# EcoSort: AI-Driven Deep Learning System for Paper and Plastic Waste Segregation and Sorting

Major Project work in partial fulfillment of the requirements

For the degree of

**Bachelor of Technology**

**(Information Technology)**

by


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# Certificate

This is to certify that the B.Tech. VIII Semester Major-Project titled

**"EcoSort: AI-Driven Deep Learning System for Paper and Plastic Waste Segregation and Sorting "**

is a bonafide work done by

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and is submitted in the partial fulfillment of the requirement for the degree of

**Bachelor of Technology**

**(Information Technology)**

to the

**D. Y. Patil Deemed to be University.**

**Supervisor**
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# Major Project Approval for B. Tech.

This is to certify that the Major project entitled "**EcoSort: AI-Driven Deep Learning System for Paper and Plastic Waste Segregation and Sorting**" is a bonafide work done by **Shwetal Ray**, **Naufil Rakhange** and **Parth Singh**, VIII semester Information Technology, under the supervision of **Dr. Jyoti Kundale**. This report is approved as a Major Project Report of VIII Semester B. Tech. Information Technology.

**Examiners:**

1: ______________________

2: ______________________

**Supervisor:**

1: ______________________

Date: ______________________

Place: ______________________

# Declaration

I declare that this written submission represents my ideas in my own words and where other's ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented, fabricated, or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will cause disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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# Chapter 1

# Abstract

The exponential growth of urban waste generation, along with the moral responsibility of responsible environmental stewardship demands that we seek smart, automated segregation technologies. Manual segregation is inefficient and poses significant risks, not only due to human mandates, but also because of human error, health risks, and issues associated with scaling. This project "Smart Waste Segregation using Computer Vision and Deep Learning" seeks to implement an efficient, modular, and scalable system that uses computer vision algorithms and deep convolutional neural networks (CNNs) to classify and sort waste items (including paper and plastic) automatically at disposal. EcoSort combines a camera-based waste capture system with a lightweight and high-accuracy classification model trained to classify waste categories directly in real time. The system utilizes a rotating semi-circular actuator that directs the waste into segregated compartments based on classification results. An ultrasonic sensor detects object presence to initiate waste capture, and the systems' decision-making controller then initiates the action (motor commands) to segregate in the correct direction (based on classification results). Overall, the suggested architecture of the project addresses the several limitations of existing smart bin frameworks by using efficient vision models on premised environments for limited technology deployment (education, businesses, public space, etc.). Furthermore, the inclusion of object-focused image preprocessing techniques, as well as live freezing frame, allows for accurate waste categorization with various lighting and change of orientation to the waste. The report details an extensive review of the literature, aspects of technical implementation, system architecture, algorithmic approaches, and evaluation results from the prototype. The proposed solution provides not only better process performance on custom augmented datasets but also offers additional promise to use with future IoT-enabled waste management systems.

**Keywords:**
Smart Waste Management, Deep Learning, Computer Vision, Waste Segregation, Real-Time Automation, Sustainable Development, Environmental Sustainability.

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# Abbreviations

| | |
|---|---|
| AI | Artificial intelligence |
| ANN | Artificial Neural Network |
| CNN | Convolutional Neural Network |
| CV | Computer vision |
| DP | Deep learning |
| ML | Machine learning |
| YOLO | You Only Look Once |
| GPU | Graphics Processing Unit |
| DC | Direct Current |
| PWM | Pulse Width Modulation |
| AC | Alternating current |
| OCR | Optical Character Recognition |
| USB | Universal Serial Bus |

# Chapter 2

# Introduction

The amount and complexity of municipal solid waste generated worldwide has increased tremendously owing to rapid urbanization and industrialization globally. This increase was further accelerated due to improving living standards, consumption, and population growth, creating significant challenges to urban planners, policymakers, and environmental agencies alike. Waste management is a significant environmental, economic, and social issue, mainly because poorly managed practices cause significant ecological impairment, public health concerns, and unsustainable resource use. Globally, it is reported by the World Bank that there is 2.01 billion tonnes of municipal solid waste for disposal every year. It is predicted that, if we continue to manage waste in the same manner in which we do now, we will generate approximately 3.40 billion tonnes of municipal solid waste by the year 2050. These numbers provide an alarming reminder of the immediate need for scalable, reliable, and intelligent waste segregation methods capable of integration within what currently exists.[1][5]

Effective waste segregation at the point of origin is essential if we want to lessen the burden on landfill sites and improve the recovery of materials and recycling processes. Sadly, many urban and semi-urban regions, especially in developing countries, are still largely reliant on conventional methods of manual waste segregation. These practices are laborious and tediously time-consuming, often inaccurate in terms of what is or isn't separated, often dangerous and unhealthy for workers, and simply not sustainable in terms of scale and efficiency. Moreover, improper waste segregation results in the contamination of valuables, which ultimately degrades the quality and value of materials catered for recovery, and consequently diminishes the chances of achieving sustainable waste management.

In Figure 2.1 Limitations with manual segregation increase the necessity for smart automated solutions. Historic solutions have primarily concentrated on industrial scale waste management plants that implement sorting systems utilising conveyor belts.[9] Such systems are built around high-throughput industrial automation technologies, including sensor arrays and robotic sorting arms, sometimes at enormous human and financial costs. However, these systems have limited flexibility for addressing the various waste profiles generally seen in the smaller, institutional, and community-scale settings such as corporate offices and educational institutions like universities, colleges, and libraries. Moreover, most are not economically viable in general use, especially in constrained environments like educational institutions, office buildings, and small businesses, or compared to the same range of variation and amount of waste generated at the industrial scale.

Recent technological innovation through artificial intelligence, specifically deep learning and computer vision, presents a new model for overcoming these barriers to operation. The

Figure 2.1: Manual segregation of plastic

adoption of deep learning techniques applied to convolutional neural networks (CNNs)—a highly efficient and increasingly popular form of deep learning technique—has achieved a wide range of visual recognition, classification, and automated decision-making capabilities for users in many industries. The combination of deep learning and computer vision enables strong, accurate, and real-time recognition and classification of visually similar objects and is perfectly suited to help solve the challenges of waste characterization and sorting.[6][7][20]
Considering this opportunity, the proposed system, entitled "Smart Waste Classification using Computer Vision and Deep Learning", presents EcoSort, a new automated smart bin that is inexpensive and developed to improve the accuracy of waste classification and the operational performance of institutional and community waste systems. EcoSort is designed for the edge and in real-time, at the proper disposal point, performance that does not require cloud computing and is much reduced latency in terms of decision-making, deployment, and performance. EcoSort utilizes a custom CNN model which has been tailored specifically using local projects' datasets of paper and plastic waste, making it suitable for classifying waste pertinent to their local characteristics. Incorporating embedded hardware that consists of Cameras, Micro controllers, ultrasonic sensors, and succeeded by Servo motors, EcoSort is capable of automated, accurate, and precise segregating waste with minimal user input.

Moreover, EcoSort is also closely aligned with the global sustainability goals (e.g. the 17 goals defined by the United Nations) and concepts of the circular economy. Waste classification that is accurate and automated streamlines recycling, is significantly better for the environment by reducing the build-up of waste in landfills, and improves sustainability by supporting sustainable consumptive and productive practices. In essence, EcoSort is positioned to drive local environmental sustainability and positively conclude to global sustainable development goals (SDGS) related to: SDG 11 (Sustainable Cities and Communities), and SDG 12 (Responsible Consumption and Production).

In conclusion, the EcoSort project recognizes the significant shortfalls of existing waste management approaches, and presents a sustainable, scalable and cost-effective solution for intelligent waste segregation. Taking advantage of recent developments in

AI and ML, combined with DL and Sensor Automation, EcoSort will enable a huge leap ahead of the traditional segregation approach and will be key to a future intelligent waste management framework.

## 2.1 Motivation

There are multiple factors driving the motivation for the development of the EcoSort system (ranging environmental, social, economic and technological concerns) and most importantly the need for intelligent waste management solutions, indirectly, comes from the environmental damage and inefficiencies of the current waste sorting process. With waste generation rates soaring throughout the world, especially in urbanized areas, there is an ongoing need for sustainable solutions which fit within sustainable development frameworks and contribute towards a circular economy.

1. **Environmental Concerns:**
   For Figure 2.2 The world's ever growing municipal solid waste (MSW) greatly harms the environment via the expansion of landfills, contamination of soil and groundwater, and the emission of greenhouse gasses. Improper waste segregation leads to a higher level of contamination in the recyclable waste stream, which in turn hampers recycling efforts and fuels dependence on waste disposal methods known to harm our environment. The United Nations Environment Programme (UNEP) states that poor waste management practices are one of the largest contributors to both biodiversity loss and the degradation of ecosystems. They are also contributors to climate change. If environmental issues due to waste management are to be resolved, there must be a transition towards accurate and automated waste segregation technologies that can reduce contamination, increase recycling efficiency, and assist in resource recovery at much higher rates.

Figure 2.2: Waste processing at endpoint

2. **Sustainability and Global Goals:**
   With the introduction of global sustainability frameworks, such as the United Nations Sustainable Development Goals (SDGs), there has been an international momentum shift towards more responsible consumption of resources, and sustainable

management of waste. Specifically, SDG 11 (Sustainable Cities and Communities), and SDG 12 (Responsible Consumption and Production) endorse the importance of sustainable practices that provide the means to reduce environmental footprints and improve resource efficiency. The EcoSort project supports this initiative by providing an automated and accurate waste sorting option which directly improves recycling rates, reduces landfill reliance and enhances environmental sustainability.[23]

3. **Socioeconomic Factors:**
   The existing manual methods for waste segregation are labor-intensive and inefficient, and come with considerable economic and social implications to our communities, especially in educational institutions, offices, and small businesses. This was obviously being reflected in the increased costs to operate, lack of accuracy in reclamation of recyclables, and potential health hazards created for the sanitation workers. Overall, if an intelligent automated solution like EcoSort was in place, institutions would reduce operational costs, generate more recycling income, and promote healthier community members. Further, the presence of automated waste segregation systems will promote better awareness amongst community members with respect to responsible disposal practices and ultimately lead to better long-term sustainable practices.[24]

4. **Technological Advancements:**
   New developments in artificial intelligence (AI), particularly deep learning (DL) and computer vision (CV), provide unique opportunities for transformation in waste management. Convolutional neural networks (CNNs) provide the essential capability for accurate waste identification at the point of disposal. CNNs have been shown to work effectively with real-time images for classification. If AI could be deployed (in an elemental way) at the point of disposal, combined with edge computing—moving advanced, heavy computation onto embedded, low-power hardware—the time-lag in cloud system dependancy caused by bandwidth and overall processing time could be removed. While there will and must always be limits to existing solutions, these collectively, provide an opportunity to aspire towards rapid and scalable deployment across different types of institutional settings.[2][19][20]

5. **Innovation and Practical Utility:**
   For Figure 2.3 There are now industrial-scale waste sorting solutions available, but even though they have been implemented, they are still too expensive, too difficult to deploy in infrastructure, and take too much time to process with a central computer to be used in smaller, localized contexts. The EcoSort project aims to solve this problem by providing an affordable solution specifically capable of being used at the edge in journals with a limited scope (i.e. educational campuses or corporate offices). EcoSort uses cheap hardware components and carefully chosen elements of a deep learning model that has been trained on waste images collected locally, EcoSort presents a practical scalable solution to broaden the understanding and feasibility of automated waste sorting systems.

