_pin = 27
misc_pin = 22
plastic_pin = 10

# Initialize GPIO pins
GPIO.setup(glass_pin, GPIO.OUT)
GPIO.setup(metal_pin, GPIO.OUT)
GPIO.setup(misc_pin, GPIO.OUT)
GPIO.setup(plastic_pin, GPIO.OUT)

def capture_image():
    image_path = '/home/pi/captured_image.jpg'  # Define the path to save the captured image
    # Use libcamera-still command to capture an image
    subprocess.run(['libcamera-still', '-o', image_path])
    print(f"Image captured and saved to {image_path}")
    return image_path

def classify_image(image_path):
    # Load the image using Keras preprocessing
    img = image.load_img(image_path, target_size=(224, 224))  # Adjust target size as per your
model
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)  # Add batch dimension
    img_array /= 255.0  # Normalize the image data to 0-1 range

    # Make prediction
    predictions = model.predict(img_array)
    predicted_class = np.argmax(predictions, axis=1)[0]  # Get the index of max value
```

```
    # Map the model's predicted index to specific class numbers
    class_labels = {0: 'glass', 1: 'metal', 2: 'miscellaneous', 3: 'plastic'}
    predicted_label = class_labels[predicted_class]

    print(f"Predicted class: {predicted_label} ({predicted_class})")

    # Set the corresponding GPIO pin high based on the predicted class
    if predicted_class == 0:
        GPIO.output(glass_pin, GPIO.HIGH)
    elif predicted_class == 1:
        GPIO.output(metal_pin, GPIO.HIGH)
    elif predicted_class == 2:
        GPIO.output(misc_pin, GPIO.HIGH)
    elif predicted_class == 3:
        GPIO.output(plastic_pin, GPIO.HIGH)

    return predicted_class

# Main execution loop
while True:
    # Reset all GPIO pins to low
    GPIO.output(glass_pin, GPIO.LOW)
    GPIO.output(metal_pin, GPIO.LOW)
    GPIO.output(misc_pin, GPIO.LOW)
    GPIO.output(plastic_pin, GPIO.LOW)

    image_path = capture_image()  # Capture an image
    classification_result = classify_image(image_path)  # Classify the image
    print(f"Classification result: {classification_result}")
    sleep(5)  # Wait for 5 seconds before capturing the next image

# Clean up GPIO at the end of the program
GPIO.cleanup()
```

FlapControllSystem.ino

```
// With Pi
//3,5,6 servo
#include <LiquidCrystal_I2C.h>//
LiquidCrystal_I2C lcd(0x27, 16,2);

#include <Servo.h>
#define ledPin     13

Servo myServo1;
Servo myServo2;
Servo myServo3;

int IR_Sensor = 7;
int motor_Pin = A1;

int input_1 = 2;
int input_2 = 4;
int input_3 = 6;
int input_4 = A0;

// TCS230 pins connected to Arduino
const int s0 = 8;
const int s1 = A3;
const int s2 = 10;
const int s3 = 11;
const int out = 12;

int sensor_1Pin = A2;

int red = 0;
int green = 0;
int blue = 0;


uint8_t volatile  sonar_data =0;

int count = 0;
uint8_t state=0;
int count_1value =0;
int sensor_1State = 0;
int prestate1 =0;


 void setup()
```

```
{
 Serial.begin(9600);
 lcd.init();
 lcd.init();
 lcd.backlight();
 myServo1.attach(3);
 myServo2.attach(5);
 myServo3.attach(9);

 myServo1.write(0);
 delay(200);
 myServo2.write(170);
 delay(200);
 myServo3.write(180);

 lcd.clear();
 lcd.print("   WELCOME  ");
 delay(2000);
 lcd.setCursor(0, 0);
 lcd.print(" Classification ");
 lcd.setCursor(0, 1);
 lcd.print("    System  ");
 delay(2000);
 lcd.clear();

 pinMode(IR_Sensor, INPUT_PULLUP);
 pinMode(sensor_1Pin, INPUT_PULLUP);

 pinMode(input_1, INPUT);
 pinMode(input_2, INPUT);
 pinMode(input_3, INPUT);

 pinMode(out, INPUT);
 pinMode(s0, OUTPUT);
 pinMode(s1, OUTPUT);
 pinMode(s2, OUTPUT);
 pinMode(s3, OUTPUT);
 pinMode(ledPin, OUTPUT);
 pinMode(motor_Pin, OUTPUT);

 digitalWrite(s0, HIGH);
 digitalWrite(s1, HIGH);
 digitalWrite(ledPin, LOW);
 digitalWrite(motor_Pin, HIGH);

lcd.print("wait.......!");
```

```
 }

void loop ()
{
   lcd.print("Start Conveyer");
   delay(2000);
   lcd.clear();
   lcd.setCursor(0,0);
   lcd.print("wait Signal from");
   lcd.setCursor(0,1);
   lcd.print("  Raspberry Pi  ");
   state=2;

    if(state==2)
  {

  color();
  Serial.print("R =");
  Serial.print(red, DEC);
  Serial.print(" G = ");
  Serial.print(green, DEC);
  Serial.print(" B = ");
  Serial.print(blue, DEC);
  Serial.print("\t");

if (red < blue && red < green && red < 25)
  {
  //  if (green - blue >= 10 && green - blue <= 25 && green - ( 2 * red ) >= 8 )
   if (red >= 14 && red <= 20 && green>=30  && green <=50 && blue>=27  && blue <=40)
   {
    // lcd.clear();
   //  lcd.setCursor(0, 0);
   //  lcd.print("Color Detection");
   //  lcd.setCursor(6, 1);
   //  lcd.print("Color : ");
   //  lcd.print("Red");
   //  Serial.println(" - (Red Color)");
    // delay(1000);
    // lcd.clear();
   }

