IOT-ENABLED MACHINE LEARNING-BASED INTELLIGENT WASTE MANAGEMENT SYSTEM

Thesis Submitted for the Award of the Degree of

DOCTOR OF PHILOSOPHY

in

Electronics and Communication Engineering

By

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2024

DECLARATION

I, hereby declare that the presented work in the thesis entitled "**IoT-Enabled Machine Learning-Based Intelligent Waste Management System**" in fulfilment of the degree of **Doctor of Philosophy (Ph. D.)** is the outcome of research work carried out by me under the supervision of **Dr Manwinder Singh**, working as **Professor**, in the **School of Electronics and Communication Engineering of Lovely Professional University, Punjab,** India. In keeping with the general practice of reporting scientific observations, due acknowledgements have been made whenever the work described here has been based on the findings of other investigators. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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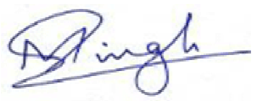
CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled **"IoT-Enabled Machine Learning-Based Intelligent Waste Management System"** submitted in fulfilment of the requirement for the reward of the degree of **Doctor of Philosophy (Ph.D.)** in the School of Electronics and Communication Engineering, is a research work carried out by **Belsare Karan Sanjayrao, 42000155**, is bonafide record of his original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.



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Name of supervisor: Dr. Manwinder Singh

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ABSTRACT

Population expansion and huge migrations of residents from urban and semi-urban regions to smart cities have created issues for these cities due to their exponential growth. Controlling, managing, and processing the everyday output of garbage is one of the biggest issues that Smart Cities face. The main causes of trash management being a difficult task are the expanding population and resource limitations in waste management operations. One of the most fundamental aspects of a sustainable economy is waste management and recycling. Better recycling safety and efficiency may be achieved via the use of intelligent devices rather than manual effort. Several trials are performed using state-of-the-art deep convolutional neural network designs to get the optimal answer using a machine learning approach. In this research, we describe a machine learning-based architecture for smart trash collection and sorting using the Web of Things and wireless sensor networks.

The goal of this research was to develop an autonomous method for producing an efficient and intelligent waste parameter monitoring system for a novel waste management system, using the Internet of Things (IoT) and Long Range (LoRa) technologies. Several possibilities are explored, all of which may be applied to the development of the three nodes. The number of trash cans, garbage stench, air quality, weight, smoke levels, and waste categories are all tracked in real-time via the Internet of Things and the ThingSpeak Cloud Platform, which can be set up in numerous places. However, a fog-deployed intelligent trash waste classification framework is developed which consists mostly of four layers: input, feature, classification, and output. Using the ThrashBox dataset, the proposed system develops a categorization method into trash classes such as household, medical, and electronic garbage, in addition to object identification. Traditional machine learning methods, such as the multi-kernel support vector machine (SVM) and the Adaboost ensemble classifier, are employed in the classification layer, while the Resnet-101 deep convolutional neural network model is used in the feature layer. Experiments were conducted to evaluate the suggested method's ability to classify garbage and provide accurate predictions about their respective categories. Compared to other state-of-the-art models, the suggested method's performance was shown to be superior in the presented experimentation.

- We found that Sensitivity of our proposed system was 97.69 % which is better than the existing methods EnCNN UPMWS [56] is 92.69%, YOLOv5x [1] is 92.2% , DNN [3] is 94.37% , mCNN[95] is 95% and CNN[14] is 95.16%.
- We found that Specificity of our proposed system was 98.9 % which is better than the existing methods EnCNN UPMWS [56] is 98.67%, YOLOv5x [1] is 96.5% , DNN [3] is 92.8% , mCNN[95] is 96.5% and CNN[14] is 98.44%.
- We found that Precision of our proposed system was 98.8% which is better than the existing methods EnCNN UPMWS [56] is 93.75%, YOLOv5x [1] is 95.9% , DNN [3] is 88.7% , mCNN[95] is 95.5% and CNN[14] is 94.24%.
- We found that F-Score of our proposed system was 98.01% which is better than the existing methods EnCNN UPMWS [56] is 93.15%, YOLOv5x [1] is 95.13% , DNN [3] is 89.77% , mCNN[95] is 94.5% and CNN[14] is 94.39%.
- When comparing and analysing the performance with the existing systems the overall accuracy was found to be 98.2% as compared to the existing methods Recycle Net[138] is 81%, EnCNN UPMWS [56] is 93.50%, SVM[120] is 87, YOLOv5x [1] is 92.6% , DNN [3] is 94.53% , mCNN[95] is 94.96% , Deep Waste[117] is 88.1, VGG19[81] is 87.9 and CNN[14] is 95.3%.

The experimental findings show that the proposed framework outperforms as compared to state of art models.

Keywords: Internet of Things (IoT), LoRa, Thing-Speak, Wireless Sensor Network, Waste Management, Smart Waste Management System, Deep Learning, Waste Classification, Machine Learning

The main objectives of the proposed model are

1. To study different methods considering key attributes related to waste management.
2. To develop an efficient IOT-WSN-based data acquisition and monitoring framework for waste management.
3. To design a hybrid machine learning algorithm to analyze extracted data for efficient segregation.
4. To compare and analyze proposed methods using potential parameters like accuracy, latency, precision, and computation time.

ACKNOWLEDGEMENT

High achievement always takes place in the framework of high expectations. It has been rightly said that every successful individual knows their achievement depends on a community of people working together. However, the satisfaction accompanying the successful completion of any task would be incomplete without the mention of the people who made it possible. The expectation was there, and I began with a determined resolve and put in sustained hard work.

This is to acknowledge with gratitude the guidance and ameliorating suggestions from my supervisor, Dr Manwinder Singh, for the support and motivation throughout the thesis work. I am grateful to the School of Research Degree Programme (RDP) members for being in my entire research progress review panel and providing valuable suggestions during the period. I am indeed thankful to all anonymous reviewers of my research papers submitted to various international journals and International conferences, due to which I was able to improve upon the work contained herein. I am indebted to the Honorable Chancellor, Worthy Pro-Chancellor, the Vice-Chancellor, and the successive Deans, LPU, for facilitating the administrative issues involved and encouraging me throughout. I express my heartfelt gratitude to the Head o of the School of Electronics and Electrical Engineering, and the Electronics and Electrical Engineering School staff for their cooperation and support. No thanks are enough to express my deepest gratitude and sincerest love to my parents, whose rock-solid faith in me kept me strong in all circumstances. I also thank my wife Komal, daughter Saavi and my friend Ashwini Patil for their wholehearted support and patience. I would also thank all the people who directly or indirectly contributed to and supervised this novel research work.

Last, I bow my head before the Almighty God for showering his mercy on me for every moment.

Belsare Karan Sanjayrao

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ABBREVIATIONS

AI	Artificial Intelligence
AdB	AdaBoost
ANN	Artificial Neural Network
API	Application Programming Interfaces
CNN	Convolutional Neural Network
FN	Fog Node
FNR	False Negative Rate
FPR	False Positive Rate
FN	False Negative
FP	False Positive
GPS	Global Positioning System
GUI	Graphical User Interface
GBRT	Gradient Boosting Regression Tree
ICT	Information and Communication Technology
IDE	Integrated Development Environment
IIoT	Industrial Internet of Things
IoT	Internet of Things
IDE	Integrated Development Environments
ML	Machine Learning
MQTT	Message Queue Telemetry Transport

MAP	Mean Average Precision
MMMT	Multimodal Multitask
NPV	Negative Predictive Value
PPV	Positive Predictive Value
PPM	Parts per million
QoS	Quality of Service
RCNN	Region Convolution Neural Network
RMSE	Root Mean Squared Error
SVM	Support Vector Machine
SDK	Software Development Kit
SVM	Support Vector Machine
TCP/IP	Transmission Control Protocol/Internet Protocol
TN	True Negative
TP	True Positive
TPR	True Positive Rate
UI	User interface
WCS	Wireless Communication System
WSN	Wireless Sensor Network

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CHAPTER 1 INTRODUCTION

1.1 OVERVIEW

Waste Management is used to describe the entire process of garbage removal. Human-generated waste is defined as any type of waste that results from an activity and must be managed to prevent harm to human health and the natural environment. Typically, garbage is handled such that materials may be recycled or reused. Waste management practises may vary from one developed nation to another, from one metropolitan setting to another, and from one industrial zone to another. Municipalities are responsible for managing garbage in both urban and rural regions, whereas waste generated by businesses is under the purview of such businesses [1-2].

Trash collection in some areas may be improved with the use of Internet of Things (IoT) technology and recycling of diverse scarce resources, which is especially important given that waste management towards a circular economy idea is a crucial present population concern. Multiple technology approaches are now being researched and developed to aid the smart waste management idea. Some of these are already commercially available for extensive use. The majority of the proposed solutions are geared towards the intelligent monitoring of garbage bins, such as the detection of filling levels, temperatures, fires, vibrations, tilts, the presence of waste operators, humidity levels, GPS coordinates, and more [4]. The Internet of Things may be used to great advantage as a backbone for intelligent waste management systems. Garbage trucks' hazardous emissions (pollutants) may be reduced if IoT technologies were employed for smart coordination of trash vehicles, hence ensuring the efficacy of waste utility firms. Managing electronic waste through the Internet of Things is crucial to ensuring a steady supply of raw materials for the electronics industry, which has previously been emphasized. Smart appliances and a refined management system enabled by the IoT might potentially play a role in lowering food waste rates. Innovative Internet of Things (IoT)-based technological solutions that might aid the circular economy concept and smart waste management systems are anticipated to be developed in the next years from the perspective of a smart city concept [7-8] Waste production has grown as cities have developed around the world. Figure 1.1 shows how much trash is produced in a few select areas of the globe.

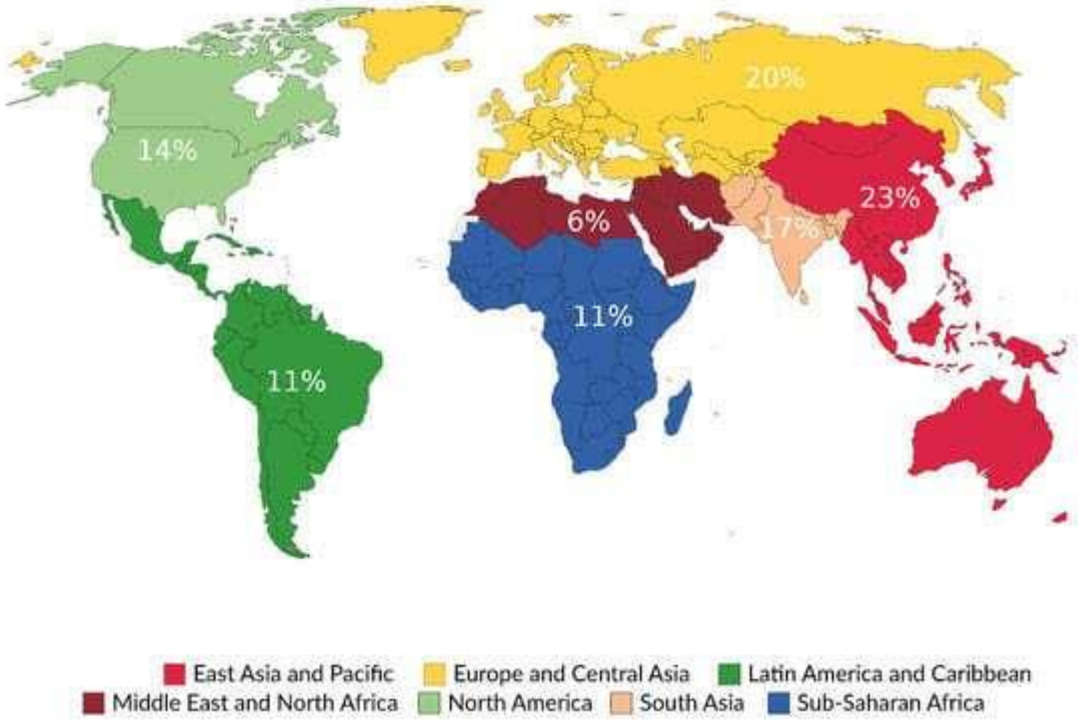

Figure 1. 1: Distribution of Regional Waste Production [1]

households [6]. Each individual produces roughly 0.74 kilograms of rubbish annually on average, with North Americans producing the most garbage at 800 kg per person annually [8]. While just 16% of the world's population lives in high-income nations, they produce 34% of the world's trash. However, just 5% of the world's garbage comes from low-income nations [9]. There are a few distinct categories of trash from the home.

- Vegetable and fruit waste.
- Bottles, glass, tins, and plastic bags or containers of waste.
- Batteries expired medications, and other potentially dangerous items like used oil/kerosene.
- Paper waste, including magazines, newspapers, etc.

Dry recyclable garbage such as glass, plastic, paper, tins, etc. accounts for 38% of the total waste created worldwide, while food and green waste accounts for 44%. Disposal habits for trash are also different on a global scale. Nearly half of all trash goes straight to landfills, while only about a fifth is recycled. Figure 1.2 shows that in low-income nations, about 93% of garbage is publicly discarded, including dumping and burning by the side of the road, whereas in high-income countries, just 2% of waste is dumped openly.

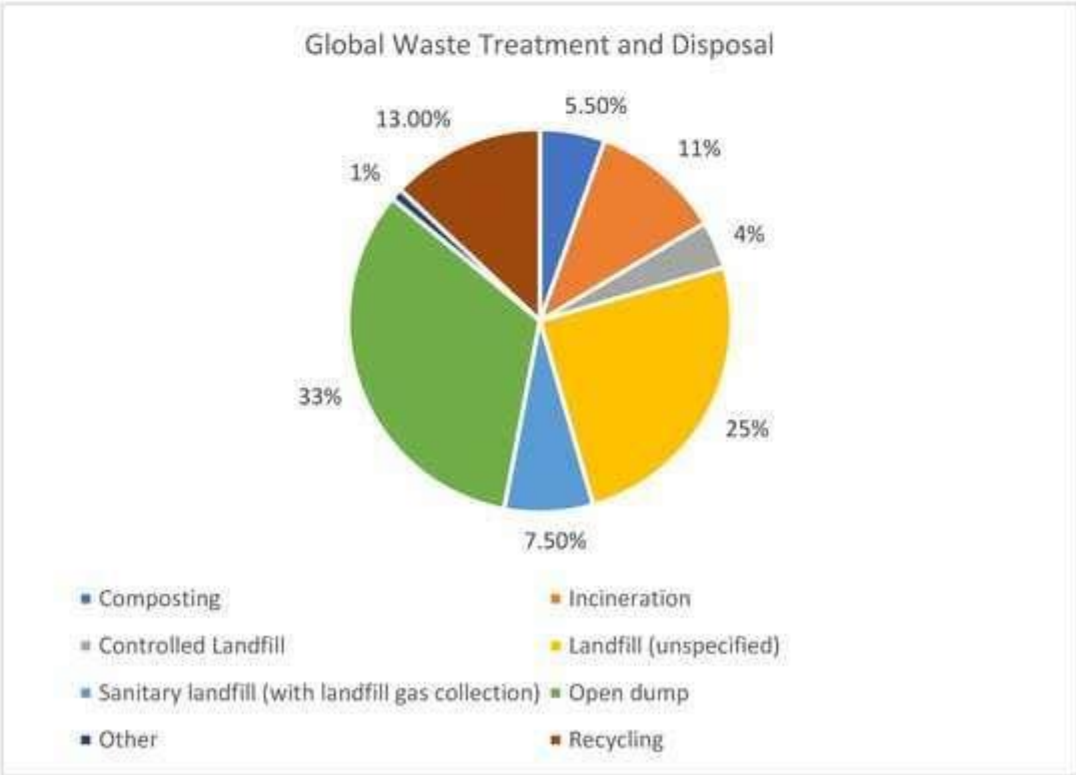

Figure 1. 2: Global Waste Treatment and Disposal [1]

In urban areas, trash management may be an everyday effort that entails establishing waste truck routes while taking into account ecological, economic, and social factors. Second, using the schematic hypothesis [8], the length has to be shortened to avoid excessive fuel expenditures and reduce the total amount of effort required. Several services have introduced IoT devices to gauge inbox saturation and relay that data online for more informed choice-making. Figure 1.3 depicts a waste management hierarchy.

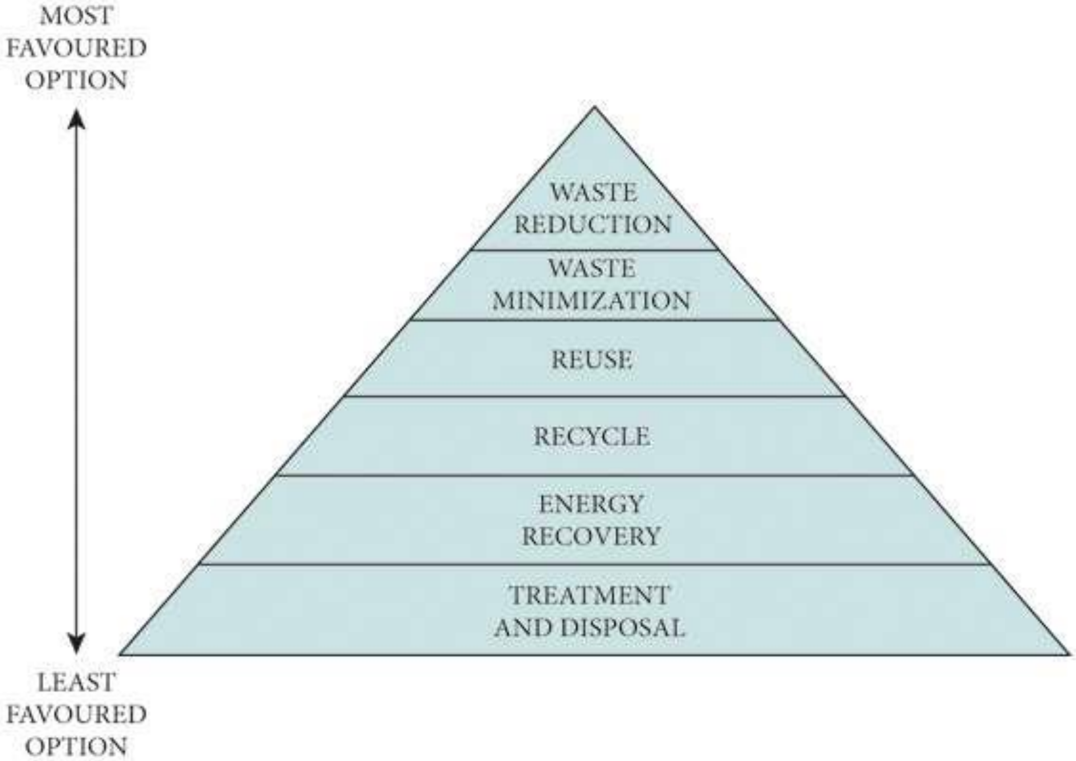

Figure 1. 3: Hierarchy in waste management

Currently, more and more local governments and public agencies are taking waste management into their own hands, with the goal of better collecting and disposing of garbage in urban areas. The rapid speed of urbanisation throughout the world, the growth of the industrial sector, and the presence of waste-generating sectors like manufacturing and healthcare mean they may already be effectively managed through the use of smart management. Waste management is an expensive endeavour due to the time and effort that it takes. The authorities have instituted the recycling container and promoted the 3 "R" s (reduce, reuse, and recycle) to improve waste management [13]. Smart thrash management is predicted to grow as rising nations embrace more advanced waste management systems and build out more robust infrastructure. These countries want to save money and time by employing these more efficient disposal techniques. Depending on its origin and final resting place, the trash produced by different sectors of society can be categorised in different ways. This categorization is essential because it paves the way for more targeted collection, recycling, and the identification of the most useful result. Municipal solid wastes include both a somewhat homogenous load of industrial and medical waste and a far larger volume of very heterogeneous stuff. When it comes to recycling, the current gold standard is based on selective collection, which also happens to be the cornerstone of effective waste management. Classification is crucial for an IoT-based waste management system, thus it's important to think about using different containers for different kinds of trash [15][18].

The Internet of Things (IoT) is a communication paradigm that foresees a future in which commonplace objects are embedded with microcontrollers and a means of interfacing with a central network. The "smart city," characterised by advanced infrastructure, knowledgeable residents, and effective teamwork, is one of the most visible results of the IoT. To make it easier for a wide range of digital services to be developed, IoT must openly and seamlessly combine several heterogeneous end systems. In the context of "smart waste management", "smart city" is a crucial concept. The efficiency of a waste management system is heavily dependent on the length of time it takes for messages to travel between the collection site and the central collection facility. Despite this, current communication technologies, such as Sigfox and LoRa, which operate on a low-power, wide-area network (LPWAN), can accommodate the long-distance communication required by the waste management system without compromising on the pace of data transfer [5][14][16]. The study of wireless communication for the IoT has recently experienced a boom. However, connection technologies like Bluetooth, Wi-Fi, and Zigbee have greater data transfer speeds, but shorter ranges. An interesting topic of study is the use of IoT and machine learning (ML) for intelligent trash management. As a result of IoT, the number of connected devices is rapidly increasing to satisfy the need for trash collection. The result is a rise in the total amount of data gathered, which can be utilised to further inform and enhance ML application's features and functionality.

1.2 TECHNOLOGY USED IN SMART CITIES

1.2.1 Internet of Things (IoT)

The term "Internet of Things" (IoT) describes a communication model that foresees a future in which commonplace things have a built-in microcontroller and a standard protocol for exchanging data. Well-known examples of IoT products include "smart cities," which combine advanced technological infrastructure with effective human collaboration. While transparently integrating a great number of heterogeneous end systems, the IoT will make available open access to specified data subsets enabling the creation of a wide variety of digital services. The Internet of Things (IoT) began with the proliferation of potentially networked physical devices [1-2]. There are several application solutions and communication technologies that may be integrated thanks to the IoT paradigm. These include identification and tracking, wireless and wired actuators, sensor networks, distributed intelligence for objects, and enhanced communication protocols. The Internet of Things (IoT) is a futuristic concept that foresees a world in which physical, digital, and virtual items are all linked together in a network to enable advanced applications in areas as varied as agriculture, industry, education, transportation, healthcare, markets, the environment, and smart cities as defined in figure 1.4. Object intelligence originates in the automatic interpretation of data from a certain context or environment. After collection, the data are sent to a central processing unit (CPU) for analysis and the creation of a reliable performance profile. Then, the smart thing obtains the actuation profile. It is important to comprehend the context in which these containers are used, as the waste management system includes a large number of containers, each of which may remain full for several days or weeks depending on the time of year, as well as having varying emptying requirements due to factors such as distance and waste kind. In contrast, the fields of medicine, electronics, and chemistry all have established collection sites, stable production, and lengthy filling times [4][8].

Figure 1. 4: A generalised IoT architecture supporting a wide range of cases.

The basic objective of the IoT is to provide effective communication between people and facilitate efficient access to the online data and process system. There are three types of connections in this internet: those between humans, between humans and machines, and between things, either wirelessly or not. To link two persons via social media, for instance, smartphone users can tap into the IoT. The IoT allows for more efficiency and productivity in daily life. Advantages of the IoT in general include:

- *Defend time and Money* - IoT-based trash management will improve waste management from the smart dumpsters' real-time fill-level information to the garbage collectors. IoT's solution improves information used to choose the most efficient routes for garbage trucks. This results in a collection method that ignores garbage cans that have been emptied, therefore conserving both fuel and labour.
- *Make a better decision* - AI and ML are used to make decisions in the IoT. Waste management IoT will be customized to each setting. The bin's built-in

sensor can detect when it's full and transmit a notice to the local government, streamlining decision-making processes in real-time. IoT will aid in the establishment of smart cities by facilitating more efficient waste management thanks to the innovative nature of its software and machine learning tools, which are being used in various countries, including Nepal, to ensure the proper management of the development of new business models.

- *Waste generation analysis*- Optimization of routes is just one part of the data analysis that goes into IoT-based waste management. The data analytics element of the commercially available IoT-based solution aids in forecasting future trash production.
- *Increase the quality and quantity of work done* - In the same way, that the IoT is helping to improve waste management processes, it is also helping to improve how human resources are evaluated for those processes. This contributes to the improvement of both the quality and quantity of waste management activity.
- *CO2 emission reduction* - The carbon footprint includes not only the production of trash but also its disposal and recycling. Less fuel will be used thanks to the IoT for waste management's analysis of optimal routes, lowering the procedure's carbon footprint and making it more environmentally friendly.

1.2.2 Machine Learning (ML)

Machine learning, which encompasses industrial informatics, holds tremendous potential to revolutionise a wide range of fields. An automated machine-learning method has been presented by several researchers as a means of rapidly applying machine learning to practical problems [4][7][9][10]. As a subfield of machine learning, deep learning (DL) has also radically altered the trajectory of computing [5-6]. Artificial intelligence has advanced rapidly in recent years, with the introduction of numerous architectures with different learning paradigms. These advancements have allowed machines to mimic human behaviour, which is extremely useful in many fields. The entire procedure consists of the five actions shown in figure 1.5. The gathered information is put to use in many ways: it is used to assess the efficacy of the currently implemented solution, the parameters of the current system are optimised and evaluated in light of the data, conventional ML algorithms can be applied, and feature engineering techniques are employed to determine if any additional features would be helpful.

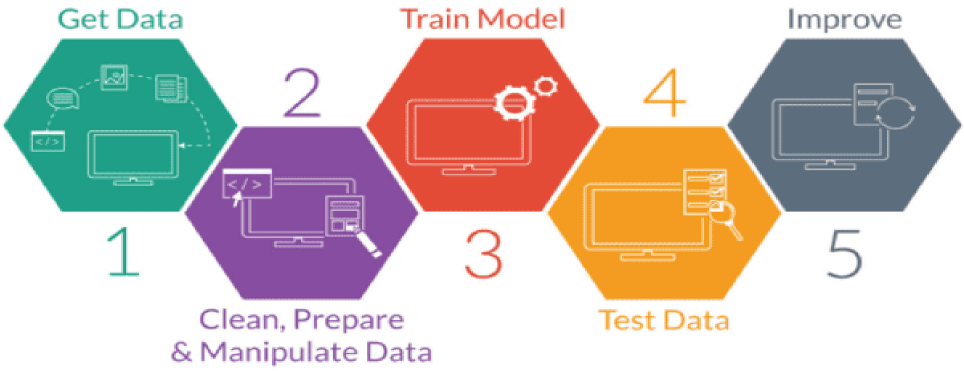

Figure 1. 5: Procedures Typically Used in Predictive Modelling

Despite these constraints, several new cutting-edge technologies are altering our perspective on and approach to these issues. ML is one of the most well-known today, a subfield of AI that employs massive amounts of data and sophisticated learning algorithms modelled on how humans learn to teach computers to perform human-like tasks such as classification, prediction, decision-making, content generation, etc. In some cases, the scalability and efficiency gained by automating such jobs with machine learning can be of great use to people.