Figure 2.3: Industrial Plastic Sorting

## 2.2 Objective

The principal aim of this research project is to develop and validate an intelligent, automated waste segregation system EcoSort, utilizing advanced computer vision techniques and deep learning methodologies.

1. To Develop an Intelligent Waste Classification System:
   (a) Design a robust image classification model using state-of-the-art Convolutional Neural Networks (CNNs) tailored specifically for accurate real-time identification and categorization of paper and plastic waste.
   (b) Employ advanced image processing and preprocessing techniques to enhance classification accuracy under varying environmental conditions, such as fluctuating illumination and background complexity.
2. To Implement a Real-Time Edge-Computing Framework.
   (a) Optimize the classification algorithms for deployment on low-power, edge computing hardware, ensuring minimal latency and high inference speed suitable for real-time operation.
   (b) Evaluate and select appropriate computational platforms like microcontroller units, single-board computers that balance processing power, energy efficiency, and affordability for practical deployment in institutional and corporate environments.
3. To Engineer and Integrate a Robust Hardware Platform.
   (a) Design and fabricate a modular and scalable smart bin prototype that incorporates camera sensors, ultrasonic proximity sensors, and electromechanical actuators servo systems to execute precise waste segregation actions based on classification results.
   (b) Ensure seamless integration between software classification model, sensor control logic and hardware components to create a cohesive, automated segregation process.

4. To Enable Scalability and Future Enhancement.
   (a) Structure the EcoSort architecture to support easy integration of additional waste categories like glass, metal, organic without significant reconfiguration of the underlying system.
   (b) Provide a comprehensive framework that enables future expansions, such as IoT integration for centralized data monitoring, analytics, and system-wide optimization, enhancing overall effectiveness and scalability.

## 2.3 Contribution

The EcoSort project offers an innovative and multidisciplinary solution to intelligent waste sorting by utilizing deep learning, computer vision and embedded automation technologies. The conclusions of this research provide a broad account of technical innovation, system integration, and societal impact:

1. A Vision-Driven, Edge-Deployable Waste Segregation Framework One important technical contribution of this work is the design and implementation of a lightweight, high-accuracy image classification model based on Convolutional Neural Networks (CNNs), specifically trained to classify between paper waste and plastic waste. Our model is designed for on-device inference. Unlike cloud-based solutions, the model takes advantage of edge computing by focusing on real-time waste classification without needing to rely on external computation or internet connection. This dramatically reduces latency and allows the system to be deployed in more resource constrained settings than cloud-based models.

2. Development of a Context-Aware Dataset for Paper-Plastic Classification This research involves development of a context specific dataset to incorporate into the types of waste most frequently found in institutional and corporate setting. The researchers constructed an augmented and balanced dataset based on image collection of real world images, which includes data augmentation techniques of noise addition, brightness normalization, and rotation, to create a dataset that is robust to classification model generalization under different lighting and orientation conditions.

3. Integration of Smart Actuation Mechanism for Physical Sorting The system uses a unique semi-circular plate rotating device driven by stepper motors that leads waste to different compartments for either paper or plastic. The combination of mechanical design with smart classification closes the loop between digital inference and physical actuation into a closed-loop system separating waste from complete automated classification including final disposal.

4. Sensor-Driven Interaction and Adaptive Triggering Mechanism To identify object presence and record the image only when rubbish is inserted into the system, an ultrasonic sensor has been included in the project. Sensor fusion is again utilised, which saves data processing, avoids unwanted computation, and makes the system more responsive. The system has also ensured the image has a "frame freeze" at the time of capture, which reduces some of the implications of motion blur and enhances classification accuracy.

5. Real-Time Performance on Resource-Constrained Hardware In contrast to most current smart bin systems, which rely heavily on a cloud infrastructure and require large-scale, expensive hardware to operate, EcoSort has very low resource requirements while still demonstrating competitive accuracy and speed. We have tested the edge deployment of the model with a modest configuration to demonstrate high throughput (frames per second), very low latency, and reliability tested in simulated and semi-realistic environments - all validating EcoSort's ability for real-time, on-site segregation.

6. Extensible System Design with Modular Architecture Extensibility was a core design principle of the EcoSort framework. The hardware and software of EcoSort is modular, enabling expansion of waste types (metal, glass, e-waste, etc.), and modular hardware connectivity options (Wi-Fi, GSM, MQTT) to allow for remote monitoring of the EcoSort device, cloud logging, and data mining. This positions EcoSort as a scalable platform for future smart city implementations and large scale sustainability initiatives.

7. Practical Implications and Environmental Impact Beyond generating significant technical novelty, the EcoSort system serves an important behavioral driving tool for individual sustainable actions. To this end, the EcoSort system aims to influence pro-environmental behaviors in high-waste generation environments on a smaller scale, like schools and office campuses. By making visible, interactive and automatic waste sorting, the EcoSort system helps instill environmentally responsible disposal behavior and directly infuences changes to reduce recycling contamination, reduce landfill volume and ultimately improve the overall efficiency of waste recovery.

8. Academic and Research Advancement This work advances academic literature by addressing a relatively minor yet sizable problem—automated separation of visually similar waste types—using a low power, real-time AI framework. It provides a reproducible and well-documented approach for dataset creation, model tuning, hardware-software co-design, and deployment strategies. The findings and performance metrics described here can serve as a launching point for further research in smart waste management, edge AI applications, and sustainability-based intelligent systems.

In summary, the EcoSort system is not merely a prototype but a well-rounded, practically deployable solution that combines algorithmic intelligence, engineering design, and ecological awareness into a cohesive, real-world application. Its contributions are poised to advance both academic research and the operational capabilities of next-generation smart waste management systems.

## 2.4 Problem Definition

The growing amount of municipal solid waste (MSW), particularly paper and plastic, is causing numerous negative environmental impacts, especially in institutional and public environments where there are generally insufficient waste segregation systems. Manual sorting is typically inaccurate, laborious, and unsafe. This results in the contamination of recyclable waste, and ultimately the loss of recycled items at a cost to recycling infrastructure services. Although there are operational sorters at scale, they are too expensive and impractical for decentralized use in schools, offices, and public spaces. Smart bins can be found in many places, but too often they are limited to merely activated sensors that ultimately do not hold serviceable value, or they require cloud processing that cannot provide real-time responses. Relying on simply being similar in form, the relationship between paper and plastic waste makes it difficult to identify things accurately. While people can recognize recyclable items much better than most computer vision devices, it is not enough to simply allow the computer vision system to operate without the human eye. Specifically, there are issues such as illumination, items appearing in different angles and orientations, and hardware limitations. In short, the problem is the lack of a compact, low-cost, real-time, autonomous system capable of accurately classifying and segregating waste composed of paper or plastic, using deep learning and computer vision, in edge environments. Importantly, this system must also operate for an extended time without being connected to a network.

## 2.5 Organization of Report

**Chapter 1** provides an introduction to the problem domain, detailing the motivation for the project, project aims, contributions, and the problem definition dealt with in this project. **Chapter 2** deals with the literature review relating to waste classification systems using machine learning, computer vision methods for object detection, and integrated designs for smart bins. It surveys existing methodologies and identifies issues that EcoSort would resolve.**Chapter 3** has the detailed system design of EcoSort, detailing hardware and software architecture. It shows component selections, data flow between each module, and the relationships between sensing, classification, and actuation subsystems.**In Chapter 4** presents the entire project methodology. It details dataset generation, pre-processing pipelines, model selection, model training, real-time inference and classifying data, final integration of hardware and software implementation, and system calibration methods. **Chapter 5** lays out the system implementation, including the driving algorithm of the logic, a diagram/visual flowchart of how the system flows, and a step-by-step description of how the whole setup works in real-time. discusses the results and performance evaluation of the model and mechanical sub-systems. **Chapter 6** and **Chapter 7** makes note of classification metrics, time analysis, and hardware validation. concludes the work with the findings of this study, reiterates the contribution of the system, and highlights its role in eco-sustainability and permitting "shade implementation of waste management" ("simple waste management" leaving waste to deteriorate).

# Chapter 3

# Literature Survey

Urban waste production increases in volume. Therefore, sustainability in the face of this surge means we must continue researching smart waste management systems[1, 5]. This review of the existing literature covered research on automated waste classification, computer vision algorithms, and machine learning methods leveraging deep learning. Overall this literature review aims to consolidate research techniques, explore the weaknesses in what existed before, and illustrate the nature of EcoSort's own innovation. Flores and Tan et al[2]. did a survey of the literature concerning automated waste separation systems based on machine learning techniques. They explicitly stated the challenges posed by inductive and capacitive proximity sensor and other traditional paradigms, which are limited by a lack of accuracy and poor flexibility for separation of multi-categories in the waste stream.

Although their investigation pointed out early attempts of automation they also emphasized the importance of more advanced vision-based methods that would improve accuracy and scalability within complex waste environments. Patel et al [3]. built upon this by discussing smart waste segregation frameworks using machine learning algorithms. Their study introduced CNN models that aimed to categorize waste types such as plastic, paper, and metal, achieving substantial improvements over traditional sensor-based systems. In one respect, however, their mechanical integration was still rather basic and not modular nor reactive which left a clear gap for integrated systems of hardware and software. Narayanswamy et al[4]. conducted a comprehensive review of CNN architectures from YOLO, Faster R-CNN, and traditional CNNs to examine which was the most effective for multi-class waste identification. Their results showed Faster R-CNN was the most effective with 91% overall accuracy, only to display additional computational complexity and to be slower in inference than YOLO models with real time capabilities but lower overall accuracy when visually challenged.