  Serial.println();
  // digitalWrite(motor_Pin, LOW);
  // state=0;
```

```
if(digitalRead(input_1)==HIGH)
{
  lcd.clear();
  lcd.setCursor(0,0);
  lcd.print("  Miscillaneous ");
  lcd.setCursor(0,1);
  lcd.print("   Detected   ");
  digitalWrite(motor_Pin, LOW);
  delay(22000);   ///////////////////////////  time Change
  digitalWrite(motor_Pin, HIGH);
  myServo1.write(70);
  delay(2000);
  lcd.clear();
  myServo1.write(10);
  delay(500);
  digitalWrite(motor_Pin, HIGH);
 // state=1;
 }

if(digitalRead(input_2)==HIGH)
{
  lcd.clear();
  lcd.setCursor(0,0);
  lcd.print("    Glass    ");
  lcd.setCursor(0,1);
  lcd.print("   Detected   ");

  digitalWrite(motor_Pin, LOW);

  delay(16000);     //////////////////////  time Change

  myServo2.write(100);
  delay(2000);
  myServo2.write(170);
  lcd.clear();
  delay(500);
  digitalWrite(motor_Pin, HIGH);

}

if(digitalRead(input_3)==HIGH)
{
  lcd.clear();
  lcd.setCursor(0,0);
  lcd.print("    Plastic  ");
  lcd.setCursor(0,1);
```

```
  lcd.print("   Detected   ");

  digitalWrite(motor_Pin, LOW);

  delay(13000);  ////////////////////////////  time Change

  myServo3.write(140);
  delay(2000);
  myServo3.write(180);
  lcd.clear();
  delay(500);
  digitalWrite(motor_Pin, HIGH);

  lcd.clear();

}

}

}
void color()
{
  digitalWrite(s2, LOW);
  digitalWrite(s3, LOW);
  //count OUT, pRed, RED
  red = pulseIn(out, digitalRead(out) == HIGH ? LOW : HIGH);
  digitalWrite(s3, HIGH);
  //count OUT, pBLUE, BLUE
  blue = pulseIn(out, digitalRead(out) == HIGH ? LOW : HIGH);
  digitalWrite(s2, HIGH);
  //count OUT, pGreen, GREEN
  green = pulseIn(out, digitalRead(out) == HIGH ? LOW : HIGH);
}
```

Glossary

List all acronyms and technical terms in alphabetical order along with their brief description, as shown below:

AC	Alternating Current
ADC	Analog-to-Digital Converter
AI	Artificial Intelligence
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
CSV	Comma-Separated Values
DC	Direct Current
FET	Field-Effect Transistor
FPGA	Field-Programmable Gate Array
FPS	Frames Per Second
EEPROM	Electrically Erasable Programmable Read-Only Memory
GPIO	General Purpose Input/Output
HDMI	High-Definition Multimedia Interface
HMM	Hidden Markov Model
Hz	Hertz
IDE	Integrated Development Environment
IoT	Internet of Things
ML	Machine Learning
SDG	Sustainable Development Goal
SPI	Serial Peripheral Interface
NPN	Negative-Positive-Negative
PCA	Principal Component Analysis
PNP	Positive-Negative-Positive

PWM	Pulse Width Modulation
PVC	Polyvinyl Chloride
TTL	Transistor to Transistor Logic
UART	Universal Asynchronous Receiver-Transmitter
VGG	Visual Geometry Group

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MACHINE LEARNING Final Year Project Report GSN: Fall 23 - 17 Group Members Muaaz Bhatti (TL) Syed Zulqarnain Hassan Mustafa Pasha 20L-1434 20L-1493 20L-1480 Advisor Ms. Akbare Yaqub Client Mr. Hamza Yousuf 3rd June, 2024 Abstract The Final Year Project encapsulates the creation of an innovative material classification system, integrating sensor fusion and machine learning to optimize industrial sorting processes. The project was conceived in response to the need for more efficient recycling systems, which are crucial for managing the growing problem of waste globally. Using a combination of IR sensors, metal proximity sensors, color sensors, and load cells, the system is designed to identify and sort various materials such as metals, plastics, and glass, based on their physical properties. The methodology involved developing a detailed hardware setup that includes a conveyor belt mechanism outfitted with the aforementioned sensors. This setup facilitates the real-time acquisition of data as materials pass through the system. Concurrently,