Machine learning can automate a broad variety of operations, which might have significant implications for sustainability and the adoption of the circular economy. Predicting data trends that improve air quality, discovering patterns in data collected to measure global warming over time, locating trash in the wild, and differentiating between different types of trash to improve the efficiency of trash treatment facilities are all examples. Therefore, a crucial step towards a sustainable circular economy model might be the accurate identification and separation of recyclable goods from the rest of the garbage. However, machine learning is already integral to more steps in environmental protection than we give it credit for. If a model correctly predicts the need for energy or a certain product, for instance, it means less of those resources will be wasted. In addition, sophisticated models can optimise the performance and recycling potential of common materials by exploring unexplored chemical configurations.

1.3 TYPES OF WASTE AND SEGREGATION METHODS OF WASTE DISPOSAL

Depending on their composition and final destination, discarded items from various social strata may be assigned to distinct containers. This categorization is helpful since it allows for more specific collection and recycling efforts, as well as easier determination of the most relevant objective. Industrial and medical garbage are also more consistently dumped in urban areas, which adds to the complexity of the materials involved. Selective collection is currently the most popular technique of recycling across the world and the basis for efficient waste management. For an IoT-based waste management system, sorting waste material into its many types is essential [1].

Figure 1. 6: Type of Waste Materials

Each type of trash has its colour code as depicted in Fig 1.6 industrial, commercial, domestic, and agricultural trash. The subsequent [1-2] explanations of the various types of trash under consideration are as follows:

- *Commercial Waste* - Waste generated by businesses. It is manufactured by corporations such as retailers of clothing, toys, and home goods. Most of this waste has a potential for recycling.
- *Electronic Waste* – It's a term for the garbage left behind by electronics. Garbage like this results from people getting rid of obsolete or broken consumer

electronics. Businesses and cooperatives dedicated to recycling are examples of suitable dumping sites. They use eco-friendly methods to get rid of this trash.

- *Green Waste* - This waste describes a category of garbage that consists mostly of tree trimmings and the resulting branches, barks, trunks, and leaves that end up in the streets. Since it is organic, it may be composted and turned into a nutrient-rich soil amendment.
- *Hospital Waste* - It's a hazardous byproduct of the healthcare industry that poses a health risk to everyone who comes into contact with it. It requires the utmost care and attention, in accordance with standard procedures. Companies that deal only with this type of garbage, which is often incinerated, can use this garbage.
- *Industrial Waste* - Materials discarded from manufacturing. Industrial byproducts are often solid wastes left over after production. It is often comprised of discarded raw materials that may be recycled or used.
- *Nuclear Waste* – It's the primary byproduct of nuclear power reactors. Since it contains radioactive elements, it is considered extremely dangerous waste.
- *Organic Waste* - Garbage is composed of organic waste. Most of them come from kitchens, eateries, and industrial kitchens. Being destined for municipal landfills, they must be segregated from other waste.
- *Recyclable Waste* - Recycling-eligible trash. The term applies to any type of waste that may theoretically be recycled into useful products or resources. It is generated in households, commercial establishments, and industrial settings, and requires sorting before it can be collected by the appropriate teams and sent to cooperatives and recycling companies.

1.4 WASTE MANAGEMENT PROBLEM IN SMART CITIES

Waste management is a major issue for modern urban centres. Despite requiring a large trash workforce, including waste collectors, recyclers and scrap dealers, smart cities can effectively manage their waste. Garbage collectors, the largest informal sector in the country, are among the worst hit by changes to the waste disposal system. All members of the families of these garbage men and women often gather trash in villages of fifty to seventy people. About 15-20% of the city's garbage is taken care of by one family, and everyone in the family works in the garbage business.

- *Improper Classification of Municipal Waste* - Municipal garbage poses serious health risks if it is not properly identified and disposed of. It has negative effects on plant development as well as human and animal health. Classifying, disposing, and treating municipal garbage correctly is the sole option [37].
- *Lack of Awareness about Waste Management* - The majority of people are unaware that pollution may result from improper garbage collection and handling. The enormous increase in population over the last few decades has made waste management a major challenge on a global scale. By hosting seminars, we can help raise awareness among the general public. The program's significance lies in the fact that it raises awareness throughout a nation's populace. Most Indians are oblivious to the distinction between dry garbage and moist waste and cannot properly dispose of either. Since most of them were born and raised in slums, they have never experienced discrimination based on race. The importance of holding workshops and seminars on effective waste management cannot be overstated in the effort to raise awareness of the need for better sanitation and trash sorting in every city and neighbourhood. Effective waste management may be improved through public education.
- *Lack of Technical Solution and Public-Private Partnership* - The IoT and ML technology, and other cutting-edge solutions are required to implement an efficient waste management system. Some emerging technologies have the potential to excel in this space. Thus, we discovered a much less need for public-private collaboration in the current context to develop this kind of system [38].
- *Participation of Organized Sector for Carrying Out Efficient Management of Waste* - As the development of an effective waste management system becomes a necessity, the participation of the people in that country in various practices for successful rubbish collection and disposal becomes increasingly vital. The rag-picker, who travels from city to city collecting rubbish, shows little gratitude for the accolades of the general public. Giving them the right guidance is, thus, crucial. Any nation or municipality may achieve zero waste pollution with the cooperative effort of all sectors [39].

- *Transportation of Waste* - Waste management across the country relies heavily on transportation. Vehicles including trucks, tractors, and others are used to haul away the garbage. Most cities in India lack a reliable public transport infrastructure, and those that do may rely on ageing vehicles that are inadequate for rubbish collection. These are the most common challenges associated with trash management. An optimized path, which may save a lot of time and money, can be provided by efficient transportation [40].

1.5 BENEFITS OF WASTE MANAGEMENT AND SEGREGATION

Waste treatment and management have several advantages, and this section will examine them in detail.

- *Better Environment* - The most obvious benefit of waste management is an improved and cleaner environment. Likewise, garbage disposals aid in the prevention of illness in communities. The best thing is that this occurs while waste is being properly and hygienically disposed of. Attempting to prepare the trash disposal process requires the placement of many waste disposal units in tier-1 and tier-2 cities. The long-term implementation of exceptional safety measures will also benefit from this.
- *Conserves Energy* - Recycling is an integral part of waste management. which also has long-term benefits for energy efficiency. The practice of recycling paper is a prime example of this benefit in action. We are probably all aware that hundreds of trees must be felled to create paper. Recycling paper reduces the number of new trees that must be planted to produce paper. You'll be saving electricity and decreasing your carbon footprint.
- *Creates Employment* - Hundreds of employment are generated only by the recycling business. More and more individuals are adopting this environmentally beneficial practice, which is great news for businesses that make and sell recycled goods. They may grow their company and employ hundreds more people as a result of this.
- *Helps Make a Difference* - When you take care of garbage, you help the environment and the community. While it's true that nobody can eliminate

waste, everyone can do their part to protect the environment by recycling more and producing less trash.

- *Reduces Pollution* - Toxic greenhouse gases, such as carbon dioxide, carbon monoxide, and methane, are commonly released from accumulated wastes in landfills, although their influence and intensity can be mitigated with proper waste management. Waste management lessens the load on landfills and cuts back on a wide range of environmental stresses.

1.6 CHALLENGES AND OPEN ISSUES

The numerous applications of the smart city concept are shown in fig. 1.7 each has its own unique set of practical challenges that must be met. The most significant challenges include, but are not limited to, the effective integration of various sensing technologies, the creation of an adequate network infrastructure, the education of the public, and the study of sustainability issues like carbon footprint. Trash cans with sensors to monitor rubbish disposals have been the focus of IoT research in the waste management sector. One of the most serious issues related to smart city applications is solid waste management because of the negative effects it has on human health and the environment. Human and animal activities produce solid wastes, which are often discarded because of their perceived lack of value. In the research, the inefficient parts of each model are used to classify the whole set of models. The physical infrastructure includes trash cans for several types of trash, including biodegradable trash, plastic trash, paper trash, metal trash, hazardous waste disposal, and general trash [1-2][4][14][32].

Figure 1. 7 Different Challenges in the Smart City Concept

The environment, public health, and standard of living all take a hit when improper measures are used to deal with solid waste. Though improvements in both practice and technology have helped, there are still barriers to effective waste management.

- *Collection and disposal infrastructure* - Inadequate collection and disposal infrastructure is a key issue in the field of waste management. The inappropriate collection, transportation, and disposal of trash has many negative effects on the environment, including but not limited to littering and illegal dumping. The buildup of waste increases the risk of disease outbreaks because it serves as a haven for rodents. Poor infrastructure can pose dangers to public health, cause social problems, and damage the environment. To solve these problems, waste management facilities need to be upgraded. As a result, communities may be safeguarded against the unfavourable effects of trash by employing efficient and responsible waste management practices.

- *Financial constraints* - Another major problem is that waste management programs are underfunded. Waste management infrastructure and programs are often underfunded, especially in low-income areas and developing nations. This might lead to insufficient resources being allocated to trash management.
- *Lack of support from localities* - There might be pushback to implementing waste management methods from a wide range of individuals, organizations, and even governments. There might be undesirable outcomes if waste management methods are not implemented. Lack of information, erroneous views, and societal and economic obstacles all play a role. People may not apply best practices in waste management if they are content with the status quo or think they are superfluous. However, businesses may be cautious about implementing best practices because of the potential financial burden of doing so. Furthermore, governments may be impeded in their efforts to implement these reforms by political and societal obstacles. That's why it's so important to get people involved in the conversation and educate them on the importance of trash management.
- *Ineffective recycling or composting* - Municipal solid waste management also faces limitations in the form of limited recycling and composting possibilities. This is because most communities just don't have the means to start recycling and composting programmers. A greater amount of garbage is sent to landfills because of a dearth of recycling centres in more remote areas. In addition, many things that may be recycled or composted are turned away by community recycling centres. Moreover, landfills and incinerators are the principal means of rubbish disposal for certain towns since recycling and composting facilities are not conveniently located nearby.
- *Ever-changing climate* – The changes in the weather are affecting garbage collection as well. Rising temperatures and varying weather patterns impact waste management in several ways, including generation, transit, and disposal. Changing precipitation patterns, for instance, may make it harder to transport garbage as temperatures rise. Landfills are particularly vulnerable to the

negative effects of climate change, which can threaten both the environment and human health. Therefore, climate change must be taken into account by waste management planners when designing new plans and procedures. It is essential to invest in renewable energy and low-carbon solid waste management technology, as well as to implement sustainable waste management practices such as waste reduction, reuse, and recycling.

- *Lack of technological advances* - This means that there are no viable options for long-term garbage management and disposal. However, inefficiencies in garbage collection and processing are a result of the outdated technology now employed in the waste management business. As a result, it is crucial to modernize the garbage collection industry. The effective application of technology can facilitate financial savings, enhanced recycling procedures, and the spread of environmentally friendly waste management policies.
- *Changing consumer preferences* - E-commerce and online buying have grown in popularity due to the ever-evolving needs of consumers. The usage of more packing materials and cardboard boxes has contributed to this problem. The use of plastic water bottles and grocery bags, for instance, contributes to this problem. These packaging scraps and plastic goods are notoriously unrecyclable, and hence contribute significantly to environmental deterioration and greenhouse gas emissions when they are eventually dumped in landfills. The only solution to this problem is to push for the widespread implementation of environmentally friendly consumer trash management policies. Governments may provide a hand by establishing laws, such as taxes on single-use plastics, that encourage more environmentally responsible purchasing decisions.
- *Unclear regulations* - The recycling business also faces the problem of ambiguous rules. Disparities in waste management rules and procedures between jurisdictions might fall into this category. This might confuse the several trash management firms that operate in different areas. Simplified, transparent, and uniform rules are needed to tackle this issue. Policymaking on a national or worldwide scale is one option, as is harmonizing the definitions of recyclable and compostable products.

There are still some challenges related to solid waste management and regression in India, which are

- *Environment and health issues* - The effects of environmental degradation on human health are substantial. Without appropriate gloves, clothes, and safety equipment, formal and informal employees are at direct risk to their health. Those who reside close to landfills have an increased risk of contracting gastrointestinal worm parasites. Methane, produced during the anaerobic breakdown of biodegradable garbage at open landfills and sometimes even leading to fires and explosions, is a major greenhouse gas contributor. Leachates' smell and movement to receive water and soil are two major issues. Malaria, dengue fever, and other mosquito-borne illnesses spread when water collects in discarded tyres at landfills. Fine particles and haze, released when trash is burned uncontrollably in dumpsites, are a major contributor to respiratory illnesses. Gases such as carbon dioxide (CO2), carbon monoxide (CO), particulate matter (PM), mercury, polycyclic aromatic hydrocarbon (PAHs), and dioxins and furans from plastic pyrolysis, and even arsenic in water can cause cancer and death, especially in newborns and adults. The presence of microplastics in the water harms marine life and the food web.
- *Infrastructure and finance management* - Without a stable financial and managerial structure for their garbage industries, cities and ULBs are failing. Waste segregation has not been widely adopted and maintained since it is not economically beneficial. Under the 12th and 13th finance commissions, the government of India approved grants and funding of around Rs.20,000,000,000 for the Swatch Bharath Mission, which would be used to advance SWMS throughout the country.
- *Improper implementation of government policies* - Policymakers at the national level should make managing the country's solid waste a top priority. Economic development, unplanned land use, urban migration, and, most critically, the absence of adequate regulation on solid waste management are the key causes, especially in metropolitan areas. The current system of solid waste management institutions is continually evolving. The Government of India's Ministry of

Urban Development's Swachh Bharat Mission. Cities must implement open defecation and socially prioritized SWM systems as part of a nationwide effort led by urban local governments (ULBs).

1.7 COMPONENTS OF IOT ENABLED SMART CITY

For Smart Cities to function, it is essential to have a framework that takes advantage of sensing devices as a data source. Figure 1.8 depicts the components of a typical sensing node. The node's sensor component communicates with an MCU, which processes the data. While the node is connected to a specific power source, power consumption is often reduced by a power management unit [2]. Once the MCU has processed the sensor data, it passes it along to a radio unit, which then broadcasts the information using an antenna and a wireless connection.

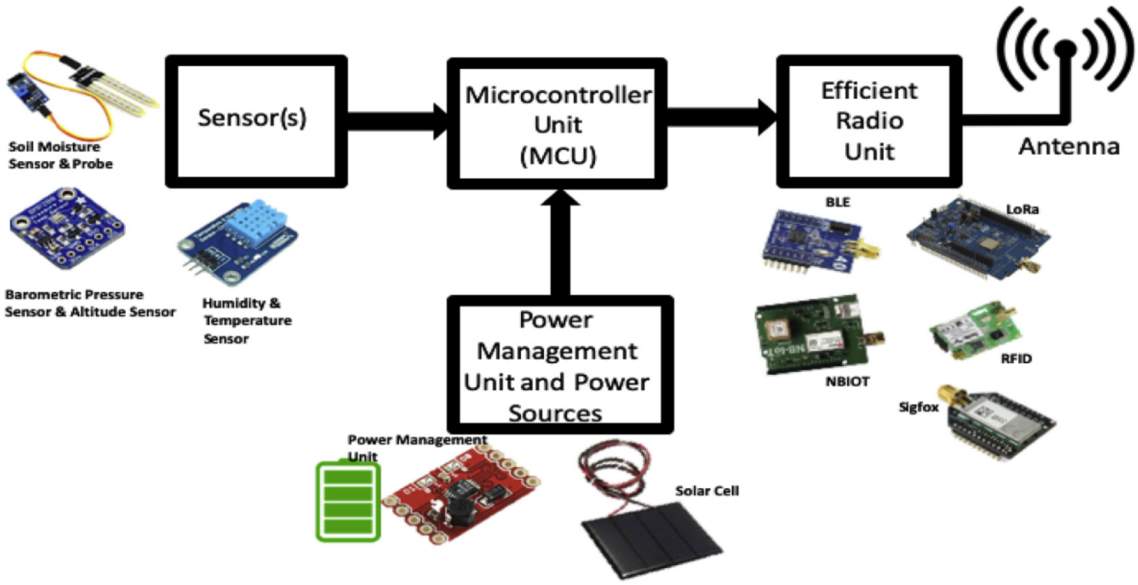

Figure 1. 8: IoT-enabled standard sensor node of Digital Municipality

The components of an IoT-enabled smart city aim to improve urban living by leveraging interconnected devices, data analytics, and automation. These components work together to create more efficient, sustainable, and responsive urban environments. Key components include: sensors, microcontroller unit, power management unit and efficient radio unit. Sensors are the backbone of a smart city, collecting real-time data from the environment. These include temperature, humidity, air quality, traffic, and energy consumption sensors. The microcontroller unit (MCU) plays a critical role by acting as the central processing unit for various IoT devices and sensors. It serves as the brain of smart devices, enabling communication, data processing, and control within the city's IoT ecosystem. MCUs gather data from sensors and process the raw data locally before sending it to central systems for further analysis. The Power Management Unit (PMU) and power resources play a crucial role in ensuring efficient energy use, distribution, and sustainability. These components are vital for the optimal operation of smart devices, sensors, and infrastructure, enabling cities to manage energy consumption intelligently and integrate renewable energy sources. Communication networks are essential for transmitting data between IoT devices and city management systems. This includes 5G, Wi-Fi, LoRaWAN, NB-IoT, and other wireless technologies to ensure continuous connectivity. The network infrastructure enables real-time data exchange across the city.

Waste management is important to the concept of a "smart city." The distance between the central trash processing facility and the garbage collection location is an important consideration when assessing the efficiency of a waste management system. Existing communication technologies, such as Sigfox and LoRa, which run on a low-power, wide-area network (LPWAN), can handle this demand with a sacrifice in data transmission speed, making them suitable for use in the waste management system. There has been a rise in the study of wireless communication in IoT. However, as demonstrated in table 1.1, communication technologies like Bluetooth, Zigbee and Wi-Fi enable better data transfer speeds while having shorter data transmission ranges. ML and IoT-based solutions are promising areas of study for the development of intelligent waste management. To address the problem of garbage disposal, the IoT is facilitating a meteoric rise in the number of interconnected devices. By increasing the amount of data collected, applications can gain more functionality and intelligence through the use of Machine Learning (ML) techniques [4][14].

Table 1. 1: Characteristics of various communication medium

Sr. No	Characteristics	Bluetooth	Zigbee	Wi-Fi	LoRa
1	Transmission Technique	Frequency Hopping Spread Spectrum	Direct Spread Spectrum Sequence	Orthogonal Frequency Division Multiplexing	Chirp Spread Spectrum
2	Data Rate	1Mbps	250 kbps	11 Mbps and 54 Mbps	290 bps to 50 Kbps
3	Peak Current Consumption	30 mA	30 mA	100 mA	17 mA
4	Max. end devices	255	More than 64000	Depends on number of IP address	More than 5000
5	Range	10 m	10 to 100 m	100 m	10 km- 15 km

1.8 MOTIVATION OF WORK

Garbage collection services have been in cities since the dawn of civilization, and as the human population has grown, so has the amount of trash produced. Around 500 BC, the lack of a reliable waste collection system made it imperative to implement measures to prevent littering the public realm, which in turn posed several health risks. In the beginning, garbage was burnt and disposed of, but this method was inefficient and a nuisance to city dwellers. rubbish segregation has become an important part of waste management as governments across the world pass legislation to reduce pollution in urban areas. Many types of rubbish may be recycled, and some can even be burned for electricity. Packaged foods and plastic bags are major contributors to modern landfills. The rapid speed of city life is a major contributor to waste pollution, which in turn has prompted the need for rubbish sorting. There is a system in place to address this issue, but it has to be refined to account for the proliferation of trash dumps. Manual waste collecting and sorting is inefficient since humans are prone to error and can easily confuse different types of trash.

The Internet of Things (IoT) underpins a smart waste management system, one of the cornerstones of the trendy new term "Smart City". In industrialized and first-world nations, in particular, there are innumerable Smart IoT-based Solutions for waste management systems now being implemented. However, trash management is a significant issue in low-income developing nations since littered roadways result from inefficient garbage collection and disposal practices. Because of several considerations, including societal and cultural constraints Since there are fundamental issues with the core duty of waste management in underdeveloped nations like Bangladesh, present smart solutions are incompatible. Today's society has a pressing need for IoT-based waste management solutions. Managing garbage is become a global concern. Without an efficient waste management system, society has faced serious ecological and economic problems. However, many communities still don't use the essential procedures for rubbish collection, resulting in foul odours and human misery. Many of the issues plaguing current manual waste management systems may be eliminated with an automated solution. Despite the obvious benefits of IoT-based automated waste management systems, such systems are currently at the development stage worldwide. In this thesis, a smart garbage collection system is proposed which is built on the IoT and ML.

1.9 RESEARCH PROBLEM

Most household and commercial trash is created in the office or at home and consists of organic materials, paper, glass, plastic, and metal. Wastes such as sewage and industrial byproducts are not included. It is hypothesised that the proportion of inorganic components in the waste stream rises as individuals gain money and move to urban centres. These items must be disposed of in a manner that does not pollute the ground, air, or water. However, due to the lack of segregation in garbage cans, rubbish disposal has become a major problem in urban areas [1]. This is because sorting rubbish on such a massive scale is difficult. It's a terrible scenario since there is nowhere to put trash and the places that do exist are overrun. Recent surveys indicate that the vast majority of waste management budgets are spent on transportation and collection, leaving only a small amount for treatment. To reduce the need for landfills and the associated costs, it is recommended that garbage be sorted at the point of generation, with recyclables going to recycling facilities and the rest going to landfills [3][6]. Trash may be divided into three categories: biodegradable, non-biodegradable, and home-hazardous. The rule for wet and dry garbage was written to be simple and straightforward. The Bureau of Indian Standard Specification specifies that any forbidden materials, such as plastics or thermocol, must be handled separately during processing. Residents are obligated to practise the aforementioned guidelines for waste sorting. Therefore, it is important to notify people of these requirements and to keep an eye on waste segregation practices [13][19][28] so that individuals who do not comply with the practices may be informed and trained.

Our major focus will be on determining the contents of dry and wet trash, as well as biodegradable and non-biodegradable waste, based on rubbish images collected at various locations and monitoring garbage levels in smart dustbins. A system is suggested to keep an eye on regions for segregation practises, in which photos of garbage bins will be monitored using IoT and analysed using Machine Learning and Image Processing to predict if the waste is dry, moist, mixed, or biodegradable and non-biodegradable.

1.10 RESEARCH CONTRIBUTIONS

The contributions of this research work are summarized as follows:

- Developed Data Acquisition and Monitoring Framework Using Wireless Sensor Networks and Thing Speak IoT Analytics for Waste Management
- Designed the hybrid learning garbage waste classification system architecture.
- Feature layer from pre-trained ResNet 101 and classification layer from machine learning algorithms are implemented to train and test garbage waste images.

- An automatic image-based garbage classification system with advanced object detection.

1.11 OBJECTIVES

- To study different methods considering key attributes related to waste management for smart cities.
- To develop an IoT-based WSN framework and monitor waste in smart cities for efficient data acquisition using image processing tools.
- To design a hybrid machine learning algorithm to analyze extracted data for efficient segregation of waste.
- To compare and analyze proposed methods using potential parameters like accuracy, latency, precision, and computation time.

1.12 THESIS ORGANIZATION

This thesis consists of the following six chapters.

Chapter 1 entitled “Introduction” is the introductory chapter. This chapter explains the research's background and motivation. It also outlines the research goal to be reached as well as the scope of work that will guide the research. It also describes the importance of the fundamentals of the proposed system keyword technology with its architecture and various features and significance related to the domain.

Chapter 2 entitled “Review of Literature”, contains a literature review on the theme related to this research. In this chapter, a literature review of existing works is presented on IoT-based monitoring systems and intelligence waste management with various machine-learning approaches.

Chapter 3 is entitled “Development of an IoT-based WSN Framework for Data Acquisition and Monitoring of Waste”. This chapter gives an explanation of the proposed framework architecture with working flow. Also, the proposed approach of having Data Acquisition based on IoT for waste management systems is presented.

Chapter 4 entitled "Development of a Data Analytics System to Analyze Extracted Data for Efficient Segregation of Waste", presents the proposed methodological approach which mainly consists of two modules, camera sensor data analytics for classification of waste images and waste environmental sensor data analytics using supervised machine learning for effective waste management.

Chapter 5 is entitled "Experimental Results and Discussion". Based on the simulations, multiple classification methods are compared in accordance with the various performance parameters primarily based on the confusion matrix and analyze the proposed system performance with state of art methods.

Chapter 6, entitled "Conclusion and Scope for Future Research Work", emphasizes the main accomplishments and utility of the research and also discusses the scope for the development of future research work.

CHAPTER 2 REVIEW OF LITERATURE

2.1 LITERATURE REVIEW

The researchers examined [1] a system that uses DL-CNN (convolutional neural networks) to predict trash by combining existing approaches to garbage classification with those for object detection and image classification. After the necessary data sets and labels have been created, the ResNet and MobileNetV2 algorithms may be used to train and evaluate the trash classification data. Garbage object data is utilised to train and evaluate three YOLOv5 family algorithms. Five separate categorization studies of trash have been brought together for one final report. The picture categorization recognition rate was raised from 2% to 4% by using a consensus voting technique. Through rigorous testing and deployment on the Raspberry Pi microcomputer, we have successfully improved the rubbish picture categorization identification rate to over 98%.

Some of the topics covered include [2] smart bins, waste-sorting machines, waste-to-energy, waste monitoring, waste-generation models, modern materials and differentiating fossil, disposal, logistics, resource recovery, illegal dumping, process efficiency, smart cities, and improved public health. Artificial intelligence might reduce waste logistics-related time spent on the road by up to 28.22%, money spent by up to 13.35%, and gasoline used by up to 36.8%. With the help of AI, trash may be classified with a prediction accuracy of 72.8% to 99.5%. AI and chemical analysis are useful in many contexts, including waste pyrolysis, energy conversion and carbon emission estimation. Also, explain how AI may help smart cities simplify and lower the cost of trash collection.

The collection of tools, techniques, and plans that make up an effective waste management system [3]. It is shown that it is possible to implement a system and method for waste disposal that works, which might be used in the future to boost output while cutting expenses. Deep learning is helping to eliminate a major roadblock to efficient trash management. In terms of accuracy, the suggested technique was superior to AlexNet, VGG16, and ResNet34.

A household garbage sorting system was developed using the TensorFlow object detection model and an Arduino microcontroller [4]. The SSD MobileNet V2 model was educated using a dataset consisting of common home garbage such as metal, plastic, paper, glass, organic waste, and an empty class to evaluate if trash is being dumped out. When it comes to putting trash in the right bin, the method developed has a recall of 88.3% and a mAP of 86.5%. If waste is sorted and recycled, landfill use can be lessened, carbon footprints can be minimised, more recyclable materials can be recovered, and greenhouse gas emissions can be lowered. Segregation at the source is preferable for municipal solid waste management due to its lower cost.