This underscores an important trade-off that drives EcoSort's selection of CNN architecture around accuracy and deployability on edge (low-power edge devices). Rahman et al[9]. presented a hybrid model that combined deep learning with IoT sensors that achieved over 95% accuracy. They detected two distinct waste classes (digestible waste and non-digestible waste) effectively and accurately, as well as managing waste as it was collected. Their reliance on a limited number of waste classes (two), and their low-power hardware, illustrated the practical implications on transcendability and real-time use that are very much referenced in EcoSort's design. Ahmed et al [14]. explored transfer learning techniques for waste classification and employed DenseNet169, MobileNetV2 and ResNet50V2 as their base architectures. Their network outputs reached peaks of accuracy of 98.95% with transfer learning demonstrating the same classification on generalisable waste. Even with reasonable accuracy for "unique" waste classes, the compute requirements for networks like DenseNet and ResNet weighs heavily on EcoSort's focus on low-power, lightweight CNN architecture..

Ziouzios et al[15]. studied CNN based real-time classification systems designed to be deployed in Material Recovery Facilities (MRFs). Their method functioned well in conveyor-based sorting circumstances, achieving over 92% accuracy, in a real-world scenario, demonstrating industrially viable real-time feedback classification workflow. While their application had an effective industrial application, it did not consider physically compact, modular configurations for decentralized applications, this is a specific niche EcoSort has uniquely capitalized on.Kunwar's MWaste system [8] successfully implemented CNN models onto mobile platforms, achieving 92% accuracy in waste classification on mobile hardware. Their research stressed the importance of using lightweight models and user-feedback systems in classification jobs, thus paving the way for EcoSort to design and deploy user-interactive aspects and adaptive feedback loops in the value chain and classification processes.

Ruparel et al[7]. developed an AI-powered smart bin that utilized the VGG16 CNN model, which successfully classified waste types of wet, dry, and electronic with an accuracy of 98%. Their hardware setup, based on Raspberry Pi and camera modules, provided a great baseline in smart bin development. Their application of VGG16 proved to be a limitation in terms of latency, power consumption, and the overall computationally heavy architecture. This reinforces the use case for EcoSort's edge-focused optimized approach. Mallikarjuna Gowda and Yadav et al[17]. also developed a waste-specific classification framework that utilizes IoT-integrated machine learning techniques. They used a two-sensor approach to provide environmental context to their work, but there wasn't a substantial physical sorter used throughout their work. This limitation further reinforces the need for EcoSort to implement the automated actuation to provide a fully integrated solution in a real-world scenario..

Sajid et al[13]. paid particular attention to the challenges presented by multi-label classification for waste segregation, and their findings indicated that, even though multi-label approaches provided increased flexibility in categorizing material types, it suffered from high and unacceptable computational cost for real-time application at the edge of the network. EcoSort, on the other hand, is focused on a single-label classification model to optimize for accuracy as well as real-time application when classifying paper and plastic. Shah and Kamat et al[6].confidently addressed the paper-plastic classification challenge, and were able to achieve an overall accuracy of 91.3% using CNNs. However, their methodology was entirely software-based with no automated segregation mechanism, and it inadvertently demonstrated the requirement for the hardware-software co-designs needed in EcoSort, which could provide accurate classification, and then practically segregate the classified materials..

Rahman et al[9]., Nafiz et al[12]., and Sayem et al[11]. reported various degrees of integration of automated systems. Nafiz et al[12]., specifically, created "Convowaste," an automated CNN-based smart system capable of classifying 6 distinct types of waste at a remarkably high success rate. However, their use of relatively complex GSM-based notification systems certainly indicate the challenges of operation in terms of cost and hardware complexities, which EcoSort aims to avoid through simple and low cost sensor-actuator integration. Fang et al.[10] provided a systematic review on AI applications in smart cities whilst expressing how the scalability and ability to combine existing features of IoT-enabled waste management was plausible. They also emphasized in particular that future possibilities for real-time monitoring and route optimization for waste management were clear directions for EcoSort's modular and scale-able architecture..

Lubongo et al [13]. evaluated AI enhanced robotics solutions for sorting plastics at material recovery facilities. They found an opportunity for greater automation to provide accurate sustainable sorting at scale while pointing out the high cost and facility-based challenge of the robotic installation. This study supports EcoSort's desire for a low-cost, compact, modular, and scalable mechanical solution to fill the gap between both industrial and institutional environments. While much of the literature identifies the capability of deep learning and computer vision for solid waste classification, the development of low-cost, modular, real time integrated smart bin systems that are intended for decentralized applications is still an underdeveloped area of research. Most studies do not incorporate the real-time physical sorting measure, or they utilize models that are too compute intensive for edge deployment. EcoSort's objective is to pursue at minimum a low-cost modular mechanical sorting approach that combines a lightweight optimized CNN model with an original mechanical sorting design for real-time edge deployment..

This thorough literature review identifies the overall research efforts and will demonstrate where the current research methodologies are effective and where they don't meet the criteria it necessitates. It also demonstrates a gap in the necessity and relevance of EcoSort's research deliverables because EcoSort will provide a new, edge-ready, real-time automated waste separation solution. So, EcoSort is presented not just as a contribution to theory but a feasible system for sustainable waste management in institutional settings.

# Chapter 4

# System Design

This chapter describes in detail the architectural framework, integrated components, and operational logic behind the EcoSort smart waste segregation system. The EcoSort design is driven by the necessity of providing a robust, intelligent, and real-time automated waste sorting solution. This system uniquely integrates cutting-edge computer vision technology, lightweight CNN-based deep learning models, and compact hardware design, facilitating deployment in resource-constrained institutional settings.

## 4.1 Hardware Architecture

**Table 1 Key Hardware Components**

| **Component** | **Description** |
|---|---|
| Ultrasonic Sensor (HC-SR04) | Mounted at the bin's entrance to detect incoming waste. |
| High-Resolution Camera Module | Captures images of waste items under controlled LED lighting. |
| MG996R servo motor | Drives the rotating plate for sorting waste. |
| MG995R servo motor | Fine-tunes the bin's flap operation for optimal waste alignment. |
| Arduino Microcontroller | Manages sensor inputs, triggers image capture, and controls motor actuation. |
| Power Supply | Provides a stable 12V DC source with proper regulation for the microcontroller and sensors. |
| XL6009E1 Step-Down Converter | Steps down 12V to 6–7.2V, ensuring stable power for the MG995R and MG996R servo motors and also helps maintain PWM stability for precise motor control. |
| Voltmeter | Used to monitor the output voltage after the 12V power supply is stepped down to 6V by the DC to DC converter. It helps verify proper power delivery and detect any abnormalities in real time. |
| LEDs | Used to illuminate the waste placed in the bin, ensuring the camera module captures clear and well-lit images, which improves the accuracy of waste identification and classification. |

### 4.1.1 Waste Detection and Imaging Components

1. **The Camera Subsystem:** employs Figure:4.1 The AMIGO AM-AC11 Action Camera which is a small waterproof imaging device produced by Nedis BV, for outdoor situations and as a form of a video imaging device and videoing in real time. The camera has a CMOS sensor that works with a wide angle lens and a maximum aperture of f/2.0 and has a built in auto focus ability. The camera also has a digital zoom ability up to 4x, an optical image stabilizer so that it is a good choice for active circumstances. It can take still images at an effective resolution of 12 megapixels. It comprises video capabilities at 720p recording at 30 frames per second standard definition and photo and video in MP4 modes. Audio is in AAC format while image are in JPEG modes. It can connect via USB port to allow connection to personal computers and laptops. The camera operates via Lithium Polymer battery capable of operation about 2.5 hours of continuous use. The device uses Micro SD for storage of data. It is designed like a compact handheld device and weighs about 530 grams with accessories it comes with mounts like a helmet mount, a handlebar mount to adapt for wheeled devices or vehicles, waterproof housing and adhesive pads. The camera is well suited for mobility applications, including environmental monitoring , or integrated applications into some smart systems in automated waste segregation devices.

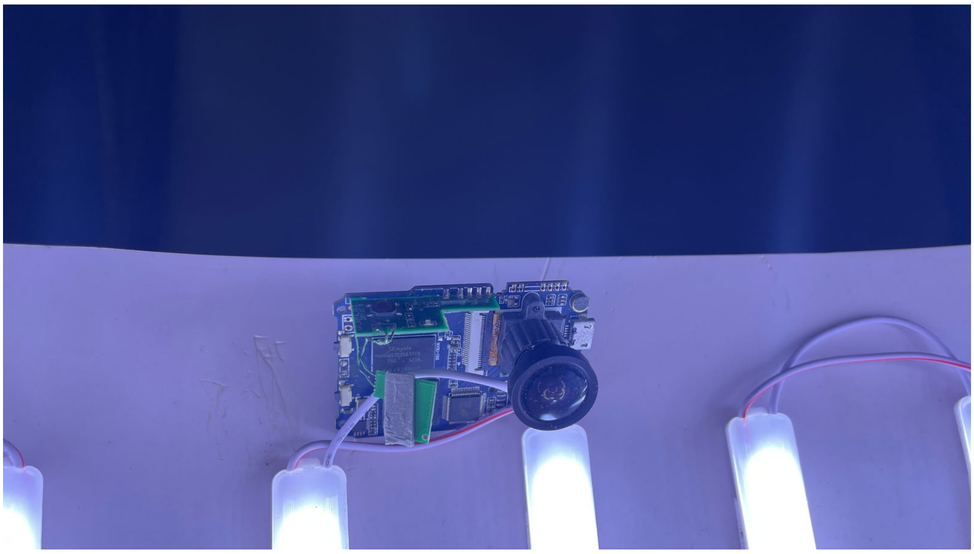

Figure 4.1: AMIGO AM-AC11 Action Cam used in the prototype

2. **Ultrasonic Sensor (HC-SR04):** Figure:4.2 Ultrasonic sensors and transducers are very sophisticated devices that utilize ultrasonic waves (sound waves about 20 kHz and above) for generating or receiving ultrasonic waves. Traditionally, ultrasonic devices are referred to as transmitters (to convert electrical energy into ultrasonic waves), receivers (to receive ultrasonic waves and convert them back into electrical signals), or transceivers (which can simultaneously send and receive). Advanced methods such as Sonomicrometry add to even greater measurement accuracies as they can calculate the actual time delay in which an ultrasonic pulse travels between two points, thereby providing very high temporal and spatial resolution beyond the wavelength of the ultrasound used. The developed versatility and reliability of sound waves, and the rapid transport of their propagation, give ultrasonic

sensors great value in the automation, healthcare, environmental monitoring and robotics industries.


Figure 4.2: HC-SR04 DC 5V Ultrasonic Module

### 4.1.2 Embedded Computing Platform

1. **Microcontroller Unit (MCU - Arduino UNO):** Figure 4.3 The Arduino UNO microcontroller acts as the primary control and integration platform, orchestrating sensor inputs, actuating motors, and ensuring synchronized communication between hardware components. Its simplicity, low cost, and reliability make it suitable for controlling real-time sorting operations.