Some of the intelligent approaches used to categorise garbage were described and studied [5], including deep learning, intending to study the qualities of solid waste. Quite a few real-world examples of model approaches to waste categorization management. The increasing volume of garbage makes intelligent waste sorting mandatory. In this article, we take a look back at the most widely used intelligent approaches to trash categorization and draw some parallels between them. A subset of solid waste was the primary focus of the categorization kinds. Multiclass was a part of it, and the top results were obtained via the CNN, Mobile net, and Resnet all had impressive accuracy rates, whereas the decision tree and random forest performed poorly. The convolutional neural networks are improved using a transfer learning approach, allowing for more accurate detection of the various forms of garbage. The efficiency and precision of the model can be enhanced. The transfer learning approach is used on a CNN to train the model to better distinguish between waste categories.

To forecast the rate at which demolition trash is produced in South Korean redevelopment zones, a hybrid model is built [6] by combining the techniques of principal component analysis (PCA), k-nearest neighbours, decision trees, and linear regression. Without PCA, the decision tree model outperformed the k-nearest neighbour's model. The predictive ability of the hybrid PCA-k-nearest neighbours' model was significantly higher than that of the non-hybrid k-nearest neighbours' model and the decision tree model. The observed data had a mean of 987.06 (kgm2), the k-nearest neighbours' model had a mean of 993.54 (kgm2), and the PCA-k-nearest neighbours' model had a mean of 991.80 (kgm2). Based on these findings, an ML-based technique was suggested called the k-nearest-neighbours model to predict the quantity of debris produced during demolition.

The prediction accuracy for monthly municipal SWG was provided [7] using an adaptive hybrid model that combines the ensemble empirical mode decomposition (EEMD) with AI models. Time series in the SWG dataset are neither stationary nor linear, thus we use a partial autocorrelation function to determine optimal antecedent values for SWG and then employ EEMD to decompose all input/output variables. Information collected in Tehran from 1991 to 2013 was used to determine how effective the strategy was. The superiority of the suggested model was demonstrated by contrasting it with other models that have been subjected to independent verification. The suggested hybrid EEMD-MARS model for SWG prediction outperformed the EEMD-LSSVM model, the baseline LSSVM model, and the MARS model based on the statistical criteria. The researchers used a Monte Carlo technique to validate the uncertainty analysis's data dependability, and they found that the EEMD-MARS model was both more accurate and more promising than the alternatives for predicting solid waste production.

The human visual system may be trained to identify trash at a glance [8]. Adding a trash proposal module that takes a comprehensive feature fusion approach is one way to make the proposed framework more amenable to waste detection. This module is meant to guide the framework in proposing more likely regions that include rubbish. To better manage spatial misalignment and enable fine-grained categorization of ideas related to trash, a waste classification module with a soft attention mechanism and foreground mask was developed. To recognise several garbage kinds with little training data, the suggested approach is a universal detection framework. The proposed system achieved 31.16% mean average accuracy across 12 waste categories with just 30 instances per category in trials, outperforming an existing few-shot detector named AFDNet by 1.68%. Reduced human effort spent on manual waste image collection and annotation enhances waste management by making robotic rubbish detection more flexible.

With the help of servo motors and deep learning, waste can be efficiently sorted and transported to the correct containers [9]. When the garbage cans are full, the gadget can send a signal to the proper authorities through dual-band GSM-based communication technology and ultrasonic sensors embedded in each may. Thanks to its automated features, the complete system may be operated from afar using an Android app to deposit the collected trash in the designated location. With this system's help, we can reuse and repurpose materials that were once destined for landfills, reduce our impact on the environment, and save money. Therefore, the system contributes to the requirements of a circular economy by optimising and extracting resources. Lastly, the system is built to be cost-effective while yet providing cutting-edge results in artificial intelligence (AI). Our deep learning model, ConvoWaste, has achieved 98% accuracy.

Data collecting strategy based on the aims of prior research [10], patterns of ML adoption, waste datasets, dependent and independent variables, and prediction models of garbage output built using AI. The majority of the research we looked at used assumptions about the types of garbage generated, the amount of waste accumulated in each site, and the overall categorization of waste. Predictive models are educated using data like demographics and images of different sorts and degrees of rubbish. Some studies have employed ANNs and CNNs to classify trash, but others have turned to alternative techniques, such as the gradient-boosting regression tree (GBRT). Lack of real-time time series waste information, unreliable analytics models, and an emphasis on short-term projections rather than the large picture all contribute to the difficulty of predicting solid waste creation and disposal. Finally, to spur more study in this field, the implications and limits of the chosen models are discussed.

Through the Internet of Things, we can now predict the potential waste of things using an algorithmic technique [11], which allows for an intelligent and effective waste management system to be realised. Waste capacity and metal and gas levels can all be tracked in real-time using IoT-based trash cans, which can be placed anywhere in the city. Then, several ML-based approaches are used to see how well our proposed solution performs. The efficacy and execution time of the method are analysed using machine learning classification techniques. The random forest method has a 92.15 percent success rate and an execution time of 0.2 milliseconds. These findings demonstrated the efficacy of the random forest algorithm, which forms the basis of the approach we propose.

Using off-the-shelf parts that can be fastened to a garbage can of any size, a smart trash disposal monitoring and prediction system was recently demonstrated [12] that relies on IoT. The proposed gadget employs a GPS module, ultraviolet (UV) and infrared (IR) sensors, and a microprocessor to screen the status of containers at set intervals. The architecture developed has no wires between the front and back ends, instead relying on a cluster network to relay information to a central processing unit. Long Short-Term

Memory (LSTM) is a neural network method used to learn and predict future rubbish based on waste generation trends. Their system also used Firebase Cloud Messaging (FCM) to alert the appropriate individuals in the event of a bin becoming overflowing. Web apps may use FCM JavaScript API to send notifications to browsers that support service work. As a result, the proposed method is socially beneficial since it helps authorities enforce stricter laws on rubbish collection and disposal. The proposed system also has an adaptable web-based data display, automated bin-height calibration, and data storage in a real-time, cloud-based Firebase database.

A powerful framework for waste management is developed [13] using DL and IoT. The CNN is used in the proposed method to accurately categorise trash as either biodegradable or non-biodegradable. The architectural idea also includes a high-tech trash can that is run by a microprocessor and a number of sensors. The proposed method employs Bluetooth and the Internet of Things to monitor your gadgets. When the IoT is paired with Bluetooth, short-range data monitoring is possible with an Android app, and real-time data may be controlled remotely from anywhere in the globe. The resulting model's efficacy is assessed by cataloguing and interpreting metrics including the precision with which waste labels can be classified, the precision with which sensor data can be estimated, and the system usability scale (SUS). The suggested architecture uses a CNN model, and its classification accuracy is 95.3125%, with a SUS score of 86%. But this clever technology will adapt to your family's habits and track garbage in real-time.

The CNN method offers a solution to the challenge of trash sorting [14]. A loss of 0.0205 is achieved in the model's accuracy of 0.9969. To this end, CNN algorithms applied to the task of trash classification improve outcomes and cut losses effectively.

The trash categorization issue has been addressed with the use of deep learning algorithms [15]. There are two main types of trash: organic garbage and recyclable trash. The accuracy of our suggested model is 94.9%. Although both competing models produce promising outcomes, the Proposed Model stands out as the most accurate. One of the biggest roadblocks to effective waste management may be eliminated with the aid of DL.

Through the MSWM process, from trash generation to disposal, ML algorithms are employed [16]. Through its analysis of unanswered questions and future potential for ML use in MSWM, theoretical and practical suggestions are offered for additional research work in the field.

The survey contributes by reviewing different object detection and image classification models [17] and their applications in waste classification and detection problems, as well as by analysing waste classification and detection techniques with precise and organised representation. We bolstered the study by talking about the drawbacks of the existing methods and the potential benefits of future innovations. This will give researchers a solid foundation in the most cutting-edge deep learning models and a crystal-clear picture of the unexplored research possibilities in this area.

The model was created [18] for intelligent DRL-based identification and categorization of items in recycling waste streams. The IDRL-RWODC approach uses DL and DRL techniques to detect and label garbage. First, a Mask Regional CNN (Mask RCNN) is used for object identification in the IDRL-RWODC approach, and then a Deep Reinforcement Learning model is used for object categorization. Furthermore, a deep Q-learning network (DQLN) is used as a classifier in the Mask RCNN model, with a DenseNet model serving as a benchmark. A hyperparameter optimizer using the dragonfly algorithm (DFA) is created to further improve the performance of the DenseNet model. Simulations conducted on a benchmark dataset corroborated the experimental findings that the IDRL-RWODC technique achieved the highest accuracy compared to other, more modern approaches to garbage categorization.

Using a multi-model cascaded CNN to identify and classify images of household trash was proposed [19]. MCCNN used the findings of three different networks to get its conclusions. To further decrease false-positive predictions, a classification model cascaded with the detection component to ascertain the accuracy of the detection findings. For training and evaluating MCCNN, a large-scale waste image dataset (LSWID) was assembled which consists of 30,000 images of household rubbish tagged in 52 different ways. The LSWID is the biggest collection of images of household rubbish ever assembled. The efficiency of rubbish recycling was also improved because of the introduction of a smart trash can in a Shanghai area. The experimental findings demonstrated cutting-edge performance, with an average detection accuracy improvement of 10%.

Research papers that were chosen have applied different DL models to garbage identification and segregation, as well as waste generation forecasting [20]. The study has established the methodology for conducting a systematic review, which includes several criteria and an evaluation method for determining the quality of research studies to be included in the review. The review provides an in-depth look at the various DL models and approaches used in SWM. It also contrasts the stated performance of chosen research and emphasises the application fields. The examined literature supports the conclusion that DL shows reasonable performance for garbage detection and classification. In addition to filling up the research gap, this article outlines the computing requirements of a Deep CNN.

Hardware for simple trash sorting is proposed in [21] using a deep learning architecture. The proposed hardware solution is based on deep learning. SmartBin uses image classification through a CNN architecture on a real-time embedded system to sort trash into biodegradable and non-biodegradable bins. Using photographs to identify garbage can help speed up the process of precisely categorising the many items that end up in the bin. Garbage detection is far more difficult than object recognition since trash can be any shape, size, colour, or texture, whereas images of objects belonging to the same category all share similar traits and properties.

The authors describe a deep learning-based classification approach [22], wherein ResNeXt serves as a deep neural network well-suited for real-world application, and wherein transfer learning approaches are used to further improve the classification accuracy. Because of its critical importance in the present environmental protection framework, we focus particularly on the problem of medical waste categorization. The method was used for 3480 photos, and it predicted the medical waste into 8 types with a 97.2% accuracy, as measured by the average F1-score of five-fold cross-validation. A DL-based approach was designed to automatically identify and categorise 8 different types of hazardous medical waste.

To better organise the heap of garbage at the dump, researchers at [23] created a system to divide it up into grid-like sections. Using a camera, an edge node receives a picture of the dump site. To make a specific garbage item prediction, a test picture for the learned DL is provided by the grid cell image segments. In this case, VGG16, a deep learning technique employed. Training takes place on a cloud server that has been moved to the edge node to reduce latency. Switching to a hybrid or distributed style of computing can reduce lag time and make better use of our computer resources. Over 90% accuracy is achieved by the taught algorithm, making it highly powerful.

Effective waste management may now be achieved with relatively little effort and cash because of the [24] proposed strategy. It's also useful for city governments since it makes it easier to automatically identify rubbish dumps in outlying regions. The automation was developed using two CNN models utilising drone-collected photos of trash. Each model was trained on the same picture dataset but with distinct training parameters, optimizers, and epochs. The selection of junk photos in this study makes advantage of symmetry. Incorporating symmetry into feature extraction results in uniformity when scaling photos.

There have been suggestions that deep learning methods may be used to develop fully automated systems for garbage sorting [25]. Yet, the vast majority of datasets employed for this function are insufficient. In this study, TrashBox, a novel dataset provided with 17,785 photos spanning seven groups, two of which (medical trash and electronic waste) are not represented in any other current dataset. Our research has led us to believe that TrashBox is the most comprehensive dataset of its kind. As part of the evaluation of TrashBox's generalizability, models are trained with transfer learning to see how well they perform, and the results are impressive: an accuracy of 98.47%. It also investigated how quantum transfer learning may be used in a revolutionary deep learning system. Promising outcomes have been found in experimental evaluations on benchmark datasets.

An enhanced ant colony optimisation (IACO) technique for HGR based on video sequences was developed and given by DL [26]. There are essentially four phases to the proposed structure. As a preliminary step, we use a video frame to normalise the database. Next, two pre-trained models, InceptionV3 and ResNet101, are chosen and tweaked to fit the characteristics of the dataset. Following this, we collected features from both revised models and trained them with transfer learning. Extractive characteristics are enhanced by the IACO algorithm. Following feature selection with IACO, the best features are sent into a Cubic SVM for labelling.

The researchers provide a deep AI model [27] that strikes a decent compromise between classification accuracy and memory utilisation. An improved SqueezeNet model with quantized weights is proposed here for use in robotic Hoover cleaners. Based on images or videos captured by robot vacuums, this model can distinguish between cleanable litter and noncleanable dangerous impediments in the home. In addition, videos are collected and stills from camera-equipped robot vacuum to round out the dataset. There are 20,000 photographs in all, taken from the floor level, depicting the dining rooms, kitchens, and living rooms of different residences in a variety of lighting settings. The suggested deep AI model uses at least 22.5 times less memory than existing methods while maintaining accuracy in object categorization at roughly 93%, as demonstrated by experimental data.

It was proposed [28] that a new framework be developed to centrally gather, monitor, and evaluate data streams from IoT sensor devices detecting trash can overflow in a decentralised scenario.

To aid in the classification and separation of problematic rubbish, the automated ML-based waste recycling framework (AMLWRF) has been described [29]. The fundamental objective of the work is to examine the use of ML algorithms in recycling systems.

For the incineration procedure in waste-to-energy facilities, an intelligent modelling strategy based on deep learning was described [30]. As a first step, the outcome factors are chosen by considering how well they balance safety, stability, and cost. Mechanism analysis was used to establish the baseline values of the output variables, and the Lasso method was employed to eliminate non-essential or redundant data before settling on the final set of input variables. Second, an input/output model was created with several inputs and outputs using deep learning and computed the delay times individually. As a final step, the deep learning model was validated against more conventional models.

Using Simultaneous Localization and Mapping (SLAM), a robot for C&D waste recycling is described in [31]. DL strategy and a high-precision 3D item pickup mechanism are built to further guarantee reliable garbage recognition and capturing. This research looked at how changes in illumination and population density affected the reliability of identifying construction and demolition debris.

Using a unique hybrid ML-based technique RF and LSTM [32], the output of biogas generation is forecasted by redefining the critical factors. The analysis employed input and output data collected from a functioning biogas factory. The proposed hybrid model outperforms its nearest competitor among traditional analytic models by 20% when it comes to estimating biogas production.

To detect and automatically categorise old textiles, [33] offers a method based on CNN and online near-infrared spectroscopy. Synthetic intelligence utilising a convolutional neural network for trash recognition and classification [34]. Deep learning and machine vision suggested fine-tuning the sorting robot's command and control system [35].

Secure Energy-Aware Meta-Heuristic Routing (SEAMHR) is a protocol designed to enhance the safety and efficiency of wireless sensor networks [36]. To achieve reliable and smart learning, the suggested protocol first employs Meta-Heuristic analysis based on Mutation Elephant Herding Optimisation. The protocol learns the best routes by accumulating hop counts, residual energy and connection integrity metrics. The protocol employs AEs (Auto encoders) and a counter-mode cryptography technique called CTR-AEDL for encrypting data and authenticating inter-routing.

A deep dive into the several Internet of Things-based methods [37] now in use for trash collection in SCs. In addition, a method is offered based on IoV for gathering data relevant to SC waste management.

The goal is to assess cutting-edge methods and tools for dealing with hazardous waste in all its forms, from collection to treatment to final disposal [38]. Additionally, the possible effects of new technology on metrics like performance, the economy, longevity, and policymaking are discussed.

Real-time monitoring of solid waste from remote locations is suggested and realised using the WPAN and cloud-assisted architecture [39].

Using deep neural networks, this system can monitor instances of illegal trash disposal [40]. The dumper's articulation points (joints) are obtained via OpenPose, and the garbage bag's type is identified via the object detection model, YOLO, allowing the proposed monitoring approach to calculate the dumper's wrist's distance from the bag and determine whether or not the dump is illegal.

Six different unique machine-learning approaches were compared for their ability to foretell CO_2 generation from composting green waste [41]. Once severe outliers were removed from the dataset, the Random Forest approach demonstrated the best performance in both the classification test with an accuracy rate of 88% and the regression task with an RMSE value of 23.3%. Guidance for lowering carbon emissions from green waste composting may be derived from total organic carbon, with the Gini index accounting for around 59%.

The deep learning networks are described for real-time, regional household garbage identification [42]. The challenges [43] of developing and deploying an IoT-based "Smart Waste Bin" that detects when the threshold for odour (biodegradability) and volume of trash in the bin has been exceeded are examined.

By analysing [44] how residents of M'sila deal with their garbage, this concept assessed the current state of such management and pinpointed the crucial elements of integrated planning for garbage disposal.

To classify and pinpoint trash, a two-stage detector was proposed [45]. We first use EfficientDet-D2 to find the precise spot where garbage is, and then we use EfficientNet-B2 to categorise that waste into seven different categories. To train the classifier, data from both labelled and unlabeled sources is used. The increasing use of AI in waste management allows for the development of more effective strategies and plans [46].

Commonplace Smart Waste Management solutions are outlined, and several scholarly works are discussed [47].

Taking into consideration physical restrictions, a novel method [48] was described for route recommendation in an IoT-enabled trash management system. It analyses the results of several studies using methods based on artificial intelligence.

Using ML and IoT, a method is suggested for more intelligent and effective trash management [49]. A novel IoT-based intelligent waste monitoring system developed [50] that may be used in private residences.

An attention-based VGG16 neural network model for sorting recyclables. After convolution, the model incorporates the attention module to zero down on the most relevant aspects of the feature map [51].

An automated plastic waste segregation system [52] that can separate garbage into the four designated categories would be useful both in a central sorting facility and in individual homes. Mobile device users now have access to a rubbish recognition tool that may be used to help clean up urban areas.

The suggested system combines IoT, Deep Learning, and Image Processing to replace the manual sorting of trash with an automated method [53]. An uneven precision measurement weighting strategy (UPMWS) is developed using an ensemble learning model, which is suggested for the classification of HSW using waste photos [54].

The ResNext model was improved using double fusion and regularisation to create DDR-net (Double fused Deep CNN using ResNext), a state-of-the-art classification model described in [55]. Actuators may be operated based on the model's output, and the suggested model can be integrated into any classification setup process that uses a camera to capture images of garbage as input.

The goal of the research work is to create an image classifier based on convolutional neural networks (CNNs) [56] that can be used to classify garbage.

Real-time trash classification using a hybrid technique is proposed as the basis for a smart waste classification model. Multilayer perceptron CNN (ML-CNN) are two of the ML models used in this implementation [57].

A waste management system designed with a focus on implementation in areas with limited financial resources and inadequate information. In such situations, local governments must make the most of the tools at their disposal. Case studies and a technique for such situations are provided in the publication [58].

For solid waste classification, MobileNetV2 is a deep learning model tailored for low-power environments and tools like mobile apps and edge computing devices [59]. The optimal network architecture, learning method, and activation functions for employing ANNs to anticipate the material makeup of physical waste streams from a given set of meteorological factors [60].

With the use of meteorological and calendar information, as well as historical data from a WtE plant, models based on the Gaussian processes regression (GPR) were constructed to estimate the daily lower heating value of MSW [61].

The suggested method classifies garbage as either dry or wet based on the relative humidity shift caused by the presence of damp garbage [62]. Municipal solid waste generation prediction using socioeconomic factors: an evolutionary machine learning technique [63].

To distinguish between trash-free and trash-filled zones, [64] proposes a machine learning-based approach. The four alternative algorithms used in our method, with kNN and Naive Bayes yielding 98.6 % accuracy, Decision Tree achieving 85.4%, and Random Forest achieving 98.6 %.

Researchers [65] examine a brand-new WTE framework using an actual dataset collected from MSW stations. Anaerobic digestion performance forecasting using machine learning and genetic data [66].

Two MSWI fly ashes from two Spanish towns were analysed physiochemically, and the results were published [67]. This study's overarching objective is to determine whether or not MSWI fly ash might be used to successfully sinter belite cement.

The study's major objective is to examine AI by investigating specific examples of machine learning algorithms in action inside recycling systems [68]. In tests with datasets of varying quality, the ANN model performed better. Both sets of modelling results show that the most percentage of food waste reduces LHV [69].

A smart waste monitoring system using IoT has been created [70]. An open IoT platform provided with a Raspberry Pi or an Arduino board for a trash-checking system [71]. The authors of [72] introduce GarbageNet, an innovative incremental learning system.

An Internet of Things framework was provided based on FIWARE to realise a highly adaptable open-source software solution based on industry standards for the creation of smart water systems [73].

Promising outcomes from implementing MMMT strategies in autonomous systems, as well as the special difficulties that must be overcome. For autonomous systems, especially those operating on power/resource-constrained or heterogeneous platforms, the MMMT model and hardware co-design [74] are crucial.

Researchers have suggested utilising AI [75] to automate the process of sorting medical waste streams for COVID from those of other types. This would allow for more informed recycling decisions to be made. An inexpensive and user-friendly solution for a household separation system is the Spontaneous Waste Segregator (SWS) [76].

U.N. Sustainable Development Goals (SDGs) [77] and the solid waste management system's circular economy approach facilitate post-COVID recovery. Using convolutional neural networks [78], specifically the DenseNet121, AlexNet and SqueezeNet networks, a smart strategy for trash sorting was created.

Automated waste classification into five types is possible by using DL and image processing [79]. DenseNet169, a transfer-learning-based model for rubbish image classification, was introduced in [80]. A "smart bin" based on IoT is created for real-time garbage management [81].

The LoRa wireless networking standard employed a TensorFlow-based deep learning model to develop an intelligent garbage collection and disposal infrastructure [82].

The application of transfer learning with a lightweight neural network in a demonstrable system for trash identification and sorting [83]. Through a process of data movement, the basic neural network MobileNetV2 is recreated. The findings of a study that compared three Deep CNN models designed specifically for waste classification [84].

An algorithmic proposed [85], computer-aided method for sorting waste based on the principles of AI. To forecast the likelihood of the waste level in garbage cans, an innovative approach has been presented [86]. The system can optimise garbage collection via the quickest route because of its use of machine learning and graph theory [87].

Smart bins with IoT are demonstrated in an effective garbage-collecting system [88]. It constantly checks on the trash cans to see which ones need to be emptied on the next scheduled garbage pickup. In addition, the system provides an improved navigation system that reveals the optimal path for collecting trash from the designated containers.

A neural network-based picture categorization and identification approach is developed. CNN to classify e-waste and a more rapid region-based CNN (R-CNN) to classify and quantify the waste equipment [89].

End-of-life management of bio-based goods is prioritised through recycling under this strategy, to minimise waste sent to landfills. The versatility and usefulness of bio-plastics make them a crucial material [90].

The major objective of the study is to assess the efficiency with which the waste management programme is carried out. [91,92]. The suggested study looked into the possibility of making money off of plastic waste as part of MSW to support MSW management in Nepali municipalities [93].

There is currently [94] an IoT-based system for managing garbage in cities. The suggested approach uses computer vision to categorise waste according to the degree of contamination [95]. Separating AI on the edge from AI for the edge is of utmost importance [96].

The goal of the study is to use a unique AI-based technique to the study of the connection between innovation management and product recycling [97].

Four widely used machine learning models are examined [98] on their ability to distinguish between biodegradable and non-biodegradable garbage.

An approach is provided for calculating landfill area [99] by combining the predictions of ANN models with prospective ultimate disposal techniques. The purpose of the research is to compare the performance of MLR and ANN models in predicting nutrient recovery from solid waste following various vermicomposting processes. [100].

An artificial neural network method for assessing MSW's physical composition is described [101] in China. A genetic method was proposed for planning efficient routes for garbage trucks. The system was put through its paces in a simplified actual condition in a specified location utilising just real data from city garbage pickups, proving its viability in such settings [102].

A machine learning and infrared spectroscopy model-based characterization method is provided to rapidly predict the elemental composition and heating value of BW. Rapid characterization data might be utilised to classify BW components in terms of the most effective ways to employ them in the final product [103]. Infrared spectra were used as part of a hybrid model that incorporated feature compression for data extraction, classification for identifying inorganic dilution, and regression for determining the elemental composition and heating value.

The trash classification dataset is reconstructed using an AutoEncoder network [104]. Two dataset feature sets are extracted using CNN architectures. The combined feature set was then subjected to the Ridge Regression (RR) technique, which significantly reduced the number of characteristics while honing in on the most important ones.

To help keep track of how much trash has been amassed in each trash can, a system for Internet of Things waste monitoring is presented with weight sensing [105].

Conceptualization of a waste sorting system is performed [106]. The system facilitates rapid queries of waste categorization information in a number of ways, so encouraging consumers to appropriately identify their household rubbish. Goals include spreading knowledge about how to properly sort trash for disposal and encouraging the continued growth of environmentally conscious communities.

The indoor air quality monitoring systems based on IoT are described, and a comprehensive appraisal of the current state of the art is discussed [107]. Using instance-level adaptation and transferable feature learning can help with the domain shift problem in cross-domain visual recognition. The proposed methodology outperforms the conventional fine-tuning method and yields desired outcomes in the new target area, even in the face of reduced labelling [108].

The primary goal is to take advantage of the widespread availability of cell phones by facilitating communication between persons and garbage collection stations about the trash that needs to be collected. By taking an image of their trash and uploading it to the garbage service's site, residents can help streamline the sorting and collecting process. The suggested solution is both server-based and app-based. For image analysis, neural networks are presented as a unique approach to classification and identification [109].

The ConvoWaste architecture presented [110] for face identification and categorization. A self-operating machine capable of identifying different types of garbage and sorting them out has been developed. Trash was fed into a conveyor belt via a funnel-shaped entrance, where it was identified using the Faster-RCNN technique and then segregated using a servo motor depending on the detection result [111].

The DeepWaste app is a user-friendly smartphone solution that uses highly optimised DL algorithms to promptly sort garbage into recyclables, trash, and compost. To identify and categorise trash, we test out several convolution neural network designs [112].

The literature on smart solid waste management systems is gathered and analysed using a systematic literature review approach [113]. There is a suggested method that can sort trash automatically into the appropriate bin (recyclable, organic, or hazardous). The technology employs deep learning algorithms to categorise garbage; the recyclable and organic garbage so separated can be put to good use in the future. This procedure will aid in making the environment more valuable and environmentally safe, paving the way for the development of a lush green ecosystem and the realisation of a brighter, more hopeful future [114].

The pre-trained ResNet-50 network was employed in the creation of a smart waste material sorting system. The feature extraction is performed by a CNN model with SVM classification that sorts trash into categories like glass, metal, paper, plastic, etc. [115].

Internet-of- An automated garbage sorting system was developed with the help of these things. A trash can is developed and equipped with sensors to record how often it is emptied and how the trash within is separated. Garbage detection and sorting using deep neural networks and picture recognition [116].

The application of neural network image processing proposed [117] to the problem of finding and labelling trash along a conveyor belt. Images captured by a camera are sent into a neural network, which then determines the objects' locations and types.

The benefits of the smart city reach well beyond its evident applications, preferences, and compelling aims [118]. Python scripts in ArcGIS [119] give a heuristic-based smart routing technique for MSW collection, allowing for the optimal solution of the model to be generated, including routes, operating time of vehicles and total travelling distances. The effectiveness of the algorithm will be tested in a case study using Sfax.

To minimise negative effects on the environment (such as carbon dioxide emissions and noise pollution) and the economy (such as the number of trucks needed and fuel consumption), scientists have designed a cutting-edge software platform and algorithm for sustainable urban transportation [120].

For IoT/WSN applications utilising multivariate sensors, a real-time data collecting model (RDCM) has been suggested [121]. There are two basic tiers to RDCM's architecture, the IoT sensor board and the fusion centre. All IoT sensor boards run the same code at the same time throughout each cycle to implement the IoT sensor board level, and the fusion centre runs the code at the fusion centre level.

The plastics were separated into groups based on their appearance and physical characteristics. It makes use of the fact that different types of recycled plastic have common properties including density, hardness, and colour. Included in these characteristics will be a dataset from which many classifiers may be learned to determine whether or not a certain plastic object in an image is recyclable. After a colour-based segmentation algorithm detects the plastic colour, a KNN classifier is used to predict that colour [122].

The system demonstrated the potential of automated machine learning by solving a real-world challenge in Smart Waste Management [123]. A strategy was proposed that combines threshold segmentation and distance transformation to identify significant differences in their spatial relationships. The recyclable bottles will be further organised using a concave point search based on a convex hull after close bottles have been located [124].

A genetic algorithm-aided fuzzy chance-constrained programming (GAFCCP) model is used to enhance MSW management under uncertainty. By fusing the GA with the FCCP method, the proposed model makes a significant new contribution towards making the optimisation model more widely applicable and usable [125].

By analysing photos taken at various stages of composting, CNNs allow for rapid assessment of compost maturity [126]. The recent developments in circuit and system design discussed have used collaborative design of architectures and algorithms [127].

A Deep Neural Network (DNN) is used to show the findings of image classification research within the context of deep learning. Since the Python programming language is included in the TensorFlow framework [128], it is useful for developing AI.

Capsule-Net was evaluated for use in solid waste management, namely the process of sorting recyclables from trash. The sheer quantity of trash created and the scarcity of available human labour have elevated this responsibility to one of paramount importance [129].

Using deep learning technology, a new categorization approach is suggested to automatically determine the kind of trash. Thus, it is also relevant to the categorization of trash that has been recycled [130].

With the use of CNN [131], drones are being used as part of a precision farming system to pinpoint problem areas in farms. Later on, with the aid of drones, targeted pesticides were sprayed on the afflicted region based on the severity of the infection.

The pre-trained CNN net ResNet-50 model is used as the feature extractor in the intelligent waste material classification system [132]. After that, the SVM is used to sort the trash into its many categories: metal, glass, plastic, paper, etc.

Popular deep convolutional neural network topologies [133] are used to test the suggested method. With a test accuracy of 90%, Inception-Resnet, Inception-v4 surpassed the competition when it came to training without pre-trained weights. Testing on ImageNet showed that DenseNet121's weight parameter fine-tuning and transfer learning achieved the greatest test accuracy at 95%.

To automatically categorise trash left by city dwellers, researchers have developed a multilayer hybrid deep-learning system (MHS) [134]. This device uses a high-resolution camera to take pictures of trash and sensors to pick up data on other features that might be helpful. The MHS uses a convolutional neural network (CNN) to extract image-based features and a multilayer perceptron (MLP) technique to collect image data and other feature information to classify waste into recyclable and non-recyclable categories.

An innovative method of implementing an integrated sensing system is offered [135]; this method automates the procedure of managing solid waste. The suggested smart trash can uses ultrasonic level sensors and other types of gas sensors to detect dangerous gases and the fullness of the trash can on their own. In the novel approach, data is monitored through the cloud via a mobile app. The gadget not only detects the presence of harmful gases but also whether or not the garbage can has reached capacity. Part two of the task is reporting the results to the right people. This unique approach was motivated by the practical, accessible, and disaster-proof qualities of cloud servers.

An innovative new garbage-collecting robot that can operate on grass is presented. The robot's accurate and autonomous waste identification is the result of its use of a deep neural network [136] particularly trained for trash identification. Following the DNN's segmentation of the terrain, a new navigation method is supplied so that the robot can explore. The robot's trash recognition and navigation features make it ideal for use in public spaces like parks and schools, where garbage may accumulate quickly and cause safety hazards.

2.2 COMPARATIVE WORK

Table 2. 1: Comparative Work Analysis

Topic	Authors	Journal Name	Methodology	Platform	Research Gaps
A deep convolutional neural network to simultaneously localize and recognize waste types in images	Shuang Liang et al. (2021)	Elsevier	Introduces a benchmark for comparing different approaches to waste management using DL, as well as a multi-task learning architecture based on CNN that can be used to identify and locate wastes in images simultaneously.	NA	NA
An Intelligent System for Waste Materials Segregation Using IoT and Deep Learning	V R Azhaguramyaa et.al. (2021)	Journal of Physics	Proposed an IoT and DL-Based Intelligent System for Sorting Garbage	IoT (Wifi) Embedded System (Raspberry Pi, IR sensor)Deep Learning (cloud)	Test Evaluation time is longer. Only classification of waste using software not prototype to separate waste Higher computation time for learning of deep learning model

Internet of Things (IoT): Opportunities, issues and challenges towards a smart and sustainable future	Sandro Nižetić et.al. (2020)	Elsevier	Knowledge of both the environmental repercussions of the widespread use of IoT goods and the state of the art in various IoT application domains	NA	NA
An Internet of Things-Based Smart Waste Management System Using LoRa and Tensorflow Deep Learning Model	T. J. Sheng et al. (2020)	IEEE Access	Created a deep learning-based, LoRa-based smart garbage collection system utilizing the TensorFlow platform.	IoT (LoRa) Embedded System (Raspberry Pi, Arduino Uno, Ultrasonic sensor, camera, RFID, GPS, LoRa, Servo motor)Deep Learning (cloud) Image Processing	Higher computation time Limited objects considered for classification

Toward a Deep Smart Waste Management System based on Pattern Recognition and Transfer learning	A. Jadli et.al. (2020)	IEEE	Smart waste management systems that use deep learning approaches to optimize garbage collection through the usage of IoT and surveillance technologies for superior QoS.	IoT (Wifi) Image Processing Surveillance camera Deep Learning (cloud)	Higher Computation time No power analysis
Waste Management of Residential Society Using Machine Learning and IoT Approach	S. Dubey et.al. (2020)	IEEE	Measuring the volume, metal content, and toxic gas concentration of trash cans in a number of different communities	IoT (Wifi) Embedded System (Raspberry Pi, MQ4 Ultrasonic Sensor) Machine Learning (Cloud)	Less Accuracy No power analysis Unable to detect all kinds of trash
Waste Profiling and Analysis	F. Shaikh et.al. (2020)	IEEE	method of sorting garbage that uses just a picture of the garbage to	Mobile Camera Deep Learning (cloud)	Less Accuracy Higher GPU requirement

Using Machine Learning			determine if it is biodegradable or not	Image Processing	to train dataset High computation time
Waste Management System Using IoT-Based Machine Learning in University	Tran Anh Khoa Han et.al. (2020)	Wiley	Using ML and graph theory, which optimizes trash pickup via the quickest route, a system for efficiently managing garbage has been developed.	IoT (LoRa) Embedded system (Atmega 328, LoRa, E32 TTL-100, ultrasound sensor) Machine Learning (regression) Shortest Path Calculation	Waste is not categorized No parameter tuning of machine learning modelling Sensor selection for trash is unable to detect various thrash
LoRa-Based Smart IoT Application for Smart City: An Example of Human	Jinkun Han et.al. (2020)	Wiley	Developed a multisensor LoRa-powered posture detection system and applied a posture identification algorithm based on it.	▪ IoT (LoRa) Embedded System (Arduino mega, magnetometer, gyroscope,	▪ No parameter tuning of machine learning classifier ▪ No feature extractio

Posture Detection				accelerometer) Machine Learning (Cloud)	n from signal directly uses feature selection
Waste Management and Prediction of Air Pollutants Using IoT and Machine Learning Approach	Hussain Ayaz et.al. (2020)	MDPI	Used an ML and DL-based model for IoT-based smart bins to control waste disposal and predict air pollution levels near the bin.	IoT (Wifi) Embedded System(Arduino, esp8266(wifi), Odor, Air, Weight, Ultrasonic) Machine and Deep Learning (cloud) Monitoring (Thingspeak)	Learning time is more ML and DL are both used which require higher configuration controller device LSTM model required a very large dataset to learn
Predicting LoRaWAN Behavior: How	Cuomo et.al. (2020)	MDPI	Applied machine learning to the analysis of a LoRaWAN rollout on a massive scale	▪ NA	Higher GPU requirement for learning

Machine Learning Can Help					Higher computation time Lack of Network optimization No parameter tuning of used classifiers
Smart Garbage Segregation & Management System Using Internet of Things(IoT) & Machine Learning(ML)	P. M. Fathimal et.al. (2019)	IEEE	IoT-based smart waste segregation and management device that uses sensor devices to detect wastes in trash cans, sort them into their respective categories, and immediately upload the resulting data to a cloud-based database.	IoT (Wifi), Embedded system (Arduino, Ultrasonic, moisture, metal sensor, servo motor) Image Processing Camera, Machine Learning (Cloud)	Less Accuracy No power analysis Simple object detection algorithm used to detect object which is not sufficient for various objects
"IoT-Based Solid Waste Managem	Pardini, Kellow et.al. (2019)	MDPI	Models of Waste Management: A Critical Review	▪ NA	NA

ent Solutions: A Survey"					
RecycleNet: Intelligent Waste Sorting Using Deep Neural Networks	C. Bircanoğlu et.al. (2018)	IEEE	Real-world instances of trash classification using Deep CNN designs for recyclables classification.	• Deep Learning ▪ Image Processing.	• Higher computation time • Consider only 6 objects for classification • Higher GPU requirement
IoT-Enabled Smart City Waste Management Using Machine Learning Analytics	T. Bakhshi et.al. (2018)	IEEE	IoT-based trash monitoring solution with machine learning data analytics for optimal waste collection and resource allocation.	• IoT (Wifi) • Embedded System (Raspberry Pi and ultrasonic sensors) ▪ Machine Learning (Cloud)	• Higher power consumption • Unable to detect all kinds of trash using sensors

Efficient Image Transmission Using LoRa Technology In Agricultural Monitoring IoT Systems	T. Chen et.al. (2019)	IEEE	Developed a new secure image delivery protocol called Multi-Packet LoRa (MPLR) for use in LoRa networks.	▪ IoT (LoRa) ▪ Embedded System (Raspberry Pi, Camera, LoRa SX1276 Module)	▪ For large areas, the error rate maximum ▪ Image quality degraded at the receiver
Machine learning approach to integrate waste management companies in microgrids	M. Graus et.al. (2018)	IEEE	Waste management firms have been integrated into microgrids using a machine learning-based strategy.	NA	▪ No parameter tuning of classifier
Deep Learning architecture for temperature forecasting in an IoT	Ben Abdel Ouahab et.al. (2019)	ACM DL	Integrated a LoRa-based IoT system with a DL architecture for weather prediction.	▪ IoT (LoRa) Embedded System(Wifi LoRa 32, DHT11, MQ2,	▪ LSTM model required a very large dataset to learn

LoRa-based system				Raspberry Pi) Deep Learning (cloud)	▪ Learning time is more
SEGRO: Key Towards Modern Waste Management	P. M. Jardosh et.al. (2020)	IEEE	Created a centralised server that communicates with every smart garbage can and handles tasks like monitoring garbage can fill levels, keeping tabs on delivery vehicles, and plotting the most efficient routes for drivers.	▪ Image Processing ▪ Deep Learning (cloud)	▪ Consider only 6 objects for classification ▪ Higher GPU requirement ▪ Higher computation time
Classification of plastic bottles based on visual and physical features for waste management	L. R. Kambam et.al. (2019)	IEEE	To determine whether or not a certain plastic may be recycled, it is necessary to first determine what kind of plastic it is.	▪ Image Processing ▪ Machine Learning (Cloud)	▪ Learning Time is high ▪ Less Accurate
Electronically	S. Nandhini	IEEE	Developed Waste is collected and sorted	▪ IoT(Wifi)	▪ No validatio

assisted automatic waste segregation	et.al. (2019)		automatically using a robotic assembly and machine learning-based categorization.	▪ Embedded System (Arduino, Servo, Ultrasonic) ▪ Deep Learning (cloud)	n of results ▪ Small dataset used to train and test
Proposal of smart home resource management for waste reduction and sustainability using AI and ML	S. Chimmani et.al. (2019)	IEEE	Developed an approach to reducing household waste and carbon emissions using AI and ML algorithms as part of a long-term strategy.	▪ IoT (Wifi) ▪ Embedded System (Camera, LCD, Weight gauge, buzzer) ▪ Machine Learning (Cloud)	▪ No validation of results
"i-BIN: An Intelligent Trash Bin for Automatic Waste Segregatio	M. Pamintuan et.al. (2019)	IEEE	Developed a trash bin equipped with sensors, which can intelligently segregate waste system that provides monitoring report of waste collection	IoT (wifi) Embedded system (Raspberry Pi, Camera, Servo, IR, Ultrasonic,	▪ Less accuracy ▪ The selection of sensors is not very

n and Monitoring System,"				DHT11, GPS) Image Processing machine learning (cloud)	suitable for the system ▪ Training data is less
IoT and ML-based Smart System for Efficient Garbage Monitoring: Real-Time AQI monitoring and Fire Detection for dump yards and Garbage Management System,	D. V. Savla et.al. (2020)	IEEE	Deployed an IoT and ML-Based Smart System for Waste Management	▪ IoT (wifi) ▪ Embedded System (Node MCU, Gas sensors, GPS, Ultrasonic) ▪ Machine Learning (Cloud)	▪ Insufficient learning of data for better classification ▪ No validation of results
Machine Learning Aided Scheme for Load Balancing	Abdallah Shami et.al. (2018)	MDPI	Developed an ML-based load-balancing approach that makes use of both unsupervised and supervised techniques	▪ Network Simulation ▪ Machine Learning (Cloud)	▪ Not much energy-efficient ▪ No paramete

in Dense IoT Networks" Sensors					r tuning of classifiers
Powering the IoT through embedded machine learning and LoRa	V. M. Suresh et.al. (2018)	IEEE	developed a method that uses LoRa for low-power transmission and machine learning on the edge device.	▪ IoT (LoRa) ▪ Embedded System (SX 1278 LoRa, ARM Cortex, MEMS accelerometer)	▪ Could be intelligent ▪ Cost is high
Implementation of Smart Bin Using Convolutional Neural Networks	K. S. Hulyalkar et al. (2018)	IRJET	Provided a method for automated sorting of trash at collection points using ML, IoT, and image processing	▪ Convolution Neural Network ▪ Image processing (Camera), PIR sensor ▪ Raspberry Pi, ▪ IoT	▪ Higher computation time, ▪ Learning Time is high

IoT-based solid waste management system: A conceptual approach with an architectural solution as a smart city application	A. S. Bharadwaj et al. (2016)	IEEE	Provides an end-to-end Internet of Things-based platform for automating and monitoring the solid waste tracking, collection, and management process.	MQTT (Message Queue Telemetry Transport) protocol IR sensor, PIR sensor, Gas sensor, Temperature and Humidity sensor, Sound sensor, Load cell Atmega328p MCU LoRa	▪ Could be intelligent ▪ Cost is high
Object Detection with Deep Learning: A Review	Zhong-Qiu Zhao et al. (2019)	IEEE Transactions	Comparative Study of CNN, Prominent Object Detection, Face Detection, and Pedestrian	NA	NA

The integration of IoT and machine learning for intelligent waste management represents a significant advancement over traditional and IoT-only systems. The use of real-time data from IoT devices and the predictive power of machine learning algorithms offers optimized resource utilization, cost savings, and environmental benefits. This approach is particularly important for smart cities where scalability, efficiency, and sustainability are critical. Conventional waste management relies on manual collection, predefined schedules, and static bin locations. These systems are often inefficient, leading to overfilled bins, unsanitary conditions, high operational costs and wasted resources. Also, traditional systems are not scalable without significantly increasing manpower and operational costs. Traditional systems are reactive, whereas IoT-enabled systems are proactive, predicting optimal waste collection times and routes using real-time data. IoT sensors are used to monitor bin levels, enabling real-time monitoring and optimized waste collection. IoT-based systems improve over traditional methods by reducing operational costs and improving bin monitoring. However, they often lack the predictive and intelligent decision-making abilities that machine learning can provide. Machine learning models are used to analyze historical data and predict waste generation trends, optimize collection routes, and even identify the types of waste for better recycling strategies. While machine learning-based systems introduce intelligence and predictive capabilities, without IoT integration, they may not achieve real-time optimization. Hence, the combination of IoT and machine learning provides a holistic solution. IoT-enabled ML systems are the most scalable, as they continuously adapt and improve based on growing data and changing conditions, making them highly suitable for expanding smart cities. The proposed system outperforms traditional and IoT-only systems by incorporating intelligence that not only reacts to current bin states but also predicts future waste generation, enabling better resource planning, cost savings, and environmental benefits.

CHAPTER 3 DEVELOPMENT OF AN IOT-BASED WSN FRAMEWORK FOR DATA ACQUISITION AND MONITORING OF WASTE

3.1 OVERVIEW

The Internet of Things (IoT) is the expansion of network connectivity to include not just computers but also everyday objects like appliances and wearable tech. These gadgets will have remote monitoring and control capabilities and will be able to connect and interact with people online. Connectivity between IoT sensor nodes and a central gateway is facilitated by WSN protocols. WSN is a subset of IoT that comprises a variety of technologies. This is the portion of the IoT where communication occurs primarily between devices themselves, independent of the internet. It's intriguing to think of everyday things we use being linked to the internet and being able to uniquely identify themselves to supplementary devices. Get data from sensors and other hardware by use electrical or other programming techniques to learn about a physical device. In this part, the IoT-based wireless sensor network (WSN) system is presented in this study for managing waste material that employs sensors to verify the garbage. Similarly, this design quickly transitioned to IoT-enabled cloud-based database storage. The microcontroller is the hub of communication between the IoT and the sensor frameworks. The Internet of Things enables near-instantaneous data collection and storage in the cloud.

3.2 PROPOSED FRAMEWORK

The proposed model primarily concerned itself with the fundamental layers that make up a basic architectural model, or with a typical architecture based on a requirements analysis. As illustrated in Fig 3.1 below, a generalised framework primarily takes into account a four-layer design consisting of application, middleware, network, and perception layers.

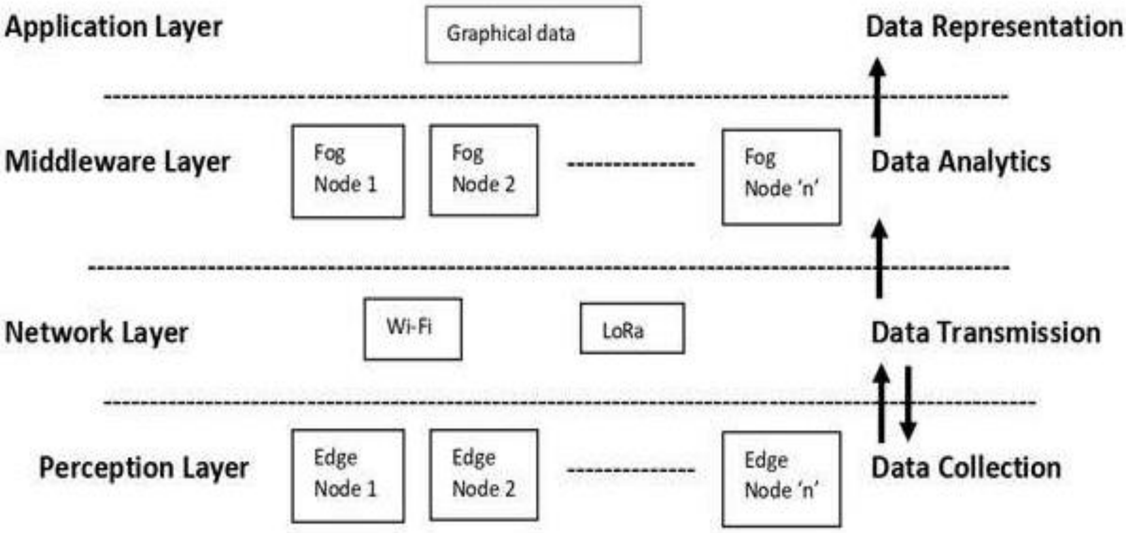

Figure 3. 1: Generalized IoT-based WSN Framework for Waste Monitoring

3.2.1 Perception Layer: The hardware-based layer collects raw data, processes it, and sends it up over encrypted channels to the software-based layers above. It uses technologies for the detection of parameters of physical features via specific sensors, such as the detection of poisonous gas levels, the detection of trash levels, waste images from cameras, etc., in addition to gathering information for item identification.

3.2.2 Network Layer: This layer uses Z-wire, ZigBee, GSM, Infrared, Wi-Fi, and LoRa, medium to share the gathered information from the perceptual layer with the upper layers, which contain the processing systems. The network layer is responsible for basic tasks like routing and data storage in addition to cloud computing and data management. The IoT infrastructure includes messaging protocols that facilitate the smooth exchange of information between devices. Message Queue Telemetry Transport (MQTT) is the de facto standard messaging protocol for TCP/IP-based, low-power devices.

3.2.3 Middleware Layer: The ability for IoT devices to communicate with one another relies on a software layer or set of layers. Concurrency is essential because it facilitates interaction between the application and perception layers and ensures that both can communicate effectively. In this context, machine learning is mostly used for data analysis. This is the fog layer, another name for it. Systems can do as much processing and analysis as possible as near to the source as feasible thanks to the fog IoT layers.

3.2.4 Application Layer: Although it is not directly involved in the building of an IoT architecture, the application layer is where the different services are developed that connect with users, i.e. where the information is interpreted and made available. This layer is responsible for building business models and graphs. Waste data in real-time may be tracked and analyzed with the aid of this additional layer.

3.3 DESIGNED EXPERIMENTAL SETUP

A wireless sensor network–based scenario, as depicted in Figure 3.2, is proposed as prototype part of the smart city's design in light of the IoT-based framework in waste monitoring for intelligent waste management.

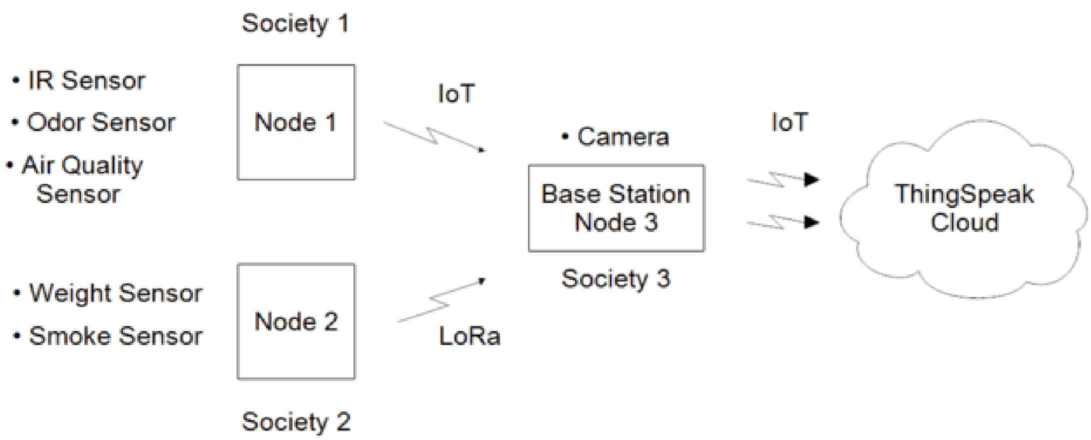

Figure 3. 2: Designed experimental setup

There are three nodes used in this experimentation. The first node is set up with an infrared (IR) sensor, an odour (Odour) sensor, and an air quality (Air Quality) sensor, all of which are interfaced with the microcontroller on the node's board. Node 2 placed in the second society is wired to a Weight sensor and a Smoke sensor, all of which are controlled by the Node MCU. These nodes are programmed in Embedded C language using IDE software. Finally, in the third node, the camera is directly connected to Node 3 base station controller which can be FOG device and set up to capture a picture using same device which further can be used to categorise trash material by the predictive analytics deployed at FOG node. In proposed assumptions, laptop computing device acts as FOG node in which predictive analytics model is programmed using MATLAB language. Figure 3.3 shows the interfacing diagram of sensors with a microcontroller unit (MCU) for node1 and node2.