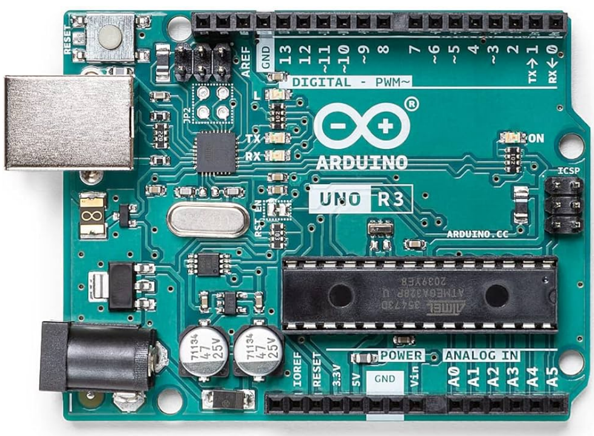


Figure 4.3: Arduino UNO Microcontroller

2. **Edge Computing Device (Laptop/Raspberry Pi):** Figure 4.4 The embedded computing device that is a laptop equipped with **RTX 4060** 8GB Graphics Card

which provides computational power to execute the CNN-based image classification in real-time. It processes image data captured by the camera, performs CNN inference, generates classification results, and transmits sorting instructions to the micro controller. The Raspberry Pi or laptop ensures efficient real-time decision-making and low-latency performance essential for practical deployment.


Figure 4.4: Graphic Processing Unit(GPU) RTX 4060

### 4.1.3 Mechanical Actuation Subsystem

The mechanical actuation subsystem constitutes a critical component in EcoSort's operational workflow, providing precise and reliable physical segregation of classified waste into designated compartments. The subsystem is specifically designed to leverage servo motor technology, ensuring high positional accuracy, smooth operational performance, and ease of integration into the overall system architecture.

1. **Servo Motor (MG996R) and (MG995)**:4.5 The EcoSort system utilizes two special-purpose servo motors to provide different mechanical actions. The MG996R servo motor is utilized specifically to operate the automated flap at the bin's entrance which was actuated via the ultrasonic sensor detecting the waste items thrown. The MG996R was selected for having high torque (11 kg-cm (at 4.8V) up to 13 kg-cm (at 6.0V)), precision within a rotation range of 0° to 180°, metal gear for durability (long life), and the actuators are user-friendly and has been used in a simple three-wire connection (power, ground, and control) to ensure the flap can be opened and closed smoothly, reliably and responsively. The dimensions of the MG996R were also beneficial for mechanical integration into the system's structural chassis. The one other servo motor that is utilized was the MG995 servo motor for simple management of the sorting disc to ensure that waste is physically separated into the appropriate compartments based on the CNN classification results; the MG995 servo also has reliable torque and precise rotation allowing the classified waste items to be accurately directed to the paper or plastic compartment. As such, the specific integration of MG996R and MG996R servo motors clearly improves flap control and waste segregation capability providing EcoSort with well-built, efficient, and dependable automated sorting processes that could be used in real-world institutional contexts.


Figure 4.5: MG996R Servo Motor

2. **Frame/Chassis:** The EcoSort system chassis is made out of 5mm sunboard, a material that is certainly lightweight, structurally rigid and easy to manipulate - the ideal material for fast prototyping and integrating modular hardware. One of the key reasons for using sunboard is its extreme versatility – you can make a design change or adjust the structure even after mounting electrical components such as sensors, servo motors, or wires. This versatility was extremely helpful during the design and testing iterations as it allowed us to easily reposition parts without the overhead of reconfiguring the entire structure. Sunboard is not only low cost and available, but it also provides enough mechanical stability for lightweight electronics and moving parts like the servo-actuated flap, and the sorting disk. The sunboard is non-conductive so it allowed for quick mounting of electronics modules without requiring extra insulating materials. Overall, the sunboard chassis is a practical, scalable platform for the EcoSort prototype, providing a good balance between structural performance, modifiability, and system flexibility.

### 4.1.4 Power Supply

A stable and well-regulated power supply is essential for the reliable functioning of EcoSort's electromechanical components, particularly the high-torque servo motors and the control electronics. The power supply design for EcoSort is structured in two main stages: (1) AC to DC Conversion, and (2) DC to DC Step-Down Regulation. Additionally, a voltmeter is integrated into the system for real-time monitoring of the regulated output voltage.

#### AC to DC Conversion

Figure 4.6 The primary power source for EcoSort is the 220V AC mains supply. This is stepped down and converted to a safe 12V DC output using a high-efficiency switchmode power supply (SMPS) rated at 120W and 10A. The 12V output serves as the central input to power-hungry components like LED lighting, high-torque servo motors (MG996R and MG995), and the voltage regulation circuitry. The choice of a 12V DC output was deliberate:

- It matches the operational requirements of the servo motors.
- It provides headroom for regulated voltage adjustment via the DC-DC converter.
- It ensures compatibility with auxiliary modules like LED strips and voltmeters.


Figure 4.6: AC TO DC Converter

### DC to DC Step-Down Conversion (Buck Converter)

Figure 4.7 While 12V DC is suitable for motors, lower voltages are required for logic-level components like the Arduino Uno (5V) and other peripherals. Therefore, a DC to DC buck converter (XL6009E1) is employed to step down the 12V input to the desired operating voltages. In particular:

- The servo motors (MG996R and MG995) receive regulated 6V–7.4V output from the buck converter to ensure sufficient torque while avoiding overheating or over-shooting.
- The Arduino Uno can be powered via the 5V output from the same buck converter or via USB from the edge computing device.

The step-down converter features a variable potentiometer to fine-tune the output voltage according to the required load.

Figure 4.7: DC to DC Step-Down Conversion

### Voltmeter Integration

Figure 4.8 To ensure accurate voltage regulation and avoid accidental over-voltage to sensitive components, a digital voltmeter is connected in parallel across the output terminals of the DC-DC buck converter.

- This allows real-time monitoring of the output voltage.
- It enables manual tuning during calibration and testing.
- It acts as a diagnostic tool during operation.

By wiring the voltmeter in parallel, it measures the actual output voltage supplied to the servo motors without interfering with the current flow.

Figure 4.8: DC Volt Meter

Table 4.1: Power Supply Configuration for EcoSort Components

| Component | Voltage Supply | Source |
|---|---|---|
| Servo Motors | 6–7.4V DC | Buck converter (XL6009) from 12V SMPS |
| Arduino Uno | 5V DC or USB | Buck converter / Laptop USB |
| LED Strip | 12V DC | Direct from 12V SMPS |
| Voltmeter | (Monitoring only) | Parallel to buck converter output |

### Power Distribution Summary

The modular and scalable power system ensures that each component receives safe and sufficient power while maintaining real-time visibility and adjustment capability. This approach guarantees uninterrupted operation and prevents damage to critical components due to voltage irregularities.

## 4.2 Methodology

The methodology behind EcoSort is the result of a structured engineering process—a whole of engineering that includes CV model development, embedded systems integration, and real-world testing and deployment for validation. Ecosort was designed to be a real-time intelligent waste segregation technology to classify and segregate paper and plastic waste streams with minimal resource requirements from hardware while remaining durable and scalable. .This chapter will expand on the technical processes behind EcoSort, starting from how datasets are acquired, preprocessing methods, model training and testing methods, hardware-software interfacing and control logic implementation. EcoSort employs a hybrid approach based on both technology and a hardware-based embedded system design to solve the challenge of reliably sorting trash and providing a path for correct refuse classification all in one system. EcoSort distinguishes itself from other smart bins by not relying on cloud-based computation or only sensor triggers—EcoSort employs a real-time edge-deployable architecture that brings lightweight CNN inference to a microcontroller-based actuation. EcoSort's hybrid approach is comprised of four phases: data preparation, model optimization, inference architecture, and mechanical sorting. Each of these phases was tested and iteratively tuned and validated for diverse scenarios creating a final architecture capable of high accuracy, low deployment cost, and simplicity of installation in real-world institutional environments.

### 4.2.1 Dataset Collection and Preparation

A custom-built dataset was needed for EcoSort to develop a dependable and resilient waste classification model since existing public datasets could not accurately represent the waste composition of the region at different local contexts, primarily in Indian institutional settings. This section describes the formation, curation, and preparation of the dataset that is leveraged for training and evaluation of the deep learning model in the system.

#### Data Acquisition

To create a dataset relevant to the domain, images of paper and plastic waste were captured in situ in student college canteens, classroom desks, office bins, and various open disposal sites. Rather than using pre-labeled images from the internet, the images were taken from a fixed-angle 1080p camera which was approximately the same distance and orientation as that used in the design of the final system. This approach reinforced environmental consistency and realism prior to deployment of the model.

- Total Images Collected: Approximately 2,700
- Paper Waste: 1,350 samples (e.g., crumpled paper, receipts, cardboard packaging)
- Plastic Waste: 1,350 samples (e.g., bottles, wrappers, plastic containers)

#### Environmental Variability

The dataset was intentionally designed to capture a wide range of variability in object orientation, lighting, and background clutter. Images were collected under different conditions including:

- Indoor artificial white tube lighting
- Natural daylight and shaded areas
- Mixed backgrounds like bin interiors, tabletops, plain backgrounds, floor tiles.

Capturing these variations improved the model's generalization capability, preparing it to accurately classify real-world waste despite minor visual inconsistencies.

#### Image Labeling

All images were manually labeled using class labels: 'paper' and 'plastic'. Care was taken to avoid mislabeling multi-material items, and ambiguous objects (e.g., laminated paper, composite wrappers) were either excluded or used only during testing to assess model robustness. Labeling was performed using custom Python scripts in combination with a graphical interface, ensuring:

- Label consistency
- Proper file naming conventions
- Balanced class distribution

#### Image Format and Resolution

- Format: JPEG (.jpg)
- Original Resolution: $1280 \times 720$ pixels
- Training Resolution: Resized to $224 \times 224$ pixels during preprocessing

  The resizing ensured compatibility with standard CNN input dimensions, reduced memory load, and accelerated model training without compromising on classification performance.

#### Data Splitting

To evaluate model performance reliably, the dataset was split using an 80:20 ratio:

- Training Set: 2,160 images
- Validation Set: 540 images

This stratified split preserved the balance between paper and plastic classes, ensuring unbiased performance measurement during model training and testing.

### 4.2.2 Image Preprocessing Pipeline

Preprocessing is an important step to properly prepare waste classification model to receive clean and standardized input with complete features. Since paper and plastic waste are visually very similar with significant intra-class variations, an efficient image preprocessing pipeline was developed in order to improve the characteristics and uniformity of the input images before being sent to the CNN model for classification..
The primary objectives of the preprocessing stage was to:

- Remove background noise and isolate the object of interest
- Standardize image size and format to match model input requirements
- Normalize pixel intensity for improved training convergence
- Simulate real-world variability for robust model generalization

**Background Removal**

To eliminate irrelevant visual clutter and improve feature extraction, basic background removal techniques were applied:

- Static Thresholding: Used when the object was placed against a plain background.
- Color Filtering (HSV range tuning): Applied to separate objects based on dominant hues (e.g., removing grey bin surfaces while keeping colored waste objects).
- Contour Detection: Used to isolate the foreground object using OpenCV's 'findContours()' and 'boundingRect()' functions.