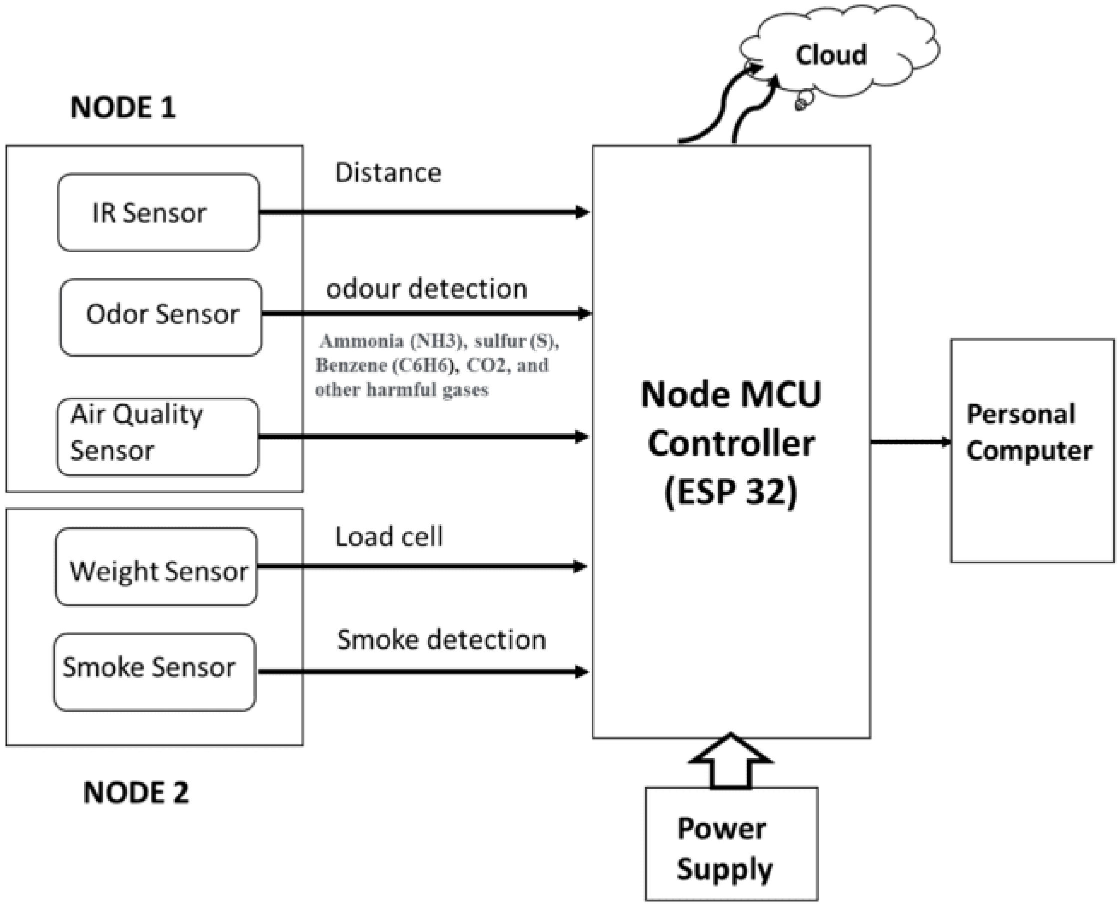

Figure 3. 3: Interfacing diagram with MCU

3.4 FLOWCHART OF PROPOSED SYSTEM

The proposed architecture presented for a wireless sensor network-based scenario for smart waste management in a city that relies on the Internet of Things is depicted in Figure 3.4. At the start, all sensors interfaced to the controller are powered on and initialized from Node MCU ESP 32 controllers. At an early stage, data from all sensors are acquired from the various sensor's edge nodes and monitored in real-time. Then transmit every sensor node's data to the fog node using data transmission media defined for each sensor node. The all-sensor data are collected for each node as per the context defined to it and monitored for normal and abnormal events. Data analytics is applied to collect data and predict the output which is nothing but the control signal generated as per predicted output. Also, processed data is sent over the ThingSpeak cloud by establishing an internet connection through nearby Wifi services. The real-time data is visualized on Desktop or Mobile applications of cloud services. The data is uploaded on the cloud server periodically over a certain period.

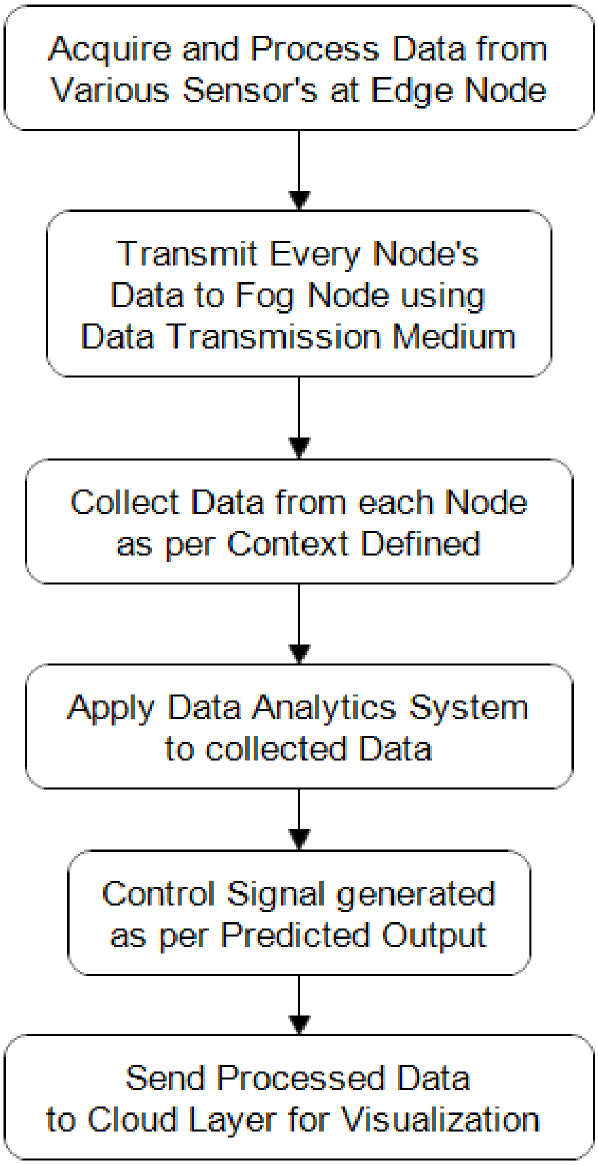

Figure 3. 4: Working Flowchart

3.5 DESCRIPTIONS OF COMPONENT

The component used in the proposed system is depicted in Fig 3.5-3.7. The suggested work's block design is depicted in Fig. 3.2, where two nodes each include an MCU microcontroller. Various sensors are linked to monitoring a parameter according to a scenario built for an IoT and LoRa environment.

Figure 3. 5: Node MCU microcontroller

Figure 3. 6: IR Sensor, Odour Sensor and Air Quality Sensor

Figure 3. 7: Weight Sensor and Smoke Sensor

IoT messaging is standardised through the MQTT protocol. A scalable and dependable method of connecting devices via the Internet is the MQTT publish/subscribe protocol, which is standardised by OASIS and ISO. The Gas Sensor MQ2 is useful for detecting gas leaks in industries. H2, LPG, CH4, CO, alcohol, smoke, or propane can all be detected using this device. The presence of items in industrial settings may be detected using an infrared proximity sensor such as an E18 IR. The MQ 135 gas sensor is used to detect CO2 while gauging the quality of the air around us. The MQ135 is a gas sensor used to check the air quality, making it possible to maintain a safe and healthy workplace. A trash can's heaviness may be determined by employing a special weight sensor. Infrared (IR) sensors, air quality sensors, odour sensors, smoke detectors and weight sensors are among the sensors utilised in the above-described experimental setting.

Proximity IR E18 Sensor

The presence of items in industrial settings may be detected using an infrared proximity sensor such as an E18 IR. When anything approaches a certain range, the non-contact detecting sensor will send out a digital signal. This sensor is low-cost, easy to assemble, and scarcely noticeable in its natural surroundings. has the capability of measuring distances without physical touch. One module serves as both a transmitter and a receiver. The transmitter sends out a modulated infrared signal, which gets reflected off of any objects in its path. The transmitter then sends a digital signal to the microcontroller based on the reflected signal it has received.

Odour Sensor

These sensors are calibrated to pick up on a very specific fragrance. The MQ7 is the sensor of choice for odours. An easy-to-operate CO sensor might be used to check the air quality for carbon monoxide (CO). This sensor is both very sensitive and responsive. The output of the sensor is an analogue resistance.

Air Quality Sensor

Air quality sensors are used to detect pollutants in the air. Particles, pollutants, and harmful gases are all examples of this category of chemicals. The MQ 135 gas sensor monitors indoor air quality and has a CO2 detection range, allowing for more secure working and shopping environments.

Weight Sensor

A garbage bin's weight is measured using a sensor. One type of transducer is the weight transducer, sometimes known as a weight sensor. A mechanical force, such as weight, tension, load, pressure, or compression, provided as an input is converted into another physical variable by this device.

Smoke Sensor

A smoke sensor is a device used to detect smoke, typically as an early warning of a fire. The Gas Sensor MQ2 can detect gas leakage in industrial settings. H2, LPG, CH4, CO, alcohol, smoke, and propane are all within the detection range of this device.

To help enhance the nodes' battery life and network capacity, LoRa also includes an adaptive data rate mechanism. The LoRa protocol has a variety of layers, including encryption enabling secure communications at the device, application, and network levels. Specifically, radio bands designated for industrial, scientific, and medical (ISM) uses are used by the low-power LoRa protocol, which is designed to function over long distances using unlicensed spectrum. Although the accessible bands are limited and certain countries have severe regulations regarding how frequently a device on these bands may transmit, Long Range (LoRa) devices may exchange data over great distances using sub-gigahertz frequencies.

IoT messaging is standardized through the MQTT protocol. A scalable and dependable method of connecting devices via the Internet is the MQTT publish/subscribe protocol, which is standardized by OASIS and ISO. It is a simple protocol made for publishing and receiving messages. It uses less power and has very little bandwidth requirement. Fig 3.8 shows the data handshaking of MQTT using publisher, subscriber and broker.

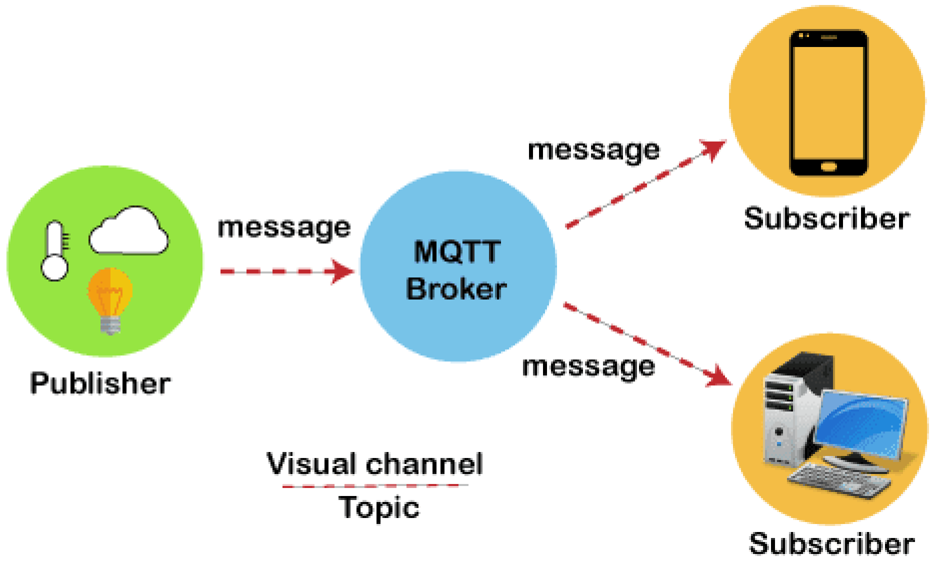

Figure 3. 8: Data Handshaking with MQTT Protocol

3.6 HARDWARE SETUP

The proposed architectural framework makes use of elements typical of IoT layer-wise design. Node 1 and node 2 employ sensors connected to the open-source Node MCU platform to track environmental data at closed and open waste facilities, respectively. The shield and microcontroller that the smart devices use to communicate with one another are linked. For reading sensor data, the Arduino IDE may be used to build embedded C software. LoRa and IEEE 802.11 Wi-Fi are used to transmit this data wirelessly. Anywhere the coordinator has Wi-Fi, they can log into the cloud server. Using the MQTT protocol, the perception layer takes in information from sensors, analyses it, and stores it in a database momentarily before transmitting it to the Thing Talk Cloud platform. This is all depicted in Figure 3.1. Figure 3.9 depicts the experimental setup as it is planned.

To assess the system's performance in multiple ecological tasks, wearable sensor parameters are tracked, researched, and analysed. When examining normal and abnormal circumstances in the same domain, the sensor reading parameters are monitored for two different sensor nodes placed in an open and closed environment.

Figure 3. 9: Experimental Setup

As seen in Figure 3.9, a laptop computer is interfaced with two sensor nodes as per the context defined, connected serially via USB. Figure 3.10 shows the setup for node1 in which three sensors interfaced with the Node MCU ESP 32 microcontroller unit. Figure 3.11 shows the setup for node2 in which two sensors interfaced with the Node MCU ESP 32 microcontroller unit.

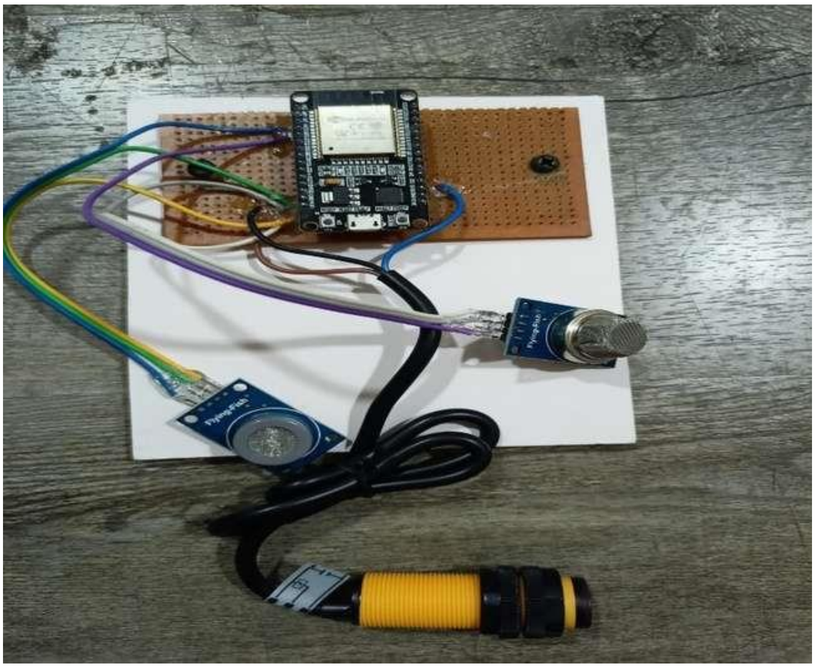

Figure 3. 10: Experimental Setup of Node1

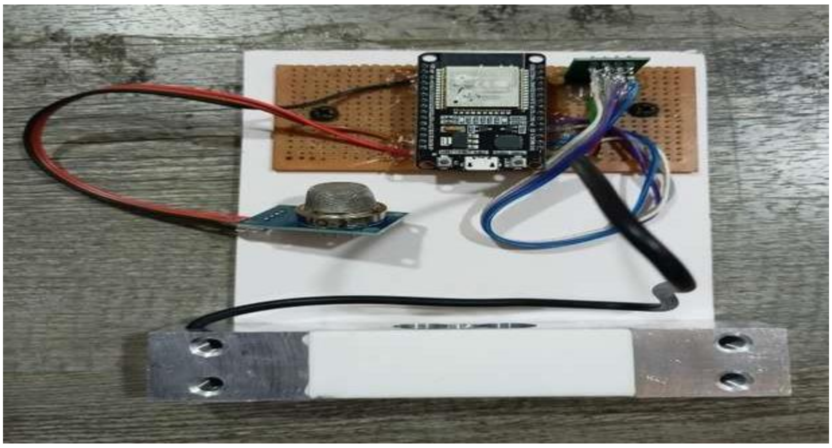

Figure 3. 11: Experimental Setup of Node 2

Two sensor nodes' data is being tracked in real-time on a serial monitor, with the time stamp values for each node displayed in Figure 3.12 and Figure 3.13. The values of two gas sensors with the status of object detection can be seen in Figure 3.12 with real-time stamp values. Also, the values of the gas sensor and weight value with the status of LoRa transmission with the third node can be seen in Figure 3.13 with again time stamp values. It also shows the packet delivery status as “success” or “fail”.

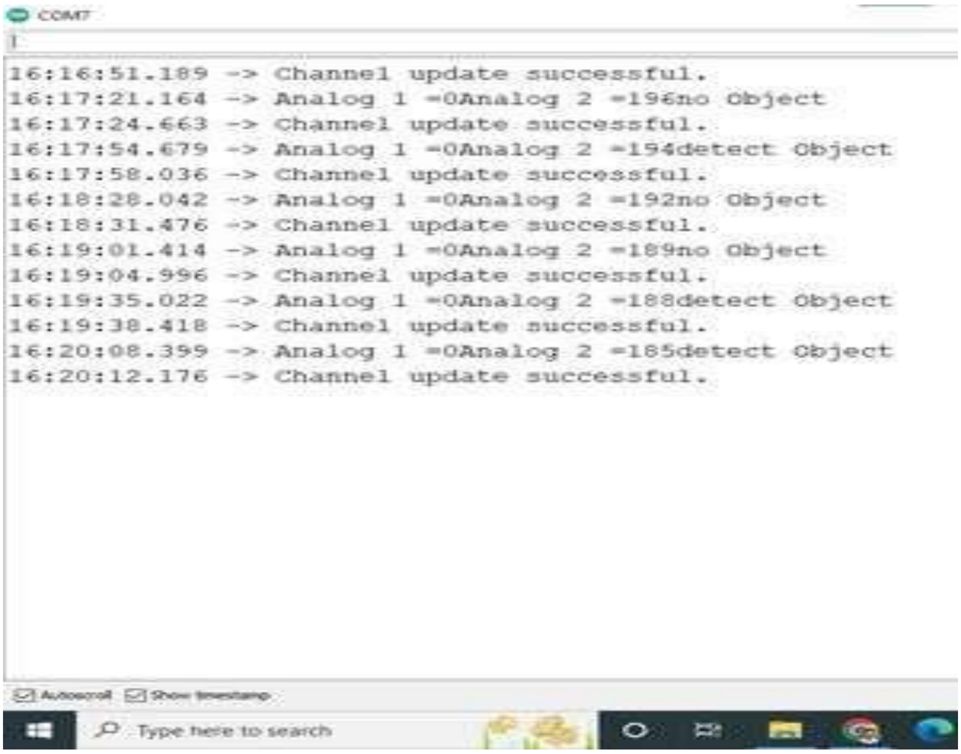

Figure 3. 12: Sensor's output of node 1 on serial monitors with timestamp values

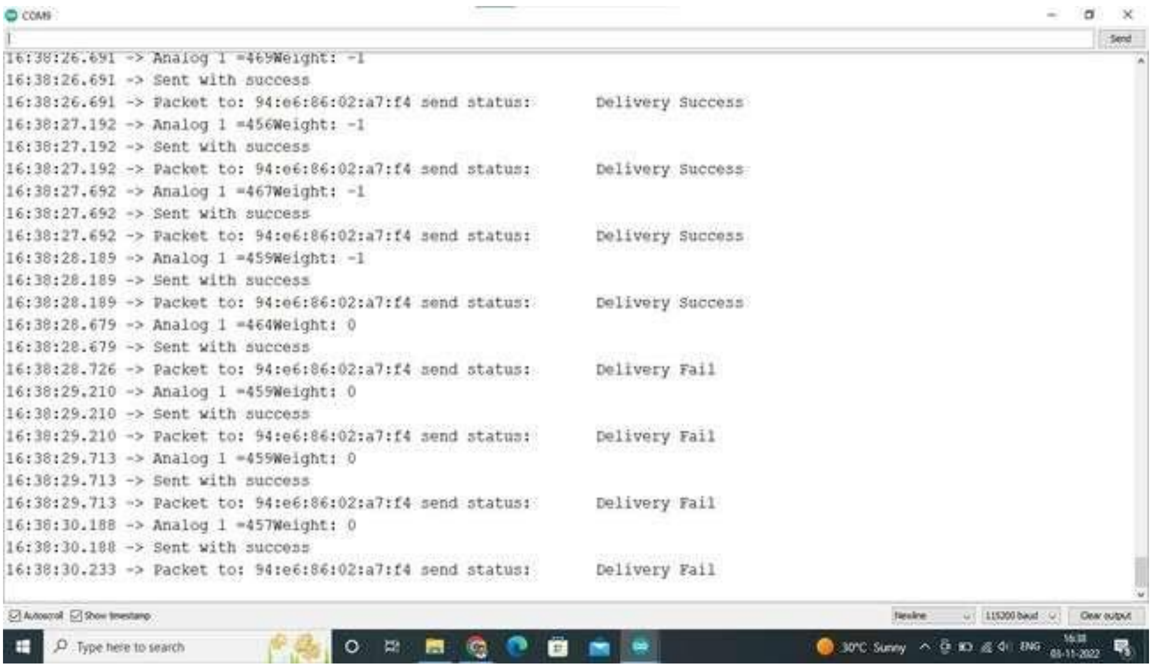

Figure 3. 13: Sensor's output of node 1 on serial monitors with timestamp values and status of data transmission through LoRa

3.7 DATA MONITORING ON THE THINGSPEAK CLOUD PLATFORM

ThingSpeak is an IoT application development platform that offers several specialised services. It allows users to collect data in real-time, display that data graphically through charts, and build plugins and apps that integrate with other APIs and social networks. As can be seen in Figure 3.14, the perception layer processes sensor data and stores it in a database until it can be transferred to the Thing Talk Cloud account via the MQTT protocol. Figure 3.15 shows the sequence diagram between the MQTT client and Thing speak MQTT Broker, the first client is communicated with a broker, and acknowledgement is received back to the client. The client is subscribed with a broker to the received message after getting the acknowledgement. On a smartphone, tablet, or monitoring screen, a dashboard with a graphical user interface (GUI) displays data with the Thing-Speak cloud platform as depicted in Figure 3.16. As can be seen in Figure 3.17, the Thing-Speak cloud platform makes use of a graphical user interface (GUI) dashboard to present information on a mobile device or monitoring screen.

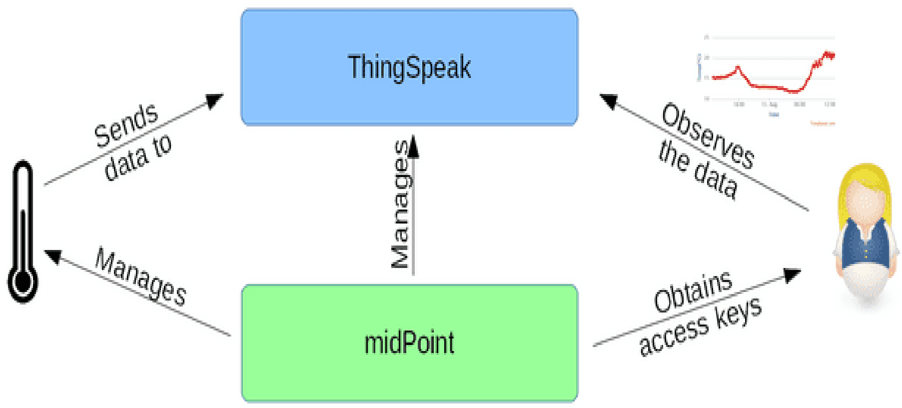

Figure 3. 14: Data handshaking with Thingspeak cloud platform

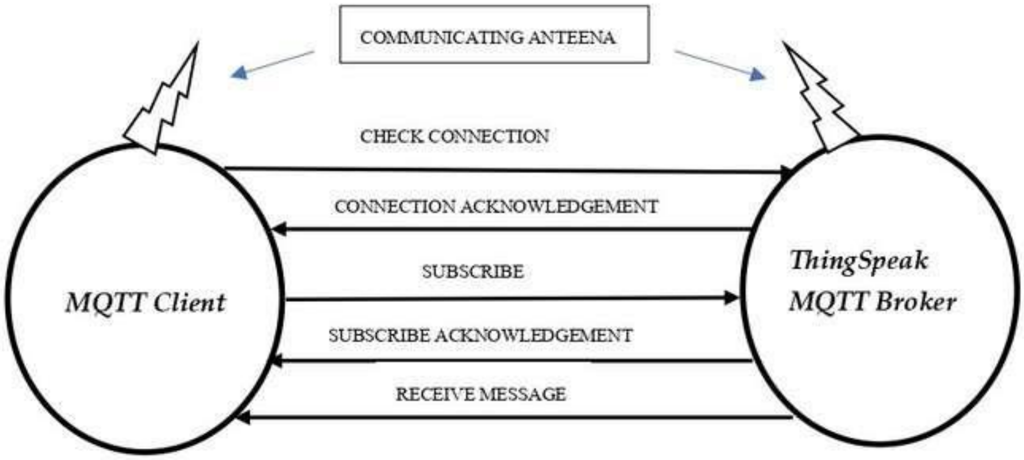

Figure 3. 15: ThingSpeak MQTT Communication between devices

The sensor distribution values for node 1 are represented statistically on the cloud as seen in figure 3.16 and 3.17. An alert is issued to the appropriate supervisor or responsible person for each anomaly discovered in values that meet the given threshold.

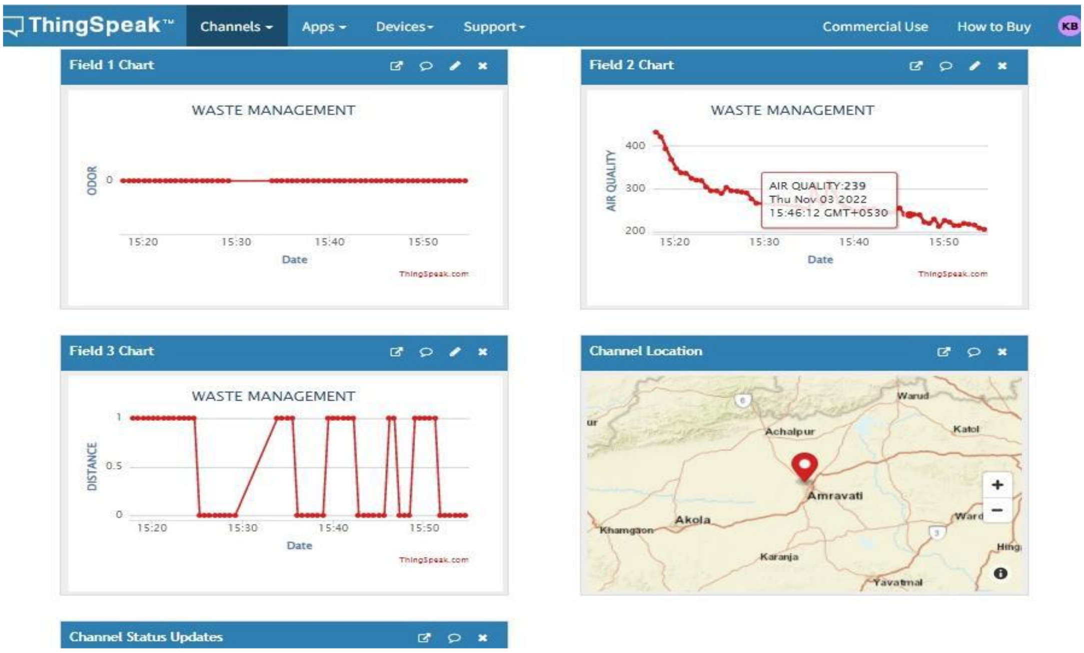

Figure 3. 16: Thing Speak Dashboard with other sensing Data Representation

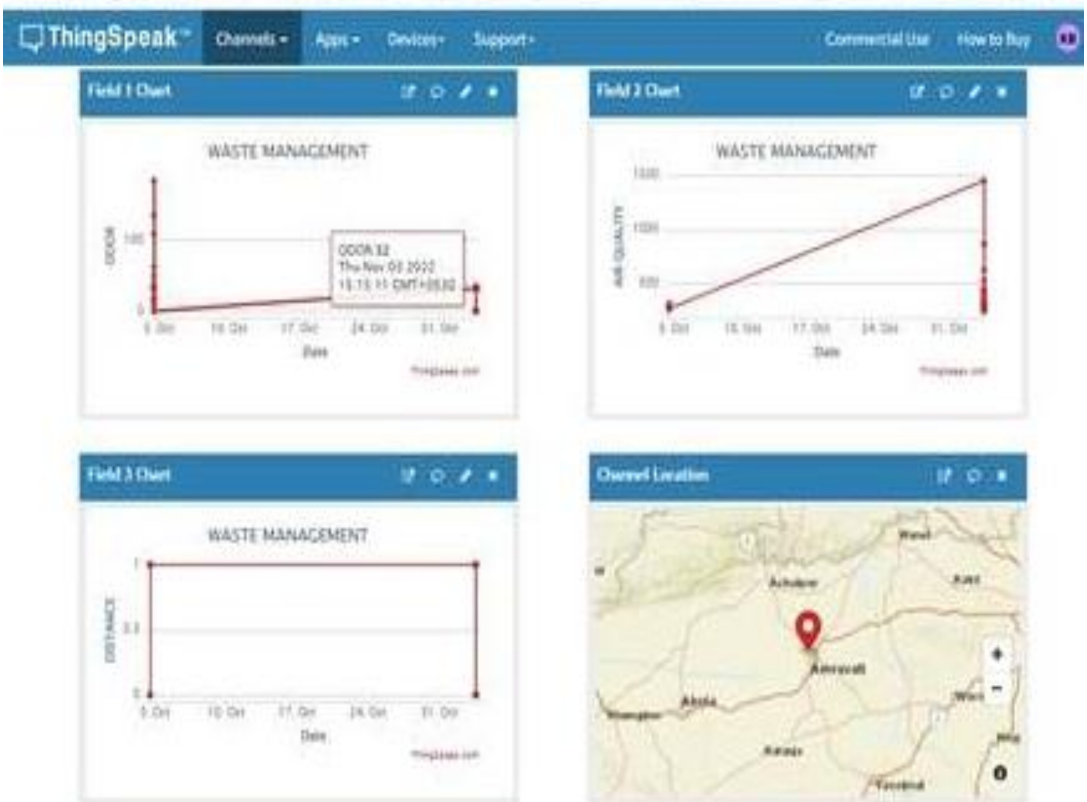

Figure 3. 17: Thing Speak Dashboard with other sensing Data Representation

3.8 DATA INTERPRETATION

The plot of distance using odour level, IR sensor, weight level, air quality level, and smoke level data parameter is shown in Figures 3.18-3.22, in which periodic data is collected at the different conditional waste environments.

Figure 3.18 represents the data which indicates the level of waste in cm, The threshold defined in blue colour categorizes the level of waste, above the threshold level acts as no waste is found in the dustbin.

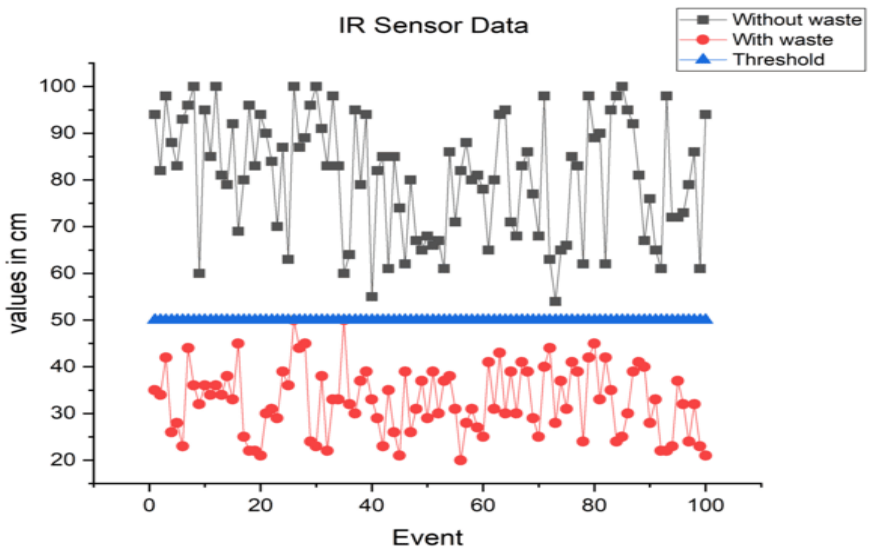

Figure 3. 18: IR sensor data

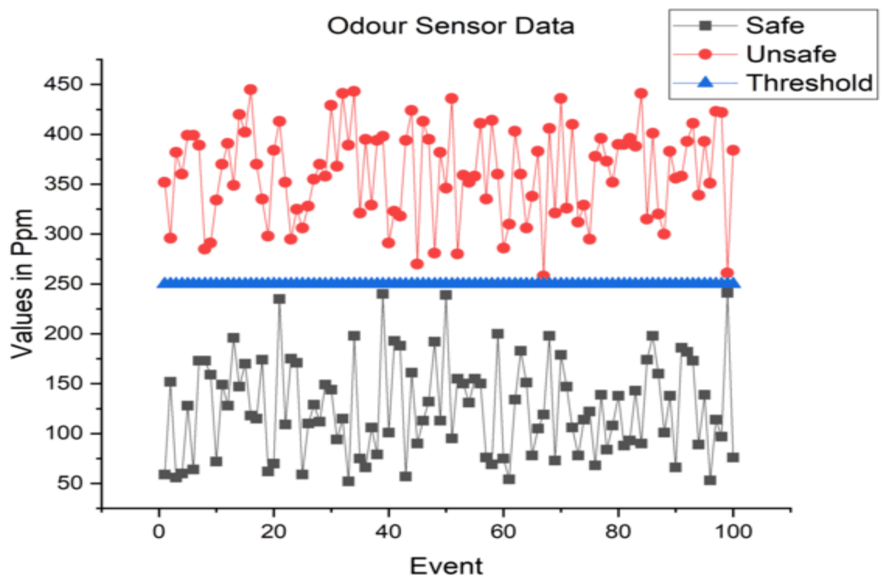

Figure 3. 19: Odour level data

Figure 3.19 depicts that data shown in black colour is represented as safe and red is represented as unsafe for various discrete events under environmental conditions for the odour Sensor and the threshold mentioned in blue colour acts as a threshold that discretized the safe and unsafe values.

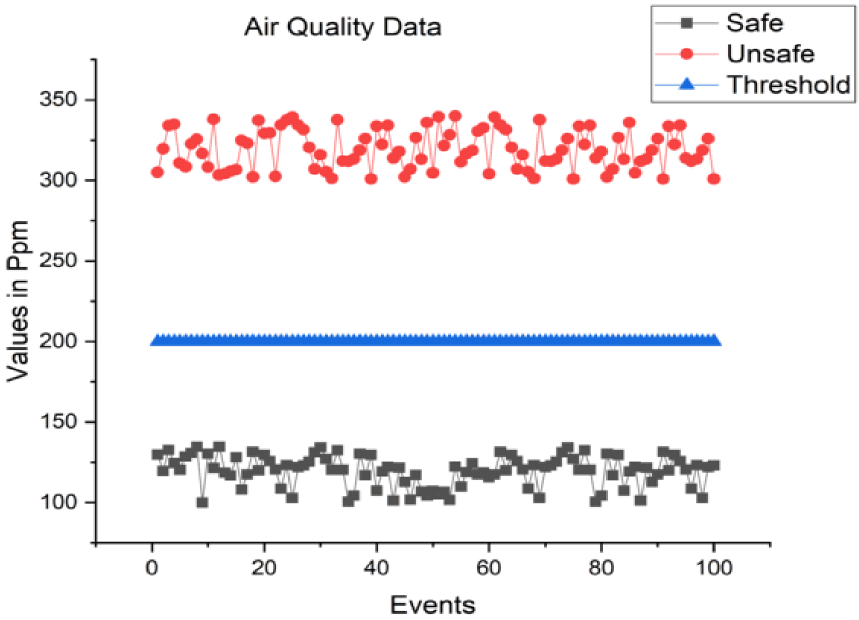

Figure 3. 20: Air quality level data

Figure 3.20 depicts that data shown in black colour is represented as safe and red is represented as unsafe for various discrete events under environmental conditions for the Air Quality Sensor and the threshold mentioned in blue colour acts as a threshold that discretized the safe and unsafe values.

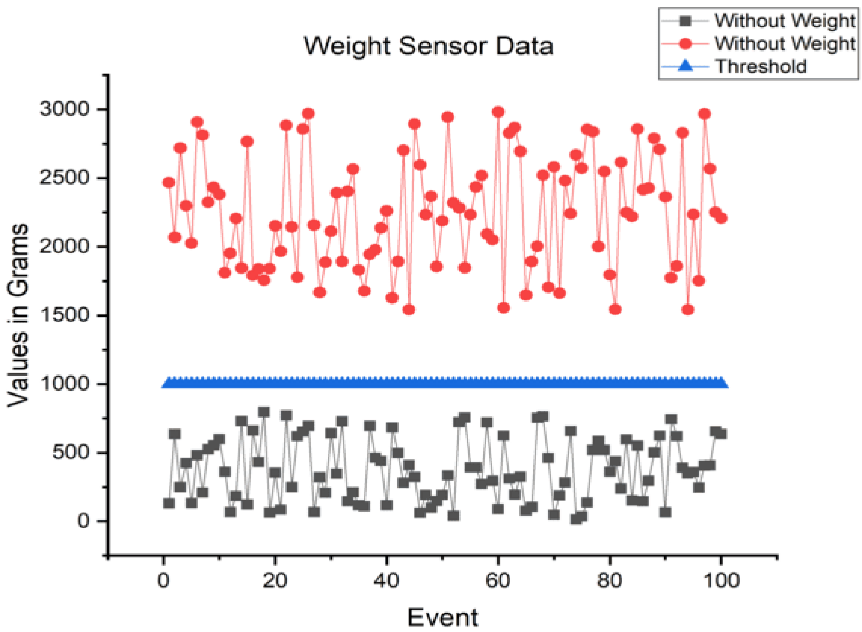

Figure 3. 21: Weight sensor data

The weight sensor data is represented in Figure 3.21. The value of weight above the threshold acts as the weight of the dustbin in grams of various waste collected and below the threshold indicates the minimal weight.

Figure 3.22 depicts that data shown in black colour is represented as safe and red is represented as unsafe for various discrete events under environmental conditions for the Smoke Sensor and the threshold mentioned in blue color acts as a threshold that discretized the safe and unsafe values.

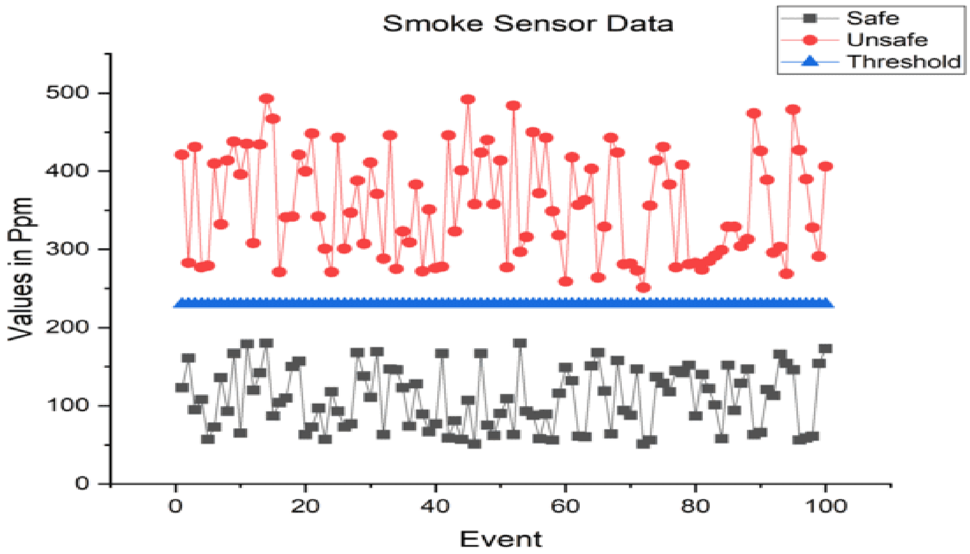

Figure 3. 22: Smoke Sensor data

To assess the system's performance in multiple ecological tasks, wearable sensor parameters are tracked, researched, and analysed. Two sensor nodes, one in an open environment and one in a closed environment, have their sensor data tracked to compare normal and aberrant conditions in the same domain. The cloud serves as a statistical representation of the distributions. If an abnormality is found in values that exceed the specified threshold, an alert will be sent to the relevant responsible party or supervisor.

3.9 SUMMARY

This chapter introduces an IoT-based WSN framework for data collecting and monitoring waste materials, complete with an efficient and trustworthy data monitoring system. The framework is divided into four primary layers: the application layer, the middleware layer, the network layer, and the perception layer. The primary goal of this framework is to design and implement a prototype system, comprised of three nodes, capable of real-time waste and type monitoring via a cloud server infrastructure under a variety of conditions. In the proposed experimentation, sensed data is monitored for sensor nodes on a ThingSpeak cloud server platform and the data on the IoT cloud platform using MQTT protocol with its data interpretation.

CHAPTER 4 DEVELOPMENT OF A DATA ANALYTICS SYSTEM TO ANALYZE EXTRACTED DATA FOR EFFICIENT SEGREGATION OF WASTE

4.1 OVERVIEW

Reusing, recycling, and recovering materials from trash is made easier by meticulous waste sorting. Since less garbage is sent to landfills, costs go down and the environment benefits as well. Separation is useful for public safety reasons. Waste sorting aids recycling efforts. It will facilitate the recycling of non-biodegradable garbage and the direct processing of biodegradable waste. A data analytics environment is presented here to enhance waste management processes. To optimise its operations, a waste management business may use this platform's collected sensor data from trash cans in conjunction with a variety of analytical tools and historical records. In addition to describing the platform properly, this article delves further into the algorithms and techniques used in data analytics. Data from a camera sensor used to take pictures of rubbish and data from a trash can sensor used for continuous monitoring form the basis of the suggested analytics model for the prototype system.

4.2 CAMERA SENSOR DATA ANALYTICS FOR CLASSIFICATION OF WASTE IMAGES

The waste object of garbage is the focus of the processing, analysis, and classification phases of the garbage waste classification system. The training and testing phases make up the entirety of the recognition system method. Figure 4.1 is a simple representation of a categorization system that has been presented. The suggested system begins with the same pre-processing and feature extraction processes at the beginning of both the training and testing phases.

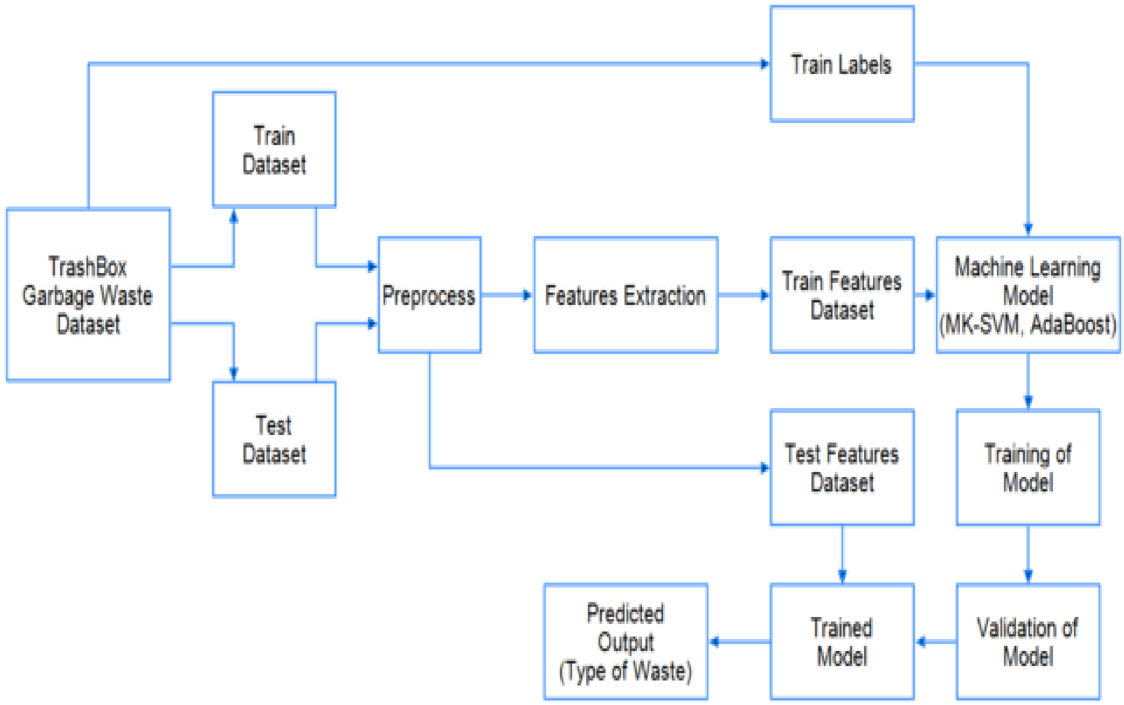

Figure 4 1: Garbage Waste Classification Framework

4.2.1 TrashBox Dataset

TrashBox, a standard benchmark dataset [26] stocked with junk from different settings. Domestic, medical, and electronic garbage were the primary categories used to categorise the photographs in TrashBox. future, table 4.1 describes how these classes are broken down into subclasses to make it easier to differentiate between different types of garbage items and to promote future study in this area. To make TrashBox, the first photographs of common waste items are gathered by doing a thorough online search. Figures 4.2-4.4 display some examples of the photographs used in experimentation.

Figure 4.2: Images of Class I i.e., Domestic Waste

Figure 4.3: Images of Class II i.e., Medical Waste

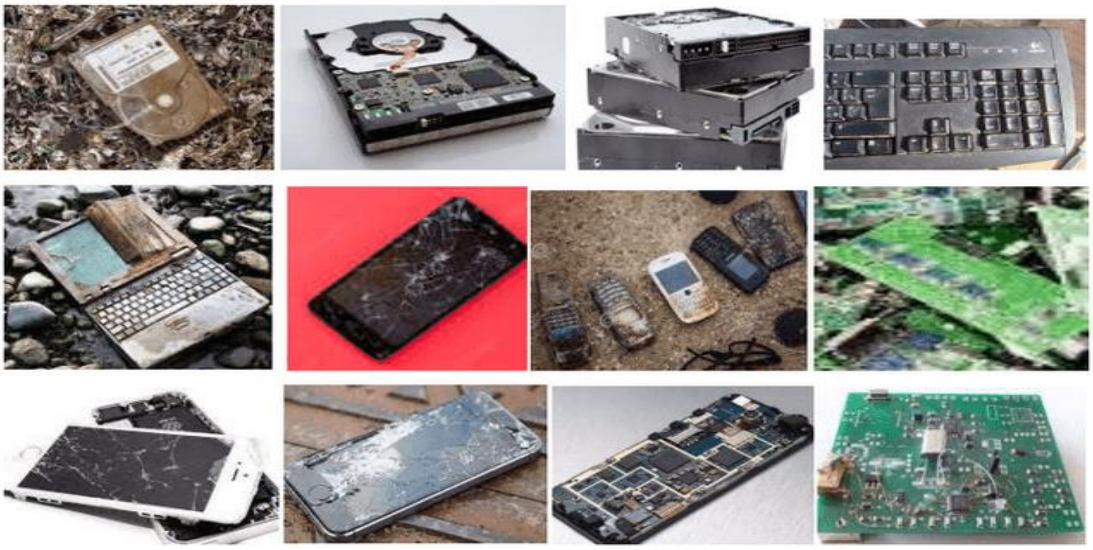

Figure 4.4: Images of Class III i.e., E-waste

Table 4. 1: ThrashBox Dataset – Classwise Statistics

Thrash Class	Sub-classes	No of Images	Total
Domestic Waste	News Papers	200	4476
	Paper Tissues	1062	
	Paper Cups	639	
	Bottles	571	
	Bags	504	
	Spray Cans	500	
	Beverage Cans	1000	
Medical Waste	Syringes	507	2010
	Surgical Gloves	496	
	Surgical Masks	500	
	Medicines	507	
E-Waste	Electronic chips	615	3437
	Laptops and Smartphones	774	
	Appliances	926	
	Electric wires	568	
	cords and cables	554	

4.2.2 FEATURE EXTRACTION USING PRE-TRAINED RESNET-101 DEEP CONVOLUTIONAL NEURAL NETWORK MODEL

To assess the feature set from the images, the proposed method employs a deep convolutional neural network (DeepCNN) pretrained model Resnet-101. In feature extraction, the representational power of a deep network is put to one of its simplest and most immediately useful uses. To start, we input in a network that has already been trained to recognise several different object categories from a large number of images. Therefore, the model has been educated to represent several image types, each with its own unique set of attributes. The network generates a tree diagram to represent the images it is given. Features at a higher level are layered on top of features at a lower level. To acquire the feature representations of the images, activations on the network's last layer, the global pooling layer, are required. The output features are a unified representation of the input characteristics across all geographic areas in the layer.

ResNet-101 is a deep-learning network consisting of 101 convolutional layers. Residual neural networks (ResNets) are an example of an ANN that is inspired by the architecture of pyramidal cells in the brain. Residual neural networks accomplish this by using skip connections, or shortcuts, to skip over certain layers. Nonlinearities (ReLU) and batch normalisation are common components of ResNet models, which are often constructed with double or triple-layer skips in between. HighwayNets are a type of model that needs an additional weight matrix to learn the skip weights. In modelling, "DenseNets" refer to models with numerous parallel skips. A neural network that does not generate residuals is known as a non-residual network or simple network. ResNet was inspired by VGG-19, another basic network architecture with 34 layers, to which we also provided a direct link. ResNet, short for "residual network," is an essential tool for addressing issues in computer vision. ResNet101's convolutional layers consist of 33 layer blocks, and 29 of those squares are recycled into later layers. The ImageNet dataset, which includes 1,000 different classes of objects, was used to first train this network. The structural plan of the pioneering design is shown in Fig. 4.5. This diagram illustrates the process of input picture segmentation into residual blocks, whereby each block is composed of many layers. Mathematically, this may be stated as:

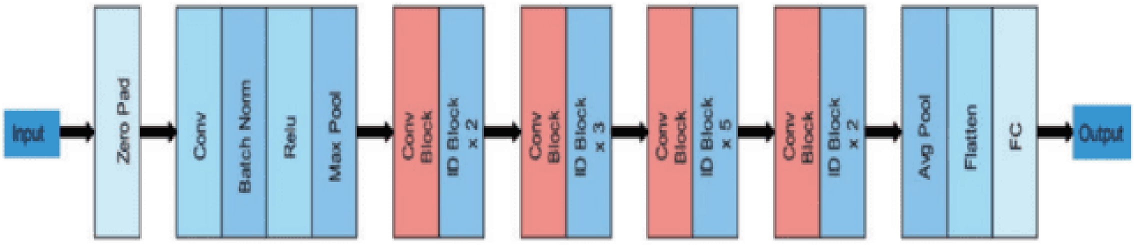

Figure 4.5: ResNet 101 deep learning model [36]

Consider,

Source Domain, $D_S = \{(\gamma_1^S,\rho_1^S),\ldots, (\gamma_i^S,\rho_i^S),\ldots, (\gamma_n^S,\rho_n^S)\}$ with learning task L_D, L_S, $(\gamma_m^S,\rho_m^S) \in R$;

Target Domain, $D_T = \{(\gamma_1^T,\rho_1^T),\ldots, (\gamma_i^T,\rho_i^T),\ldots, (\gamma_n^T,\rho_n^T)\}$ with learning task L_T, $(\gamma_n^T,\rho_n^T) \in R$;

(m, n) is the training data sizes where n << m and ρ_1^D and ρ_1^T are the labels of training data. Then the TL is represented as:

$$DS /= DT, LD = LT$$

4.2.3 MACHINE LEARNING BASED CLASSIFICATION MODEL

To provide expected output in the form of a waste type and additional object type of trash, the classification of garbage waste using two machine learning classifiers was carried out throughout the train, validate, and test stages. Machine learning classifier methods that are both versatile and reliable were used in this investigation. The K-fold validation (K=10) method is used to optimize the classification hyperparameters. This is essential knowledge due to the hyperparameters' influence on the model's efficiency. After being validated, the trained model may make predictions about the dataset's output label.

When applied to feature space instead of input space, a kernelized SVM is functionally like a linear SVM. The idea is to first do a nonlinear mapping of the data into feature space before applying a linear SVM. The kernel technique is utilized in a kernelized

SVM, therefore the real procedure looks different. The kernel function defines the implicit mapping between the data and feature space by returning the dot product of two representations of features. Suppose x and x′ are coordinates in some input space, and that the kernel function is denoted by K. We may then express the kernel function mathematically as

$$K(x,x')=\Phi(x)\cdot\Phi(x'),$$

where Φ is a function that transforms inputs into features. It is possible to construct a linear SVM that works in feature space without ever-computing by replacing the dot products in the formulation of a linear SVM with evaluations of kernel functions.

Algorithm 1: Implementation of SVM Algorithm
Step1: Initialize the input feature vector and output target vector *Step2:* Selecting the appropriate kernel function *Step3:* Defining the parameters and constraints *Step 4:* Optimizing the issue to determine the most efficient hyperplane. *Step 5:* Generating recommendations using the acquired model.

The main advantages of multi-kernel support vector machines are:

- Suitable for high-dimensional spaces and scenarios when the number of dimensions exceeds the number of samples.
- The algorithm utilizes a subset of training points known as support vectors in its decision function, resulting in economical memory use.
- The decision function may be customized using various Kernel functions, making it versatile. Standard kernels are available; however, users can also define their custom kernels.

The AdaBoost classifier is an iterative ensemble approach that combines numerous weak classifiers to produce a single, highly accurate classifier. With AdaBoost, a meta-estimator, a classifier is first fitted to the original dataset, and then further copies of the same classifier are fitted to the same dataset, with the weights of mistakenly classified examples adjusted to prioritise challenging situations. It is possible to set initial weights using,

$$W = 1/N \in [0.1]$$

Here, N represents all data points i.e. the number of records. Classify the influence using

$$\alpha = 0.5 \ln ((1\text{-TotalError})/\text{TotalError})$$

Alpha indicates how much a stump affects the ultimate choice. Total mistake = misclassified data. Update sample weights with this formula.

$$W_i = W_{i-1} * e^{+-} \alpha$$

The new sample weight is Euler's number times the old sample weight. For correctly categorized records, alpha is positive; otherwise, it is negative.