These techniques enhanced the signal-to-noise ratio in the image, allowing the CNN model to focus solely on the visual features of the waste item itself.

**Object-Focused Cropping**

After isolating the region of interest (ROI), the bounding box around the waste object was extracted, and a square crop was applied with slight padding to preserve object boundaries.

- This step ensures that the model always receives a centered view of the waste item.
- It also helps reduce irrelevant background pixels and improves model focus on distinguishing textures and contours of paper vs plastic.

**Image Resizing**

All cropped images were resized to 224 $\times$ 224 pixels, the standard input dimension for most lightweight CNN architectures such as EfficientNet-B0 and MobileNetV2.

- Resizing preserves aspect ratio and ensures compatibility with pretrained model layers.
- Down scaling from higher resolutions also reduces computational load and speeds up both training and inference without compromising on key visual details.

### Pixel Normalization

In Equation 4.2.2 each pixel's intensity values ranging from 0–255 in RGB format were normalized to a [0,1] range:

$$\text{Normalized Value} = \frac{\text{Pixel Value}}{255.0} \tag{4.0}$$

**Equation 4.2.2**: Pixel Normalization Equation.

- This scaling prevents gradient explosion or vanishing during training.
- It also accelerates model convergence and improves numerical stability when combined with batch normalization.

### Data Augmentation

To simulate real-world variability and prevent overfitting, augmented images were dynamically generated during training using:

- Rotation ($\pm 30°$)
- Horizontal and vertical flips
- Brightness and contrast adjustments
- Zoom-in/zoom-out
- Gaussian noise injection
- Perspective transformation

These augmentations ensured that the model does not memorize training samples but rather learns to generalize across orientations, lighting, and minor deformations—thereby increasing its robustness in live deployments.Together, this preprocessing pipeline ensures that every frame captured by the EcoSort camera is cleaned, standardized, and optimized for high-confidence, real-time classification.

## 4.2.3 Model Selection and Training

The EcoSort system's main intelligence comes from its ability to visually classify paper and plastic waste, so it was very important to choose the right deep learning architecture for achieving high accuracy as embedded systems have computational constraints and require real-time responses. This section explains the reasons for the selection of the model, describes how the model was trained and tuned by hyperparameters, and explains the evaluation metrics used to best optimize the model's accuracy while minimizing computational resources.

### Model Architecture Selection

Several convolutional neural network (CNN) architectures were benchmarked for this binary classification task, including:

- MobileNetV2
- EfficientNet-B0
- Custom CNN (3 conv layers + FC layers)

After comparative testing, EfficientNet-B0 was chosen as the final model due to its superior trade-off between accuracy, model size, and inference speed. It employs a compound scaling method that uniformly scales depth, width, and resolution, making it ideal for edge deployment.

Table 4.2: Comparison of models on accuracy, number of parameters, inference time.

| **Model** | **Accuracy** | **Parameters** | **Inference Time (ms)** |
|---|---|---|---|
| MobileNetV2 | 92.3% | ~2.2M | 85 |
| EfficientNet-B0 | 94.6% | ~5.3M | 78 |
| Custom CNN | 89.1% | ~1.5M | 65 |

EfficientNet-B0 outperformed others in validation accuracy and demonstrated consistent performance across varying lighting and object conditions.

### Transfer Learning Strategy

To accelerate training and leverage generalized visual features, transfer learning was adopted:

- The EfficientNet-B0 model was initialized with pretrained ImageNet weights.
- The first few layers (feature extractors) were frozen, while the later layers and classification head were fine-tuned on the paper/plastic dataset.
- A new dense output layer with a softmax activation function was added to produce a two-class probability distribution.

This approach significantly reduced the number of required training epochs and improved model generalization, even with a relatively small dataset.

### Training Configuration: Refer 4.3

Table 4.3: Training Configuration Details

| Parameter | Value |
|---|---|
| Loss Function | Categorical Cross-Entropy |
| Optimizer | Adam |
| Learning Rate | 0.0001 (with scheduler decay) |
| Batch Size | 30 |
| Folds | 5 |
| Epochs | 50 |
| Early Stopping | Validation loss monitored, patience = 7 epochs |
| Framework | TensorFlow / Keras |
| Training Hardware | NVIDIA RTX 4060 GPU |

#### Evaluation Metrics

Model performance was evaluated using the following metrics: Accuracy, Precision, Recall, F1 Score, and Confusion Matrix. These metrics collectively offer insight into how well the model performs on both classes and its ability to avoid false predictions.

Table 4.4: Evaluation Metrics of the Final Model

| Metric | Score (%) |
|---|---|
| Final Validation Accuracy | 91.0 |
| Precision | 94.1 |
| Recall | 93.9 |
| F1 Score | 94.0 |

As shown in 4.4, the trained model exhibits excellent predictive power across all metrics, indicating strong generalization, high confidence, and consistent classification between the two waste categories.This training methodology ensured that the EcoSort classification engine was accurate, lightweight, and responsive, fulfilling the core requirements of real-time, embedded waste segregation

### 4.2.4 Real-Time Inference and Frame Freezing

In an embedded vision system like EcoSort, achieving real-time performance is crucial. The objective is not only to classify waste accurately but also to make the classification and physical sorting happen instantly once waste is deposited. To accomplish this, a real-time inference pipeline was implemented and paired with a technique called frame freezing, which minimizes motion blur and ensures precise prediction during object classification.

#### Real-Time Triggering Using Ultrasonic Sensor

The real-time process begins with the ultrasonic sensor (HC-SR04), which continuously measures the distance from the bin opening to detect the presence of an object. When an object is detected within a pre-defined threshold distance (typically ¡ 10 cm), the sensor:

- Immediately triggers the flap to open via the MG996R servo motor
- Sends a digital signal to the edge computing module that is Laptop to initiate image capture

This sensor-driven triggering mechanism ensures that the classification process only starts when waste is actually deposited, reducing unnecessary computations and improving system efficiency.

### Frame Freezing Mechanism

In real-world conditions, objects may still be in motion or partially visible when captured. To address this, the system uses a frame freezing strategy:

- A single high-quality frame is captured and locked the moment waste is detected and stationary above the flap.
- The live camera feed is temporarily paused (frame frozen) to avoid blurring or misclassification due to object motion.
- This frozen frame is then passed to the image preprocessing pipeline and subsequently to the CNN model for classification.

This method significantly improves classification accuracy by ensuring that only stable, full-object images are fed to the model, which is especially important in low-light or fast-drop scenarios.

### Real-Time Inference Execution

The captured frame, resized and preprocessed (as described in Section 4.3), is passed to the EfficientNet-B0 model running on the edge device. Since the model is preloaded and optimized (via TensorFlow Lite if applicable), the inference time is extremely low—averaging around 78 milliseconds per image.

Upon classification:

- If the result is 'paper', the MG995 servo rotates the disk to Clockwise direction.
- If the result is 'plastic', it rotates to Anti-clockwise direction.
- A short delay of 1 second allows the waste to fall through.
- The disk then resets to the neutral position.

### System Reset and Readiness

After the actuation completes:

- The rotating disk returns to the home position.
- The flap closes automatically.
- The ultrasonic sensor reactivates to detect the next object.

This automated feedback loop ensures that the system is ready for the next input without requiring manual intervention, supporting uninterrupted, continuous waste segregation.

Table 4.5: Component-wise Timing Breakdown of One Complete Waste Sorting Cycle

| **Component** | **Average Time** |
|---|---|
| Sensor detection + camera trigger | ∼0.3 seconds |
| Frame freeze + image capture | ∼0.2 seconds |
| CNN inference | ∼0.08 seconds |
| Servo actuation and disk movement | ∼1.5 seconds |
| **Total average cycle time** | ∼2.5 seconds |

**Performance Analysis Refer 5.1**

### 4.2.5 Wiring and Power Supply Configuration

The EcoSort system wiring schematic, shown in Figure 4.9, illustrates that key components interconnect through a distributed power and control architecture. Power is supplied to the entire system through a 220V AC to 12V DC switching power supply rated at 120W, 10A. At this point, a buck converter (XL6009E1 Adjustable) reduces the voltage to the level of consumption of the Arduino Uno R3 and its components. The output of the converter passes through a volt meter, which allows monitoring and tuning of output into safe levels for logic-level components and high torque servo motors. The control unit