Algorithm 2: Implementation of AdaBoost Algorithm
Step 1: Initially, all observations are weighted equally. *Step 2:* Subset of data is used to build a model. *Step 3:* This model is used to make inferences over the whole dataset. *Step 4:* The deviation between the forecast and the actual number is used to determine the error. *Step 5:* Next time around, more consideration is given to the data points that were mistakenly anticipated. *Step 6:* The error value can then be used to assign weights. For instance, an observation may be given greater credence if it has a larger margin of error. *Step 7:* Repeat this step until either the error function stabilises or the maximum number of estimators is achieved.

The main advantages of the Adaboost classifier are:

- Reduced susceptibility to overfitting due to the independent optimization of input parameters.
- Successfully integrate many underperforming classifiers to generate powerful classifiers with exceptional accuracy.

- By prioritizing misclassified instances and modifying the weights assigned to each sample, it reduces the likelihood of overfitting the training data.

4.2.4 ALGORITHM STEPS

Algorithm 3: Data Analytics Considering Camera-based Image Data
Input: *Thrash Image Dataset, Domestic, Medical and E-waste Image Class*
Output: *Type of waste and its label of waste*
Procedure: *Step1:* Prepare waste image dataset containing the type of waste materials *Step2:* Split the waste image dataset into train and test into 70-30% ration *Step3:* Apply image processing operation on both train and test image set *Step4:* Extract the features from the train and test image set using a pre-trained deep convolutional neural network *Step5:* Prepare the train and test image features dataset for training of model and result prediction *Step6:* Initialize the input feature vector and output target vector for training *Step7:* Selecting the appropriate hyperparameters for both machine learning classification model *Step8:* Train and validate the model using finetuning of the classifier *Step9:* Load the trained model for each classifier *Step 10:* Make predictions based on the learned model to get the type of waste and its label.

4.3 SENSOR DATA ANALYTICS USING SUPERVISED MACHINE LEARNING FOR CONTROLLING ACTUATORS

The proposed sensor data analytics to generate the control signal for controlling the actuators of the hardware system using supervised machine learning is depicted in Figure 4.6. The proposed framework begins with data feature engineering, feature dataset splitting and machine learning modelling for result prediction.

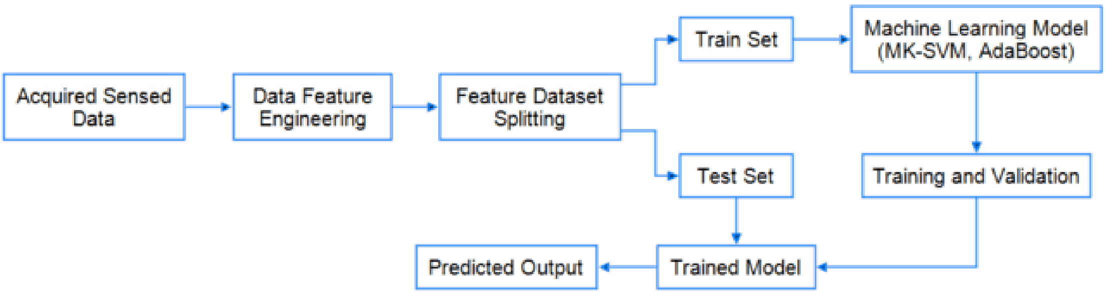

Figure 4.6: Garbage Waste Classification Framework

4.3.1 ACQUIRED SENSED DATA

A prototype hardware-based system is used to implement the proposed experimental architecture, and this system has undergone extensive testing. The acquired dataset has feature attributes of waste detection level using IR sensor (cm), Odor level (ppm), Air quality level (ppm), weight of smart dustbin (gm) and Smoke Level (ppm) for two different nodes. For node1, the actuator control for dustbin is represented by dustbin status and poisonous waste status. For node2, the actuator control for dustbin is represented by dustbin status and harmful gas status. This dataset includes hourly readings recorded over many days and under a variety of weather situations.

4.3.2 DATA FEATURE ENGINEERING

Data transformation into machine-learning-friendly features is called "feature engineering." To improve the quality and performance of ML models, feature selection, extraction, and transformation are performed. The quality of the characteristics used to train ML models is crucial to the success of those models. These methods improve the machine learning model's ability to learn from data by drawing attention to the most relevant patterns and correlations in the data.

One definition of a feature variable in the context of machine learning is a discrete, quantifiable quality or characteristic of a data item that serves as input to a machine learning algorithm. Features are data representations that can be either numeric, categorical or even textual, depending on the nature of the problem at hand. In proposed algorithm approach, cleaning and transforming data are prerequisite processes on sensor’s data which acts as feature data. The process of "data cleansing" entails finding and fixing any mistakes or inconsistencies in the data collection. This process is crucial for ensuring the data is correct and trustworthy. The purpose of data transformation performed is to make the variables in a dataset more amenable to machine learning by transforming and scaling them. Methods like standardization, and normalization used.

The model's efficacy is tied to the care and attention paid to the data before it is used. However, if we build a model without any sort of pre-processing or data management, it may not provide reliable results. However, by employing feature engineering on the same model, we may improve its predictive performance. In machine learning, feature engineering is used to boost the model's effectiveness. Some reasons why feature engineering is important are listed below.

- Better features mean better results
- Better features mean simpler models
- Better features mean flexibility

4.3.3 FEATURE DATASET SPLITTING

In feature splitting, one variable is divided into several smaller ones. This is commonly done when a variable comprises sub-components that can be better analysed independently. The term "feature split" refers to the process of dividing a feature into subfeatures. A date feature, for instance, may be broken down further into its parts (year, month, and day). Machine learning models can benefit from this since more data details are captured. The dataset is split into two parts: the training set and the testing set. The standard split is 70% for training and 30% for testing, however, this might change based on the size of the dataset and the specific application.

A 70-30 split provides a balance between having enough data to train the model so that it can learn effectively and also enough data to test it on unseen examples so that it can accurately evaluate its performance. Ultimately, the exact split is not rigid and may vary based on the size of the dataset, complexity of the model, and the specific problem at hand. The 70-30 split is a commonly accepted compromise between training and testing needs.

4.3.4 MACHINE LEARNING MODELLING

To provide expected output in the form of a waste type and additional object type of trash, the classification of garbage waste using two machine learning classifiers was carried out throughout the train, validate, and test stages. In this proposed study, we make use of the robust and adaptable machine learning classifier techniques in which two machine learning algorithms are used, decision tree bagger (DTB) and K- nearest neighbour (KNN) supervise machine learning algorithms. To get the best results from classification hyperparameter tunning, K-fold validation (K=10) is used. This is very important since the model's output is sensitive to the values of the hyperparameters. Predictions regarding the dataset's output label can be made by the trained model once it has been verified.

The main advantages of using a decision tree bagger (DTB) are:

- Used to predict both continuous and discrete values.
- Requires minimal effort for data preparation during pre-processing.
- Non-parametric algorithms do not rely on many assumptions.
- Generate intricate decision boundaries, enabling efficient resolution of non-linear problems.

The main advantages of using KNN are:

- Efficiently identify intricate and non-linear patterns within the dataset.
- The algorithm is resistant to noise and outliers when a sufficiently big value of k is employed.
- Does not require retraining or tuning.

4.3.5 ALGORITHM STEPS

Algorithm 3: Data Analytics Considering Sensor's Data
Input: *Two nodes sensor data, odour (in ppm), air quality (in ppm), smart dustbin weight (in gramme), and smoke levels (in ppm)*

Output: *Control signal for actuators*
Procedure: *Step1:* Prepare the sensor’s dataset containing various attributes of the sensor data *Step2:* Split the sensor dataset into train and test into 70-30% ration *Step3:* Apply data pre-processing operation on both the train and test set *Step4:* Select the pre-processed features from the train and test set *Step5:* Prepare the train and test set features dataset for training of model and result prediction *Step6:* Initialize the input feature vector and output target vector for training *Step7:* Selecting the appropriate hyperparameters for both machine learning classification model *Step8:* Train and validate the model using finetuning of the classifier *Step9:* Load the trained model for each classifier *Step 10:* Make predictions based on the learned model to get the prediction for the control signal for actuators.

4.4 SUMMARY

In this chapter, a data analytics model is developed using supervised machine learning for two types of data from a prototype hardware system with the classification system, camera-based and sensor-based data analytics model. The classification system for both purposes is developed using supervised machine learning algorithms MK-SVM, AdaBoost, DTB and KNN classifiers. The performance of the classification system is analysed and validated for two approaches used in the system.

CHAPTER 5 EXPERIMENTAL RESULTS AND DISCUSSION

5.1 EXPERIMENTAL SETUP

The analytics and decision-making model categorization developed having configuration of laptop running Windows 10 (64-bit) and powered by a 2.30GHz Intel i7 Core TM CPU. To create this model's code, the MATLAB IDE utilized together with the Statistics and Machine Learning Toolbox using Matlab programming language. To the Node MCU microcontroller and shield mounted on the prototype hardware system, the sensors are attached. For data collection from sensors, Embedded C programmes written in the Arduino IDE are used. Wireless transmission is achieved through the usage of the LoRa protocol and IEEE 802.11 Wi-Fi. Connecting the sensor node to the cloud server through Wi-Fi allows the MQTT protocol to continue sending data to the ThingSpeak Cloud platform.

5.2 PERFORMANCE EVALUATION PARAMETERS

The effectiveness of the proposed classification system is measured using a confusion matrix. The confusion matrix parameters True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are used to compute accuracy, sensitivity, specificity, and f-score for the classification model and RMSE for the regression model.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

$$\text{Sensitivity} = \frac{TP}{(TP + FN)}$$

$$\text{Specificity} = \frac{TN}{(TN + FP)}$$

$$\text{F-score} = \frac{2*TP}{(2TP + FP + FN)}$$

5.3 PERFORMANCE ANALYSIS OF DATA ACQUISITION FRAMEWORK

To assess the system's performance in multiple ecological tasks, wearable sensor parameters are tracked, researched, and analysed. When examining normal and abnormal circumstances in the same domain, the sensor reading parameters are monitored for two different sensor nodes placed in an open and closed environment. The distributions are represented statistically on the cloud. An alert is issued to the appropriate supervisor or responsible person for each anomaly discovered in values that meet the given threshold.

The mean values of different waste condition parameters are shown in Tables 5.1 and 5.2 for abnormal and normal activities over a day using sensor monitoring anomaly detection, which lowers the cost of maintenance for smart waste management.

Table 5. 1: Sensor Parameters Mean values at node 1 for day hours

Sensors Parameter	**Unit of Measurement**	**Threshold Value**	**Mean Value**	
			Abnormal	**Normal**
IR sensor	Cm	50	32.53	80.8
Odour Sensor	Ppm	250	363.79	121.73
Air Quality Sensor	Ppm	200	319.27	119.43

Table 5. 2: Sensor Parameters Mean values at node 2 for day hours.

Sensors Parameter	**Unit of Measurement**	**Threshold Value**	**Mean Value**	
			Abnormal	**Normal**
Weight Sensor	Gm	1000	2256.66	374.42

Smoke Sensor	Ppm	230	357.69	109.9

5.4 PERFORMANCE ANALYSIS OF CAMERA BASED SYSTEM

This section analyses the suggested categorization model. Domestic garbage, medical waste, and electronic waste make up the bulk of the typical standard benchmark dataset, Trashbox [25] utilized in experimental settings. Several images from a benchmark dataset have been extracted and organized into three semantic categories for this collection. All images are full colour and have been downsized to a 256x256 resolution. To evaluate the proposed model, 70% of available data was utilised for training, while only 30% of data used for testing. In the proposed study, multi-kernel support vector machine (SVM) and Adaboost classifier, these two-classifier models are used for evaluation. The training parameters are fine-tuned via hyper-parameter optimization based on a grid search. All performance parameters are analysed using the confusion matrix. We have used a confusion matrix and the performance assessment criteria to gauge how well the planned work measures up. An error matrix (also known as a supervised learning error table) is a type of table used to demonstrate the performance of an algorithm.

Table 5.3 shows the results of a performance evaluation of the two algorithms in terms of the amount of time needed to classify each of the three categories. Training and testing the classification step with Ada boosting algorithms took longer, as seen in Figure 5.1.

Table 5. 3: Performance Evaluation Time

Classification Phases	**Training Time (sec)**		**Testing Time (sec)**	
	MK-SVM	**AdaBoost**	**MK-SVM**	**AdaBoost**
Category I	81.54	90.16	35.90	42.46
Category II	64.89	78.48	29.27	32.85
Category III	89.41	93.71	39.50	45.37

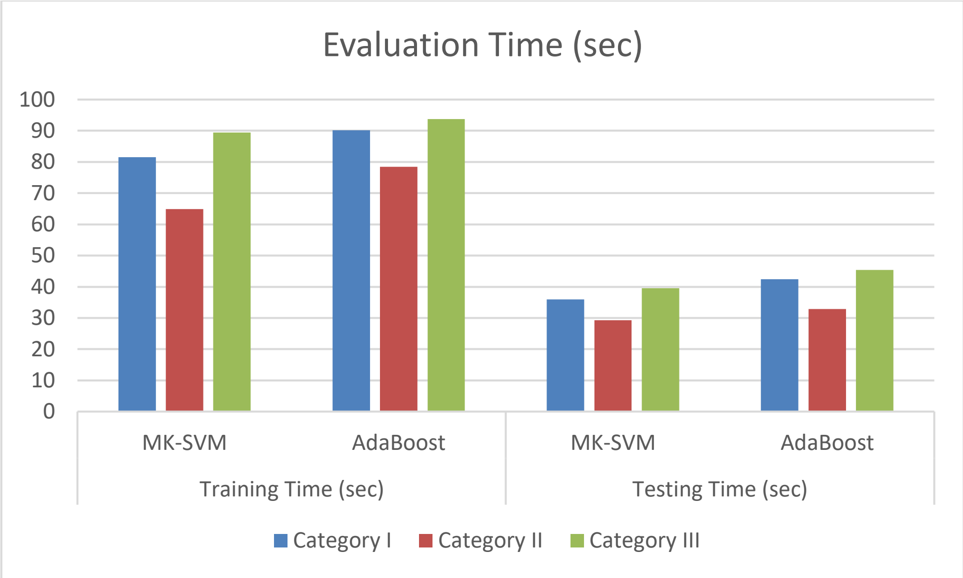

Figure 5. 1: Process Evaluation Time

The proposed intelligent model is validated and tested for all three types of waste and their types of materials. Domestic waste, e-waste and medical waste are classified using two machine learning algorithms, AdaBoost and MK-SVM algorithms as shown in Figure 5.2-5.7. It shows the confusion matrix, sample test images considered and results evaluation parameters.

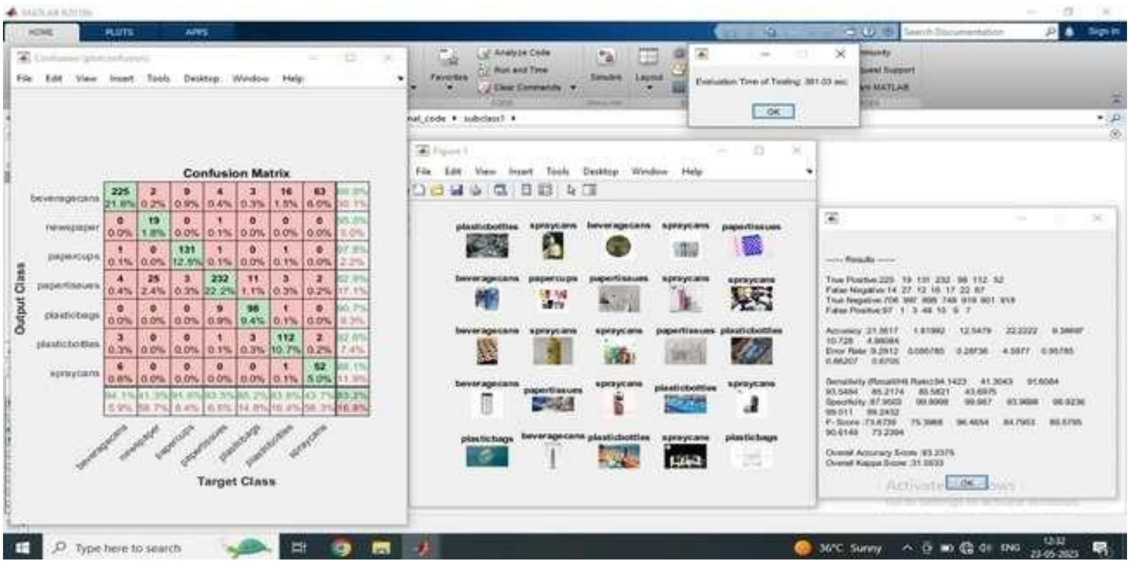

Figure 5. 2: Prediction Results of Domestic Waste Classification using Adaboost

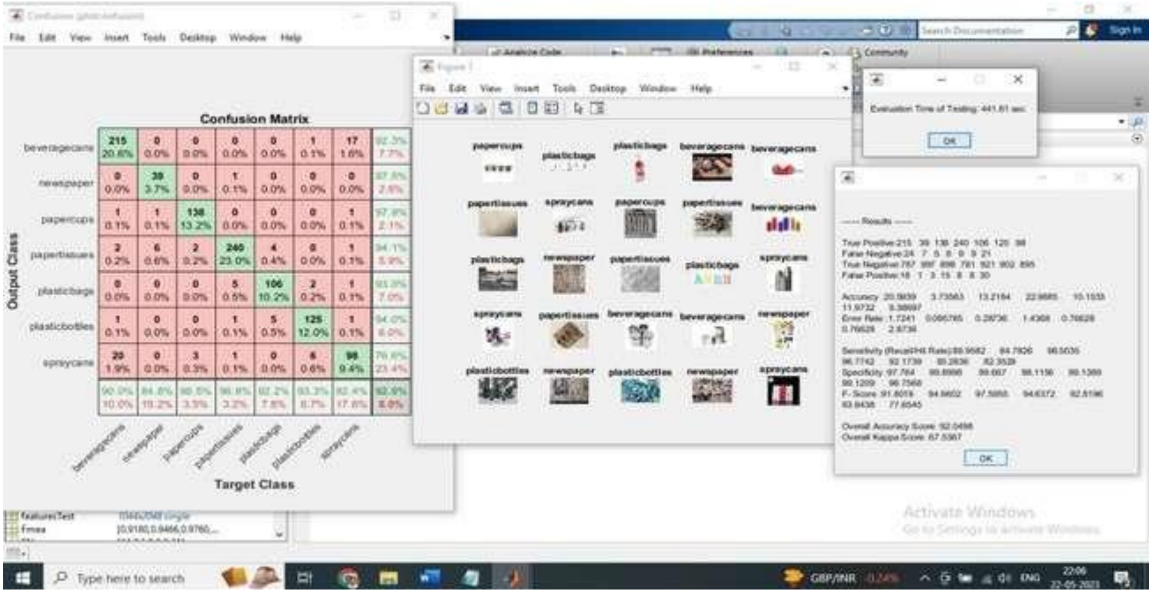

Figure 5. 3: Prediction Results of Domestic Waste Classification using MK-SVM

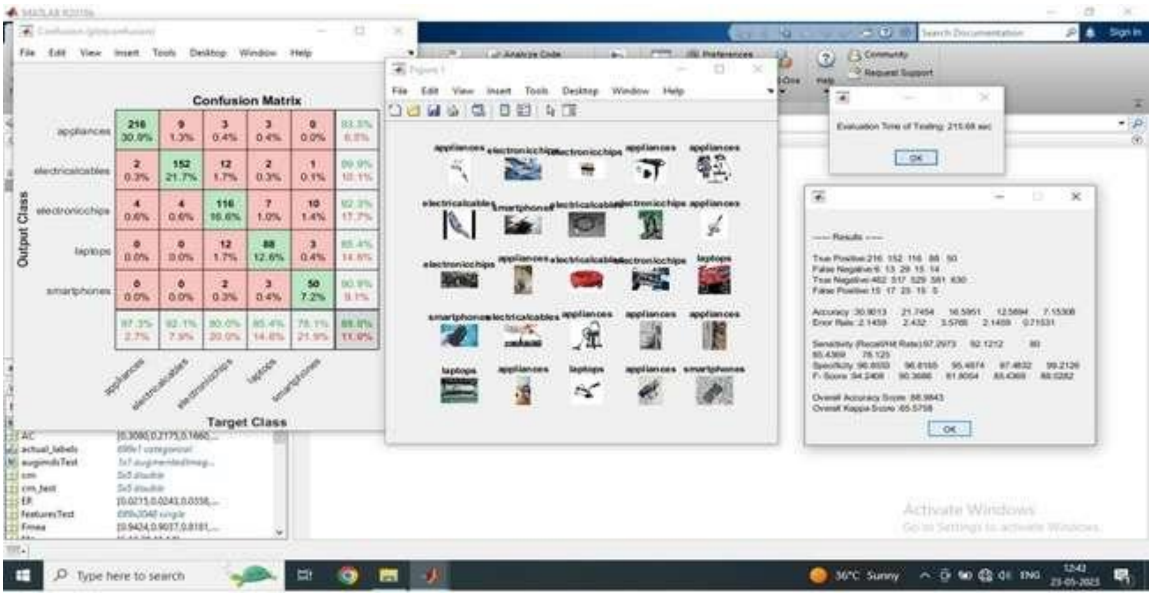

Figure 5. 4: Prediction Results of E-Waste Waste Classification using Adaboost

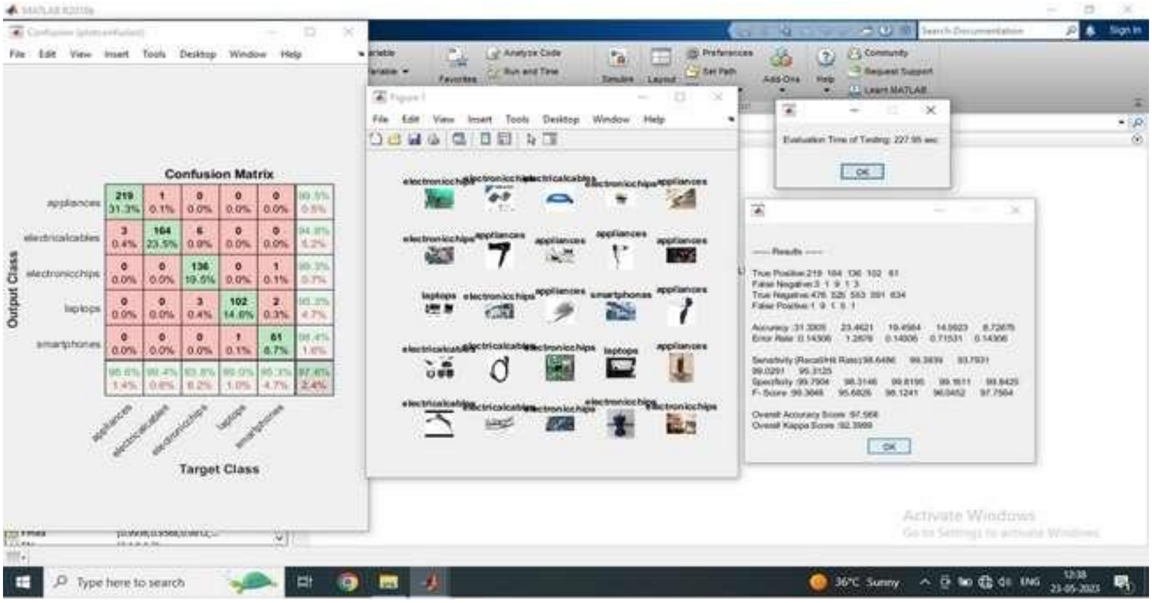

Figure 5. 5: Prediction Results of E-Waste Classification using MK-SVM

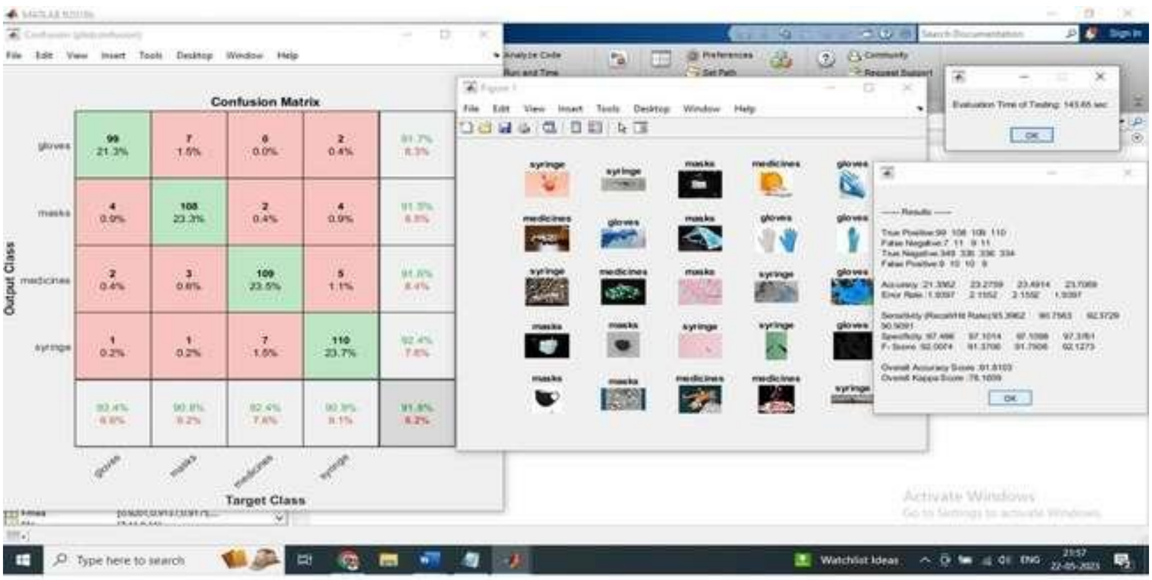

Figure 5. 6: Prediction Results of Medical Waste Classification using Adaboost

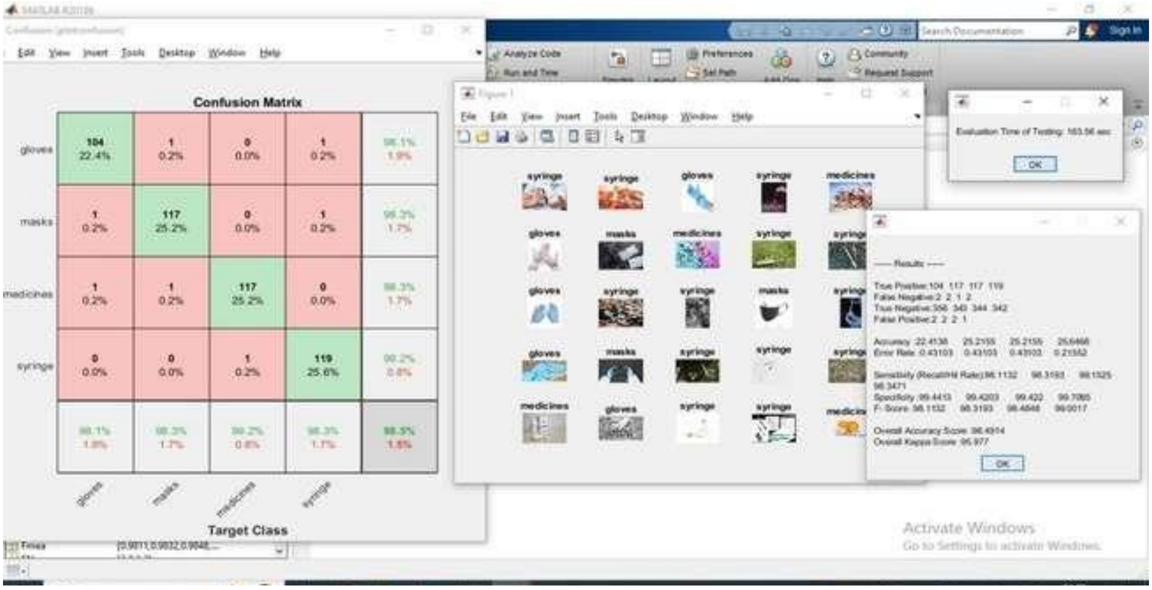

Figure 5. 7: Prediction Results of Medical Waste Classification using MK-SVM

The sample test images from each category are predicted on an intelligent model for the prediction of waste label data and its type as shown in Figure 5.8-5.14.