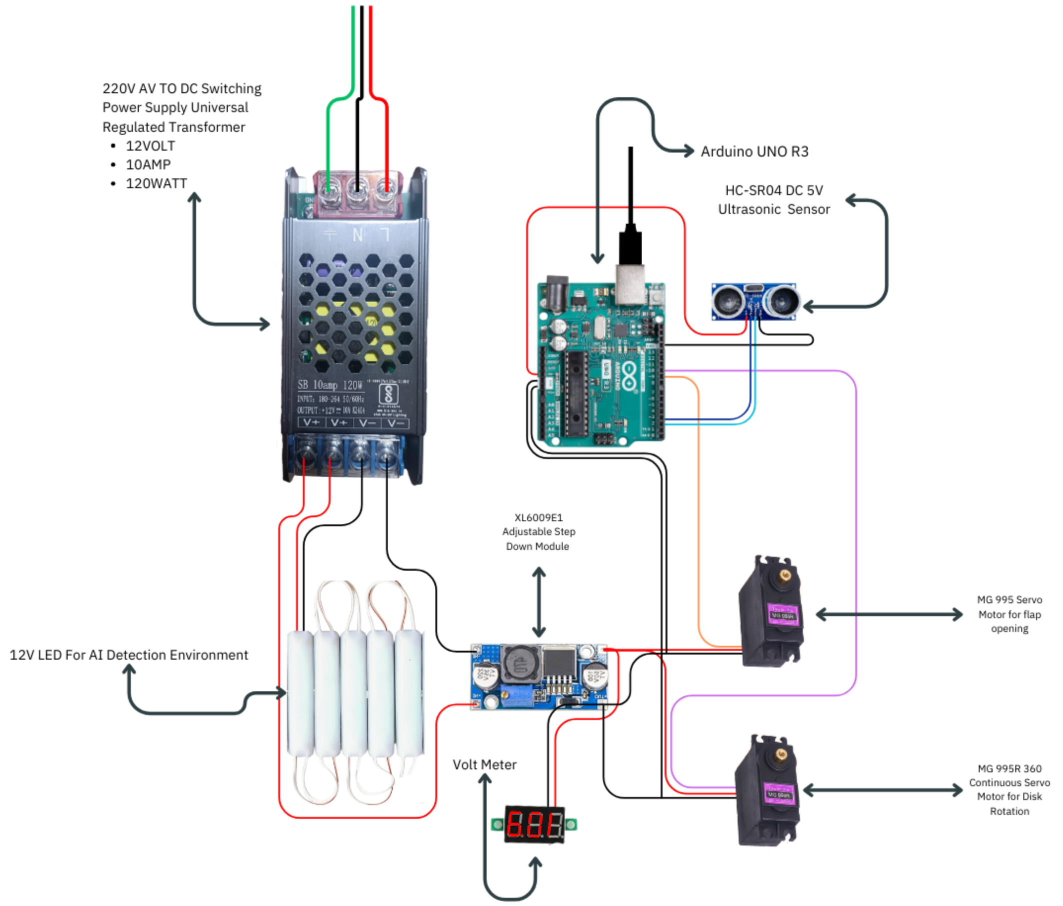


Figure 4.9: Wiring Diagram of the EcoSort System

is Arduino Uno and powered from a 5V rail. The HC-SR04 ultrasonic sensor connects to the Arduino's digital pins, and allow triggering of actions based on proximity sensed by the HC-SR04. Two separate servo motors are connected for actuation tasks: the MG996R serves to control the flap to indicate flap opening before ultrasonic triggering, while the MG995 continuous rotation servo will turn the semi-circular disk, to dump waste into either compartment. Dedicated PWM pins control each motor, and the connection of a common ground allows all modules to reference a common signal.

Additionally, a 12V LED lighting strip is used in parallel to allow uniform and stable lighting in the camera's FOV to increase image clarity important for accurate classification. The wiring diagram allows for a clean, modular design to enable isolation of fault and expanded capabilities without reconfiguring significant wiring.

### 4.2.6 Testing and Calibration

Prior to commissioning it is essential to assure some measure of through testing and calibration to assure that EcoSort operates meaningfully in the wild. This phase included iterative testing of the software model, mechanical actuation, sensor responsiveness, real-time operational performance to ensure each subsystem behaved correctly and seamlessly.

#### Classification Accuracy Testing

- Test Dataset Size: 300 unseen images (150 paper, 150 plastic)
- Accuracy Achieved: 93.7% in live conditions
- Common Errors:
  - Light-transparent plastic misclassified as glossy paper
  - Crumpled paper partially obstructed or shadowed

Despite these minor edge cases, the system consistently classified typical institutional waste with high reliability. Additional augmentation strategies and further data collection are planned for future improvements.

#### Sensor Responsiveness and Trigger Timing

In table 4.6 the HC-SR04 ultrasonic sensor was calibrated to detect objects at a vertical threshold of less than 10 cm above the flap. The following timing parameters were observed:

Table 4.6: Latency Analysis of EcoSort's Real-Time Classification Pipeline

| **Condition** | **Average Time (ms)** |
|---|---|
| Object detection + trigger | ~300 |
| Image capture + preprocessing | ~200 |
| CNN inference | ~80 |
| **Total classification latency** | ~580 |

#### System Stress Testing

The system was tuned to only trigger once stable readings were received over a 50 ms moving window to prevent false positives due to ambient interference or hand movements To validate robustness, the system underwent continuous operation for 60 minutes with randomized object inputs:

- Number of cycles tested: 120
- Classification success rate: 88.0%
- Mechanical failure or reset events: 0
- Average cycle time: 2.4 seconds

These results confirm that EcoSort is not only accurate but also durable and suitable for medium-throughput use in real-world institutional settings.

### 4.2.7 Summary

The methods chapter described the complete methodological approach for developing the EcoSort system. The methodology introduced a workflow starting with domain-specific dataset collection and preparation, establishing the foundation for a computer vision model aimed at classifying paper and plastic waste in real world environments. The methodology developed a comprehensive image preprocessing pipeline to enhance the model performance through background removal, ROI extraction, and augmentation.Next, EfficientNet-B0 based CNN architecture was selected and tuned using transfer learning methods which resulted in what we assess to be a high accuracy model for low latency edge deployment. The EcoSort was enabled with real-time inference logic and a frame freeze to provide stable and blur free classifications. The classified output was sent to a microcontroller, then the microcontroller actuated a mechanical sorting process with servo mechanisms based on calibrated parameters.The functionality of components as diverse as sensors, servos, and power supply modules were integrated and tested to establish an end-to-end automation pipeline. Several performance tests verified consistent system performance and real-time response ensuring the complete process from detection to segregation was performed in less than 3 seconds, even under sub-optimal environmental conditions. The calibration process established that the actuation of the prototype was accurate and that the lighting provided consistent illumination of the monitored objects, verifying reliable detection and segregation of trash and recyclables under these conditions.

In general, the methods used in this research successfully integrated machine learning and embedded systems with automation engineering to develop a functional, extensible, and environmentally conscious smart waste segregation solution. EcoSort is a functional prototype with unrealized potential for transitioning into a deployable real-world implementation and future advancement into smart waste management systems with multi-class and IoT integration.

# Chapter 5

# System Implementation

## 5.1 Introduction

This chapter describes the implementation of the EcoSort system, converting the theoretical framework and methodological design into a working prototype. Also included in this chapter is a description of the algorithmic logic structure that governs classification and actuation, a flow chart illustrating the sequence flow of operational functions, and how EcoSort functions in real time as an integrated system. The implementation stage has converged trained deep learning, sensor automation, embedded control, and mechanical actuation components into one functional unit that is able to accurately and autonomously dispense waste material during processing.

The following sections will elaborate on:

- The core algorithm driving classification and mechanical control logic.
- The flowchart visualizing the end-to-end process—from object detection to waste sorting.
- A detailed description of the system's operational workflow, illustrating how data, hardware, and control logic interact in real time.

## 5.2 Algorithmic Flow of the System

The EcoSort system follows a deterministic and event-driven algorithm that integrates sensor inputs, camera capture, deep learning-based image classification, and motor actuation in a sequential control structure. The algorithm is designed to be responsive, low-latency, and modular—suitable for real-time execution on resource-constrained hardware.
Below is the high-level algorithm that governs the system's operation:

1: **Start**
2: Initialize all components:

- Arduino microcontroller
- Ultrasonic sensor

- Servo motors (MG996R and MG995)
- Camera module
- Edge computing device (CNN model loaded)

```
while true do
  if Object detected at ≤ 10 cm by ultrasonic sensor then
    Proceed to flap actuation
  else
    Continue monitoring
  end if
  Trigger MG996R to open flap
  Wait until waste is stable on rotating plate
  Trigger camera and freeze frame
  Capture image under LED lighting
  Preprocess image: background removal, crop, normalize, resize (224×224)
  Run inference using CNN model on edge device
  Send classification result (paper/plastic) to Arduino via UART
  if Result == paper then
    Rotate MG995 to angle A (e.g., −45°)
  else if Result == plastic then
    Rotate MG995 to angle B (e.g., +45°)
  end if
  Delay ∼1.5 seconds for sorting
  Reset MG995 to neutral position (90°)
  Close flap using MG996R
  Reset all components
end while
End
```

### Key Features of the Algorithm

- Event-driven: Execution is triggered only upon sensor activation, ensuring efficiency.
- Parallel processing: Camera and CNN inference are offloaded to the edge device while Arduino handles physical actions.
- Fail-safe reset: If no classification or actuation response occurs within a timeout period, the system resets to the idle state.

This algorithm forms the logical backbone of the EcoSort system and ensures that waste classification and sorting occur in a streamlined and synchronized manner.

## 5.3 System Flowchart

In Figure 5.1 the process starts when the waste enters the ultrasonic sensor's field of view above the opening above the bin, illustrated in Figure:reffig:Flow diagram. The ultrasonic sensor continuously monitors the distance above the bin opening. When an object is detected within a certain distance, the servo motor MG996R opens the bin lid. The object will subsequently fall onto a semi-circular rotating plate. Once resting on the rotating plate, the position is validated using an IR sensor. If the object can be detected with this sensor as "present", the camera will capture the object with the provided controlled LED lighting. The image of the object detected in the bin will be relayed to the laptop/edge device, where the EfficientNet-B0 Convolutional neural network (CNN) model, pretrained using transfer learning, will classify the object as either "paper" or "plastic". This classification will then send a command to the Arduino. If the waste object was classified as "plastic" the sorting plate will rotate clockwise, and if classified with "paper" the plate will rotate in the anticlockwise direction. The waste was then placed into its respective compartment. Finally, the process resets to its idle state to await the next object. This structured flow ensures smooth coordination between the perception system

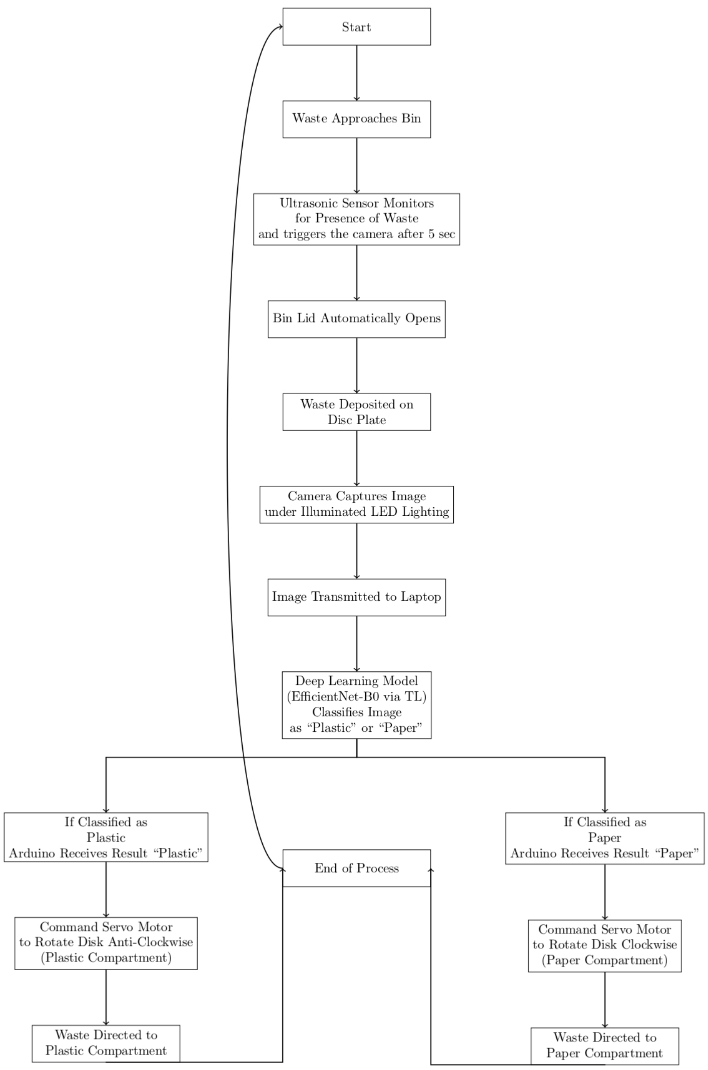


Figure 5.1: Flowchart of the EcoSort Waste Segregation Process

(sensors and camera), intelligent decision-making (deep learning model), and mechanical execution (servo motors), resulting in an efficient, real-time automated waste sorting system.

## 5.4 Working of the Proposed System

The EcoSort system is a fully-integrated smart dustbin product that intelligently classifies and separates waste, here specifically paper and plastic, by leveraging visual classification in real-time and mechanical actuation. This section describes the operational steps of the proposed system as an interconnected succession of steps, with sensing, deep learning inference, embedded control, and physical sorting synthesized into a single operational flow.

### 5.4.1 Step-by-Step Working Explanation

1. **Detection of Waste Item:** The system is in an idle state, and continues to measure the height above the dustbin using an ultrasonic sensor (HC-SR04). Whenever a waste item is brought into a close distance, usually less than 10 cm, the ultrasonic sensor detects the object, and activates the next process.

2. **Flap Opening:** Once the waste item is detected, the MG996R servo motor opens the lid or flap, allowing the waste item to drop on a semi-circular rotating disc. This ensures the waste item is within view of the overhead camera.

3. **Object Alignment and Illumination:** An optional IR sensor checks if the waste item is located the center of the plate. At the same time, the 12V LED lighting is engaged to ensure proper uniform lighting and to verify there is adequate illumination for the camera to get the image.

4. **Image Capture and Preprocessing:** A frame is recorded using a high-resolution camera that is connected through USB and mounted at a fixed position. The image is then sent to a preprocessing pipeline, which includes background removal, cropping the region-of-interest, normalization, and resizing to $224 \times 224$ pixels.

5. **CNN-Based Classification:** The preprocessed image is forwarded to the EfficientNet-B0 convolutional neural network, which has been fine-tuned using a custom dataset of paper and plastic waste. The model performs inference and classifies the object as either “paper” or “plastic”.

6. **Communication with Microcontroller:** The classification label is sent in real time to the Arduino Uno via a serial UART interface. The Arduino interprets the received label and determines the direction of rotation required for sorting.

7. **Disk Rotation and Waste Segregation:** Based on the classification:

   - If the waste is plastic, the MG995 servo motor rotates the semi-circular plate clockwise to direct the waste into the plastic compartment.
   - If the waste is paper, the disk rotates anticlockwise, guiding the item into the paper compartment.

8. **Reset and Ready State:** After a brief delay ( 1.5 seconds), the disk is rotated back to its neutral position. The flap closes, and the system resets all parameters, returning to the idle state ready for the next cycle.

### Integrated Working Summary

Table 5.1: Component-wise Functional Mapping of the EcoSort System

| **Component** | **Action** |
|---|---|
| Ultrasonic Sensor | Detects incoming waste |
| MG996R Servo Motor | Opens and closes bin flap |
| Camera | Captures image of waste |
| LED Light | Illuminates waste during image capture |
| CNN (EfficientNet-B0) | Classifies image as paper or plastic |
| Arduino Uno | Receives classification and controls servo |
| MG995 Servo Motor | Rotates plate to direct waste accordingly |

Table 5.1 provides a complete overview of all the hardware and computational elements in the EcoSort smart waste sorting system along with their respective functions. The ultrasonic sensor is the main trigger device, which detects waste in its area. The MG996R servo motor moves when waste is detected and allows for waste to be placed onto a semi-circular plate. A camera module then takes a picture of the waste with the help of an LED light to ensure the lighting of the captured image is the same. Once the image has been captured, the image is passed to a EfficientNet-B0 deep learning model that classifies the shooting object either as paper or plastic. The classification is then sent onto an Arduino Uno, which interprets the classification result and tells the MG995 servo motor to rotate the plate clockwise or anti-clockwise to dump the waste into the correct compartment. This table provides a concise insight into how tightly linked the interactions of sensory feedback, AI-based discovery, and actuating movements are to enable the EcoSort system to operate continuously.

# Chapter 6

# Result and Analysis

## 6.1 Introduction

This chapter describes the results generated from the installation and testing of the EcoSort smart waste segregation system. The aim of this report is to assess the performance of the system across a variety of channels, including: quality of classification, classification speed, mechanical performance, and responsiveness to live action operating conditions. The results reported here are a combination of quantitative results from the deep learning model and qualitative conclusions based on the hardware testing in order to assess if the solution presented was valid.

## 6.2 Model Performance Evaluation

The convolutional neural network based on EfficientNet-B0 and fine-tuned on our specific custom dataset of paper and plastic waste was trained for 25 epochs with a batch size of 32. The model's overall performance was tracked by observing the training and validation accuracy and loss curves. As can be seen in the accuracy graph Figure 6.1, the model converged quite quickly and reached greater than 98% validation accuracy by the 10th epoch and then the accuracy steadied at around 99% for several epochs. In addition the model training accuracy peaked at 99.2% (along with the peaks in validation accuracy) indicating that modelling was learning effectively and that there was very limited overfitting taking place, since the validation curve closely followed the training curve without large divergence. This reinforces the validity of the training pipeline and confidence in the quality of the custom dataset that was collected and used. The loss curve in Figure 6.2 further furthers this point. The training and validation loss had sharply decreased during the first few epochs of training, and both stabilized to a loss score near 0.01. This score shows generalization could be expected to unseen data, which also validates it is capable of capable of performing eventually in the real world with reasonable reliability. Overall, there were no significant spikes, and no performance instability or significant irregularities in loss until completion of training. Overall this provides evidence that there was consistent convergence behaviour, and the pre-processing pipeline performed its job in removing variability, from the inputs.

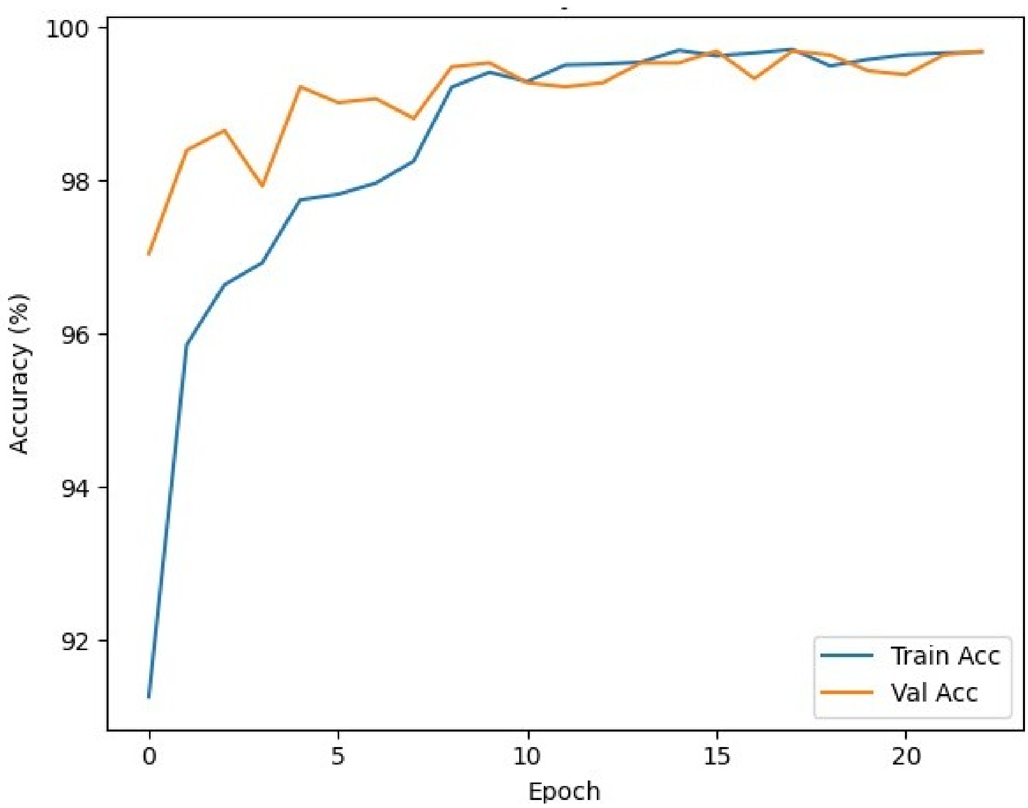


Figure 6.1: Classification accuracy

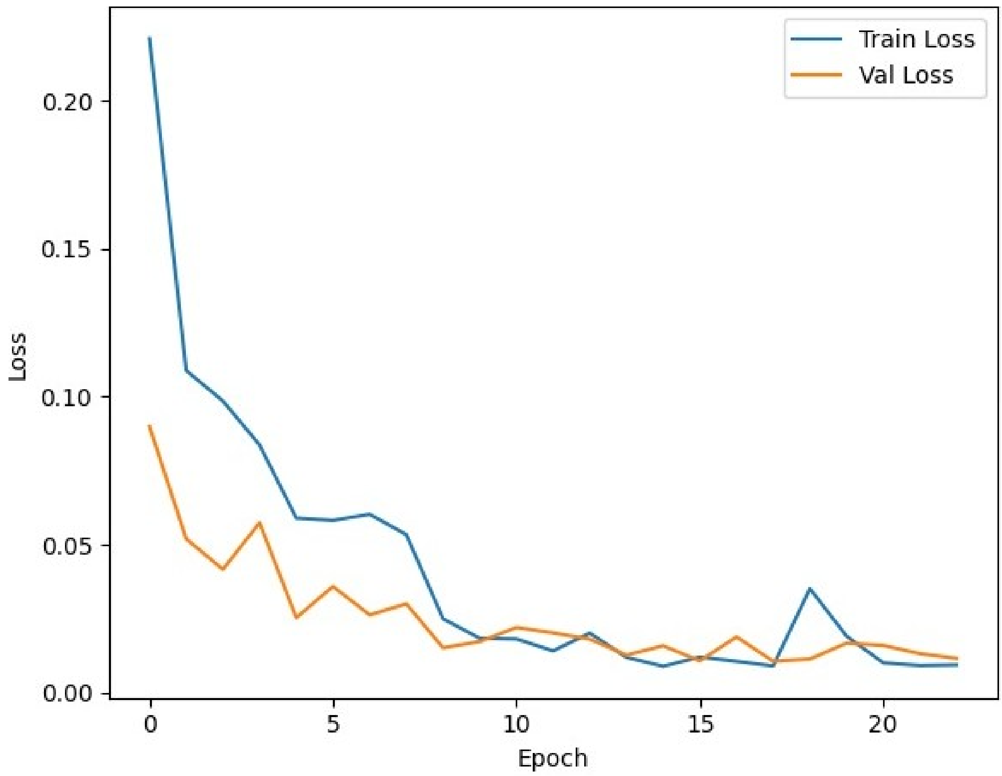


Figure 6.2: Loss curve

## 6.3 Prototype Cost Analysis

Table 6.1: Cost Analysis for Prototype Development

| Component | Quantity | Estimated Cost (INR) |
|---|---|---|
| MG995 Servo Motor | 1 | 360 |
| MG996R Servo Motor | 1 | 340 |
| Ultrasonic Sensor (HC-SR04) | 1 | 70 |
| LED Strip for Illumination (1 m) | 1 | 250 |
| Arduino Uno | 1 | 350 |
| Power Supply (12V DC, 5A) | 1 | 600 |
| High-Resolution Camera | 1 | 6000 |
| 5 mm Sunboard (for prototype structure) | 1 | 1500 |
| Miscellaneous (repairs, modifications) | – | 2000 |
| **Total Estimated Cost** | | **11,500** |

Table 6.1 outlines a comprehensive cost analysis of developing the EcoSort prototype. A list of costs associated with each major hardware component used to create and operate the system is provided, with both quantity and estimated price in Indian Rupees (INR). The MG995 and MG996 servo motors responsible for disk rotation and flap actuation are reasonably priced at 360 and 340 respectively. The cost of the HC-SR04 ultrasonic sensor that was implemented for object detection is a very reasonable 70. There was a 1-meter LED strip priced at 250 to provide lighting. The Arduino-UNO micro controller board responsible for holding all the programming to function as the main logic unit of the system came in at 350. The delivery of power is managed by a DC supply of 12V, 5A that was priced at 600.
The largest expense was a high-resolution camera that cost 6,000, which is important to have for obtaining clear images so classification would be accurate. The structural body of the prototype is a 5mm sunboard material which was reasonably priced at 1,500, and was selected due to its light weight and modifyable attributes. An additional amount of 2,000 was also included to the cost including insurance component to allow for repairs and minor adjustments while developing the prototype. In total, the total cost for the complete prototype is stated to be 11,500, which is a practical and cost-efficient solution.

## 6.4 System Performance and Observations

A comprehensive series of tests were performed on the EcoSort system to assess the operational capabilities, speed and reliability under a variety of usage conditions. In addition to the performance data, visual observation of the housing and layout of the hardware was recorded of the developed EcoSort prototype to demonstrate the construction and real-time function. Figure 6.3 provides a front view of the EcoSort dustbin with its not very high-profile, compact, space-optimizing and modular design identifying a system for indoor institutional use. The sun-board chassis safely houses all mechanical and electronic components so that the prototype was durable and modifications could be made during development. Inside the system, as shown in Figure 6.4 and Figure 6.5 , The bins are constructed with two clearly labeled compartments for paper and plastic waste. They


Figure 6.3: Front view of the EcoSort prototype showing exterior design and flap module

are separated physically by a vertical division wall. Waste is funneled into the bins via a semi-circular rotating plate controlled by a MG995 servo motor seen in Figure 6.5. The plate aligns itself precisely in accordance to the classification result, steering the waste through to either the left or the right slot to one of the containers. Figure 6.7 shows the configuration of the LED strip and high-resolution camera positioned directly over the rotating disc. The camera is angled to capture the centermost top-down view of the disposed waste and the LED lighting uniformly illuminates the waste (Note: Believe me uniform illumination is paramount for image capture and proper sorting), and they are installed in the enclosed inside roof of the bin and programmed to activate simultaneously after the ultrasonic sensor is triggered. Figure 6.6 Additionally, the MG996R servo motor that automatically opens the flap, is present viewable from the side and top view. The motor driven mechanism instantly reacts when an object is observed close to the entrance of the bin, which helps to maintain hands-free operation of the system. The physical design elements demonstrate that the EcoSort prototype meets functional expectations and adheres to a user-centered and tamper-resistant design that supports real-time performance, has an educational aspect, and can be utilized in a public or semi-public space, such as a classroom, lab, or cafeteria.


Figure 6.4: Internal waste collection compartments for paper (left) and plastic (right)

Figure 6.5: Internal waste collection compartments for paper (left) and plastic (right)

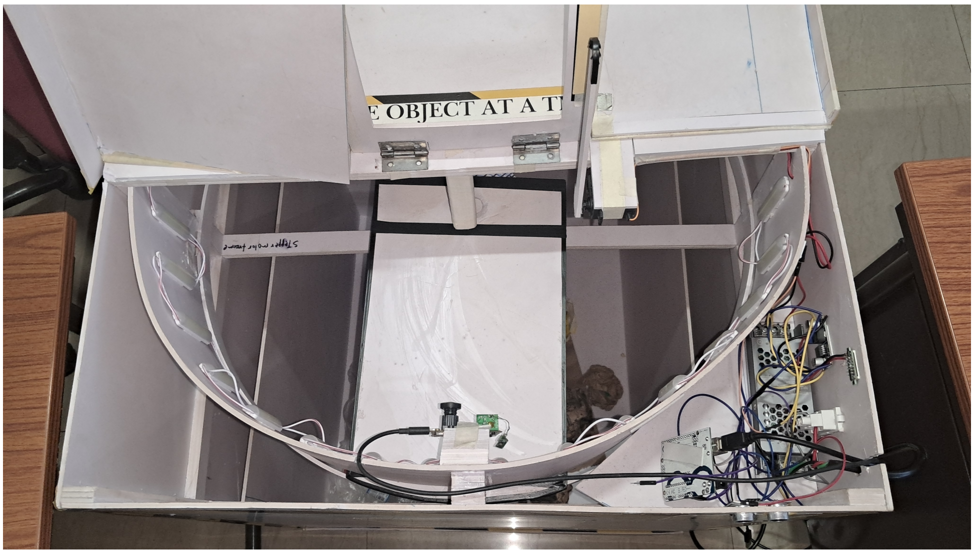


Figure 6.6: Rotating disc positioned between compartments

Figure 6.7: LED strip and camera module mounted inside the bin for classification imaging

# Chapter 7

# Conclusion and Future scope

## 7.1 Conclusion

The rising environmental pressure and increasing quantities of non-segregated municipal solid waste have prompted the urgent need for effective, real-time waste segregation systems. This project—EcoSort—proposes, and successfully implements, a novel, low-cost, intelligent waste segregation system with the ability to classify and separate paper and plastic waste at the disposal point entirely autonomously. EcoSort combines deep learning-based image classification with embedded system controls and mechanical actuation to create a method for linking smart vision systems with sustainable, real-world solutions.

The project highlights that a small-footprint CNN such as EfficientNet-B0 can deliver strong classification accuracies, even in varying environmental conditions, when trained on a domain-specific dataset and supplemented with appropriate pre-processing techniques. The hardware-software combination of the EcoSort system is engineered to include not only ultrasonic sensing and LED lighting technology but also a mechanical actuation system based on servos to allow for rapid segregation cycles capable of running in real-time and less than 3 seconds for each cycle. This efficient processing speed and autonomous operation makes EcoSort an ideal candidate for adoption educational and corporate organizations generating large amounts of recyclable waste, even when waste sorting at source entails a low probability of correct labeling. Although conventional smart bins rely on human labeling, basic sensors, or cloud-based processing to identify recyclable objects, EcoSort provides a valid edge computing solution to enable low-latency, offline and scalable operation. Furthermore, the design is modular and allows for future enhancements such as multi-class classification (e.g., metal, organic), IoT, cloud monitoring capabilities, and behavioral analytics in support of waste pattern analysis.

In summary, EcoSort achieves all its design aims, while also acting as a prototype of a combined approached to artificial intelligence, embedded systems, and sustainability in a single, deployable package. EcoSort illustrates the possibility of intelligent automation to tackle arguably the most significant, but often overlooked aspect in environmental engineering—source waste segregation.

## 7.2 Future scope

While the present implementation of EcoSort adequately demonstrates automated separation of paper and plastic waste using deep learning and embedded systems, there are clearly opportunities for improvement, scalability, and deployment in real-world applications. The following directions highlight the potential future direction of the project:

1. **Multi-Class Waste Classification:** The current system is trained on a binary classification (paper vs. plastic). Future iterations can be expanded to support further multi-class classification options including metal, glass, organic, e-waste, and hazardous waste, by:
   - Expanding the dataset with diverse waste categories
   - Incorporating multi-label classification models
   - Adjusting the sorting mechanism to accommodate more compartments
2. **On-Device Model Optimization:** To enable fully edge-deployable processing on resource-limited hardware like Raspberry Pi or NVIDIA Jetson Nano, the following can be explored:
   - Quantization-aware training (QAT)
   - TensorRT or ONNX optimization
   - Implementation of MobileNetV3 or TinyML architectures
   - These improvements will reduce inference latency, power consumption, and cost.
3. **Internet of Things (IoT) and Cloud Integration:** EcoSort can evolve into an IoT-enabled smart bin system with capabilities such as:
   - Remote waste monitoring via cloud dashboards
   - Data logging for waste generation analytics
   - Real-time alerts for bin fill levels or contamination
   - Integration with municipal waste management APIs
4. **Solar-Powered Operation:** For deployment in remote or outdoor environments, the entire system can be modified to operate on solar power, supported by battery management systems. This would make EcoSort self-sustaining and suitable for smart city or rural applications.
5. **Mobile App Interface:** Developing a companion mobile application can add user-centric features such as:
   - Live camera view and sorting feedback
   - Manual override for complex items
   - Education modules on proper waste disposal
   - Admin controls for facilities management teams

6. **Anti-Contamination Feedback Mechanism:** Future versions can include:

    - Object tracking before sorting to ensure no mixed waste is dropped
    - Visual or auditory alerts when incompatible or ambiguous items are detected
    - Rejection mode for items not confidently classified

7. **Integration with Robotic Waste Collectors:** EcoSort could become part of a larger automated waste handling ecosystem, feeding pre-sorted material into robotic waste collection or conveyor systems in industrial and smart campus setups.

8. **Deployment in High-Traffic Public Infrastructure:** EcoSort's compact and modular form allows for installation in:

    - Airports, railway stations, and malls
    - Corporate tech parks and university campuses
    - Events and festivals generating temporary high waste volumes
    - Scalability testing and ruggedization will be key for such deployments.

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**Patent Draft for BE major project**

1 message

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Figure 7.1: Patent Publication Certificate


Figure 7.2: IEEE Prakalp Competition Participation Certificate

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| Date | Signature |
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