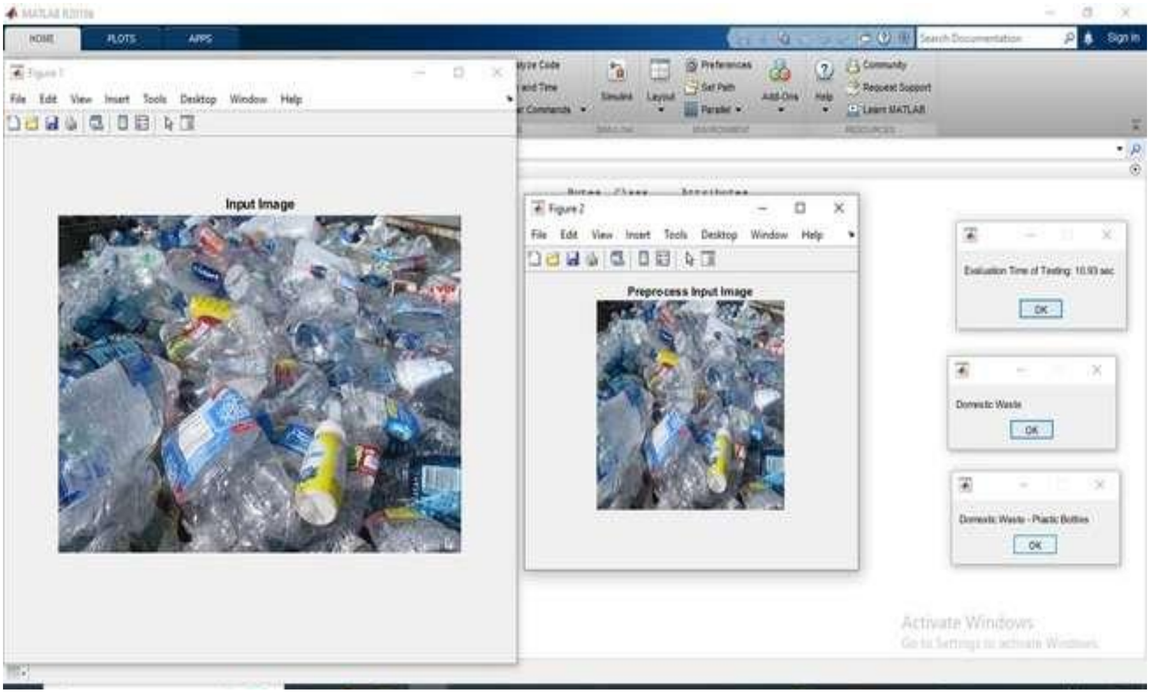

Figure 5. 8: Test Results and Type of Domestic Waste Image 1

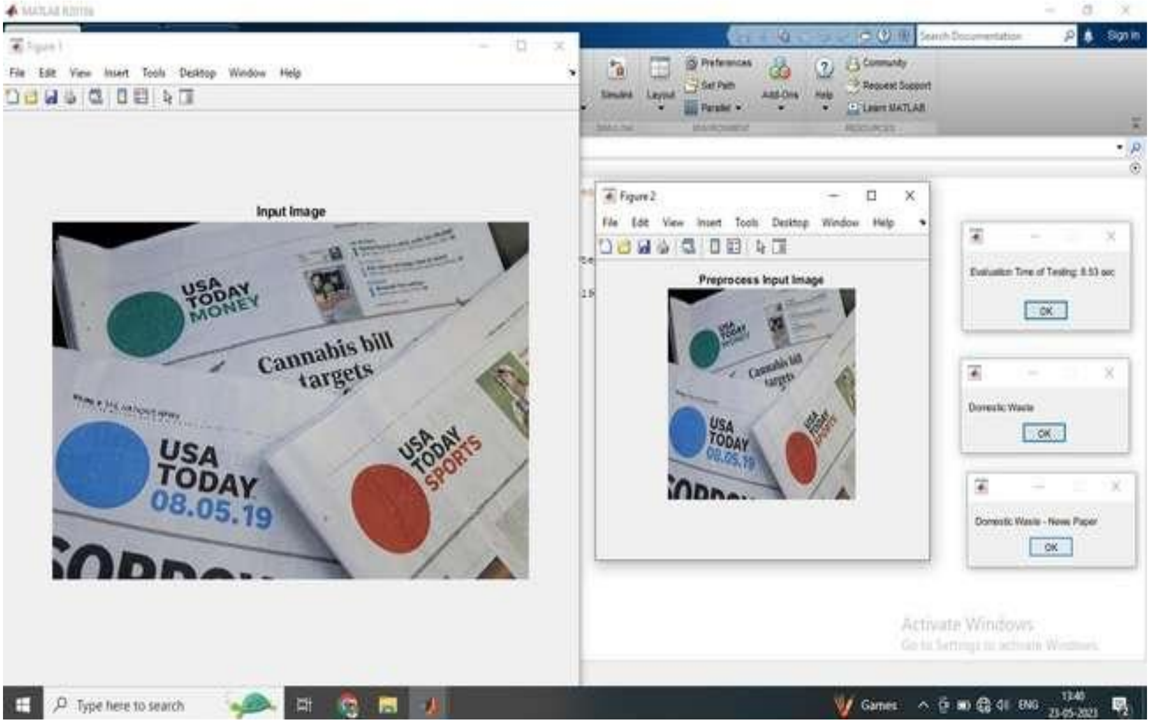

Figure 5. 9: Test Results of Domestic Waste Image 2 and Its Type

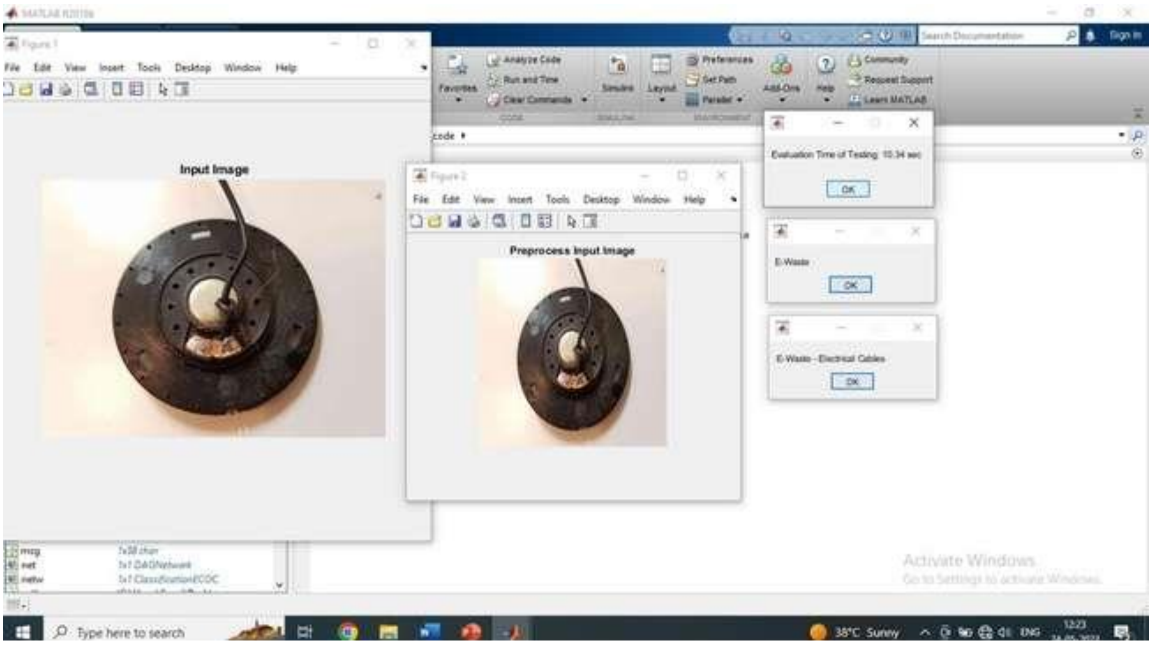

Figure 5. 10: Test Results of E-Waste Image 1 and Its Type

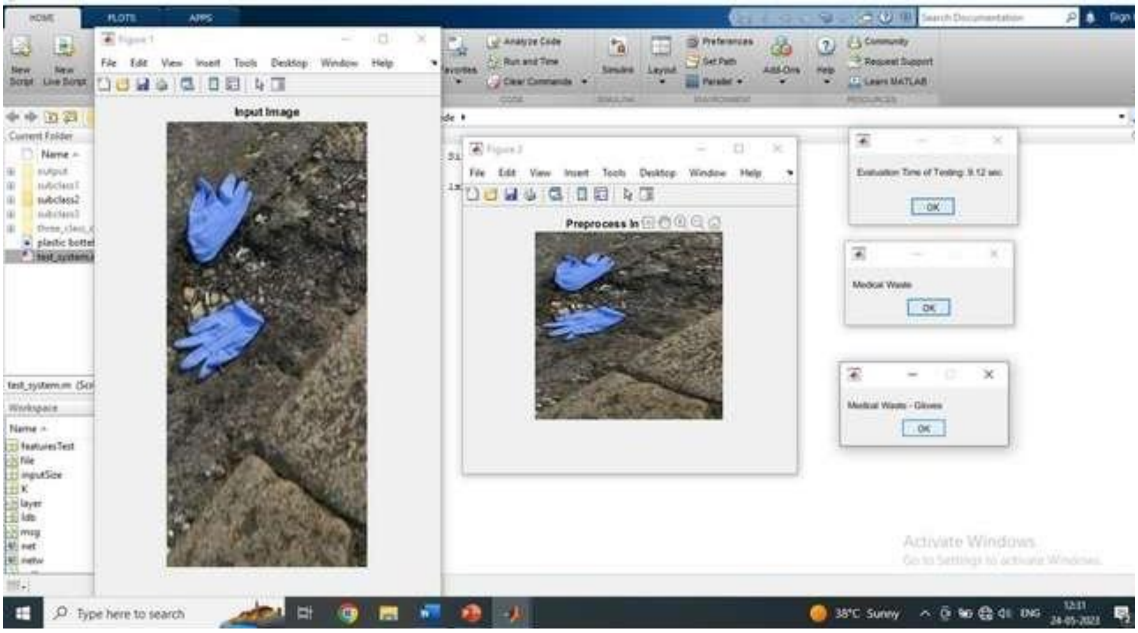

Figure 5. 11: Test Results of Medical Waste Image 1 and Its Type

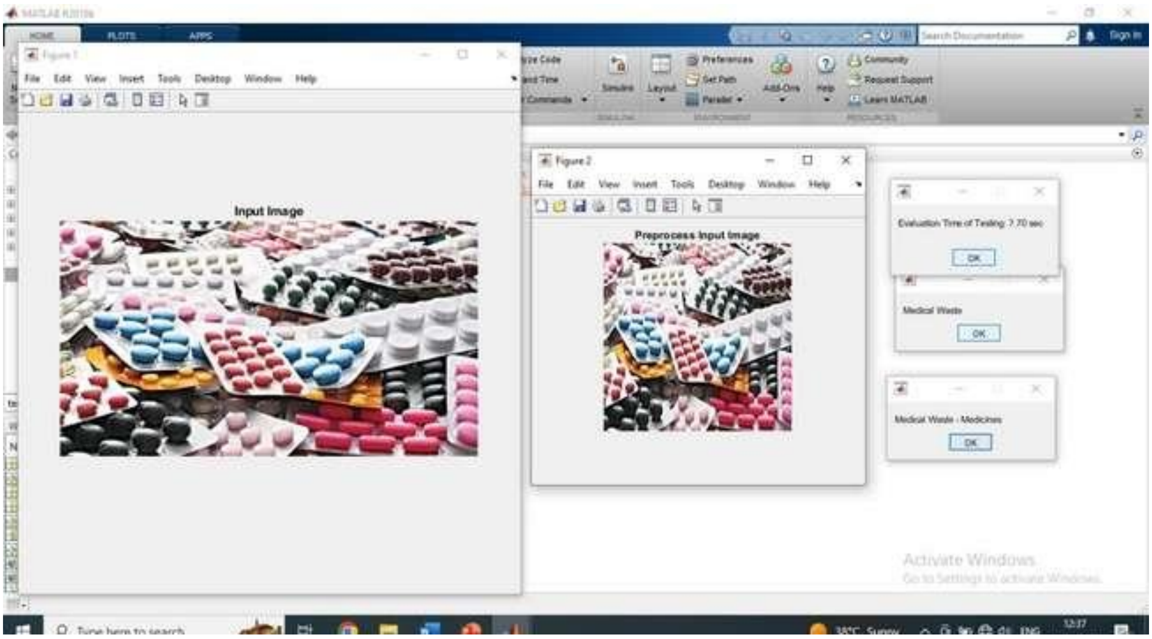

Figure 5. 12: Test Results of Medical Waste Image 2 and Its Type

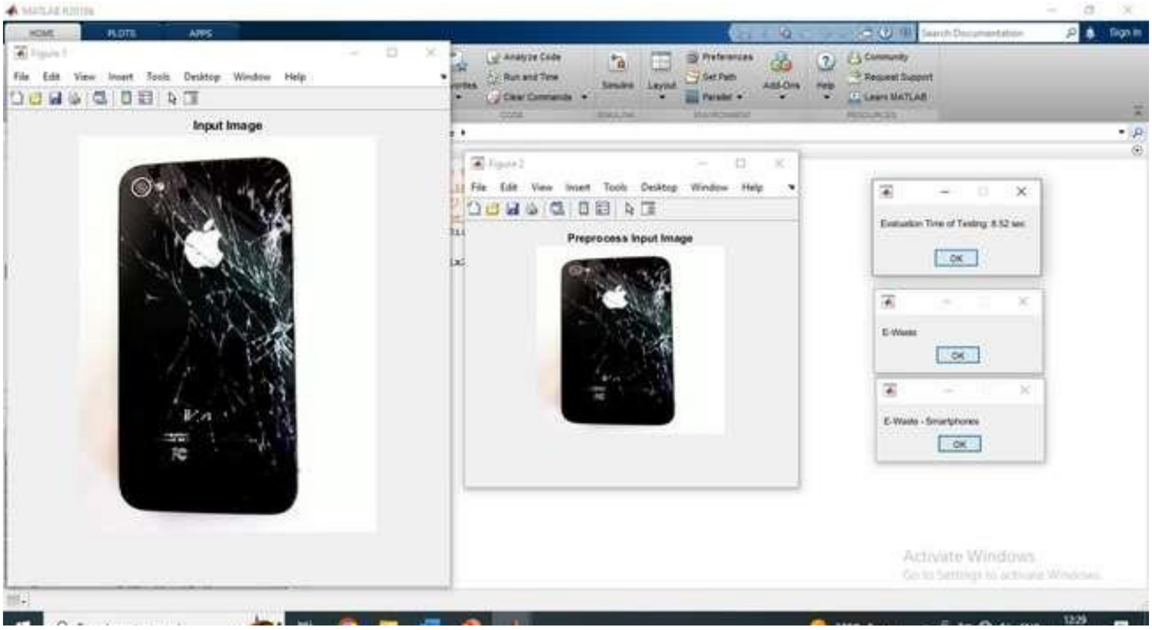

Figure 5. 13: Test Results of E-Waste Image 1 and Its Type

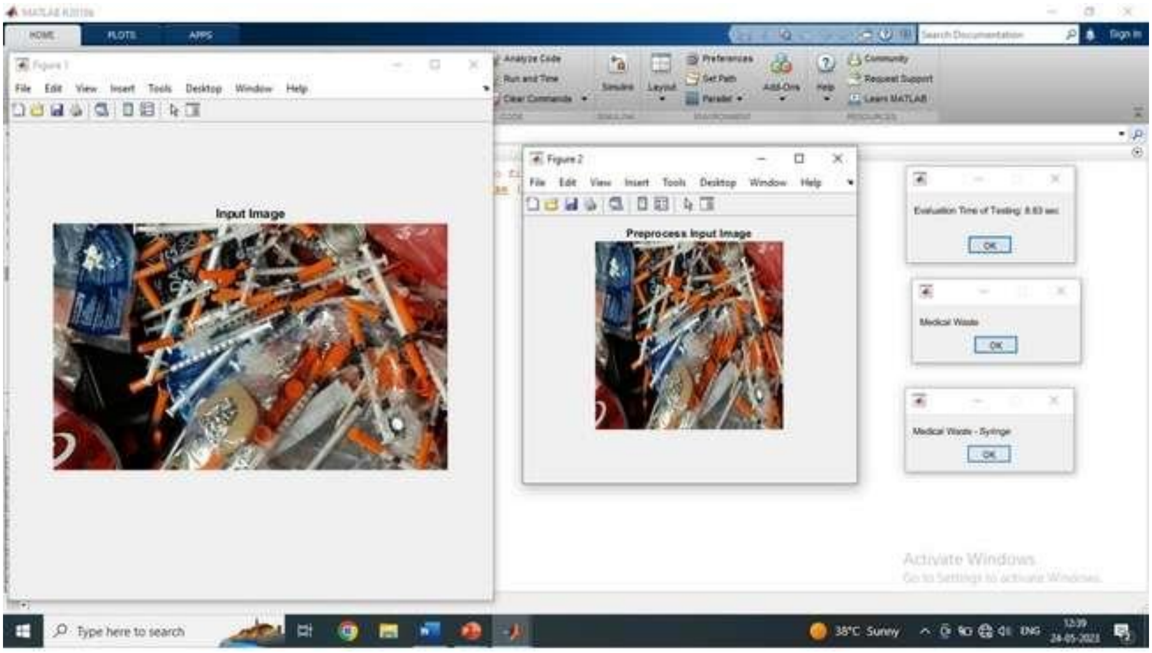

Figure 5. 14: Test Results of Medical Waste Image 3 and Its Type

The classification performance parameters, sensitivity, specificity and f-score are evaluated for three primary waste category classifications for both algorithms and mentioned in Table 5.4, Table 5.5 and Table 5.6 respectively. Each category has various output labels or classes as per the type of waste categories described in figures 5.15 and 5.16 for both algorithms for category I, domestic type of waste classification respectively. It is observed that some waste category classes are classified with maximum performance for both algorithms.

Table 5. 4: Classification Report Performance for Category I

Output Classes	**Classification Algorithms**					
	MK-SVM			**AdaBoost**		
	Sensitivity (%)	**Specificity (%)**	**F-score (%)**	**Sensitivity (%)**	**Specificity (%)**	**F-score (%)**
News Papers	86.95	100	97.08	69.56	99.17	77.66
Paper Tissues	86.36	99.18	83.33	27.27	97.74	33.33
Paper Cups	89.28	99.58	91.91	46.42	95.02	36.93
Bottles	96.29	99.79	96.29	66.66	99.17	78.26
Bags	88.23	100	97.40	70.58	99.39	77.92
Spray Cans	77.27	99.59	86.73	45.45	98.77	58.13
Beverage Cans	85.71	100	96.77	71.42	99.39	75.75

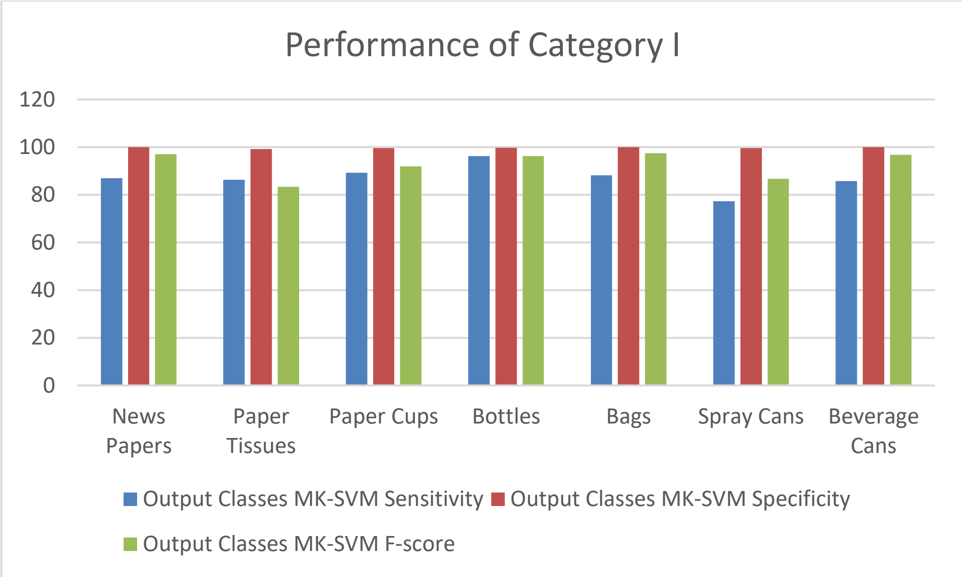

Figure 5. 15: Performance of Category I using MK-SVM

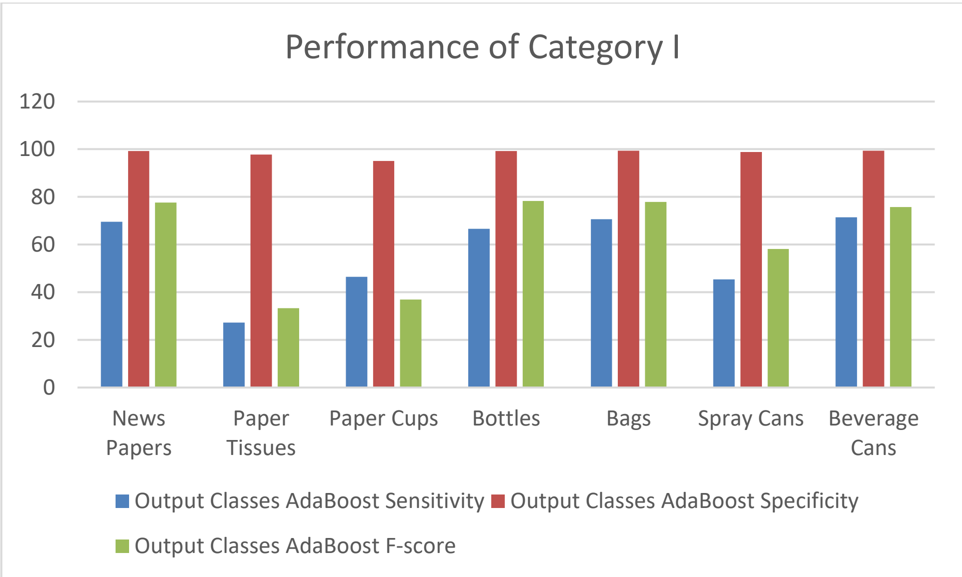

Figure 5. 16: Performance of Category I using AdaBoost

Similarly, for the classification of category II, various output labels or classes as per the type of waste categories are described in Figures 5.17 and 5.18 for both algorithms. It is observed that some waste image classes are classified with better performance of specificity rate for both algorithms. The classification of categories III with various output labels is shown in Figures 5.19 and 5.20 for both algorithms.

Table 5. 5: Classification Report Performance for Category II

Output Classes	Classification Algorithms					
	MK-SVM			AdaBoost		
	Sensitivity (%)	Specificity (%)	F-score (%)	Sensitivity (%)	Specificity (%)	F-score (%)
Syringes	72.72	99.82	88.88	77.27	99.31	80.18
Surgical Gloves	45.71	97.18	49.07	54.28	95.07	42.60
Surgical Masks	63.15	93.80	43.79	52.63	93.62	38.16
Medicines	61.29	97.02	54.28	32.25	97.20	37.03

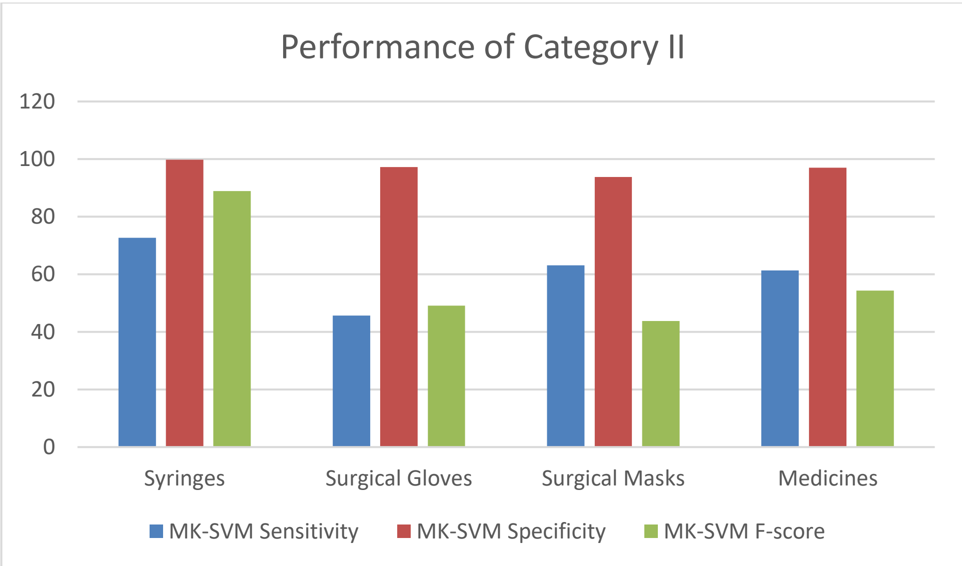

Figure 5. 17: Performance of Category II using MK-SVM

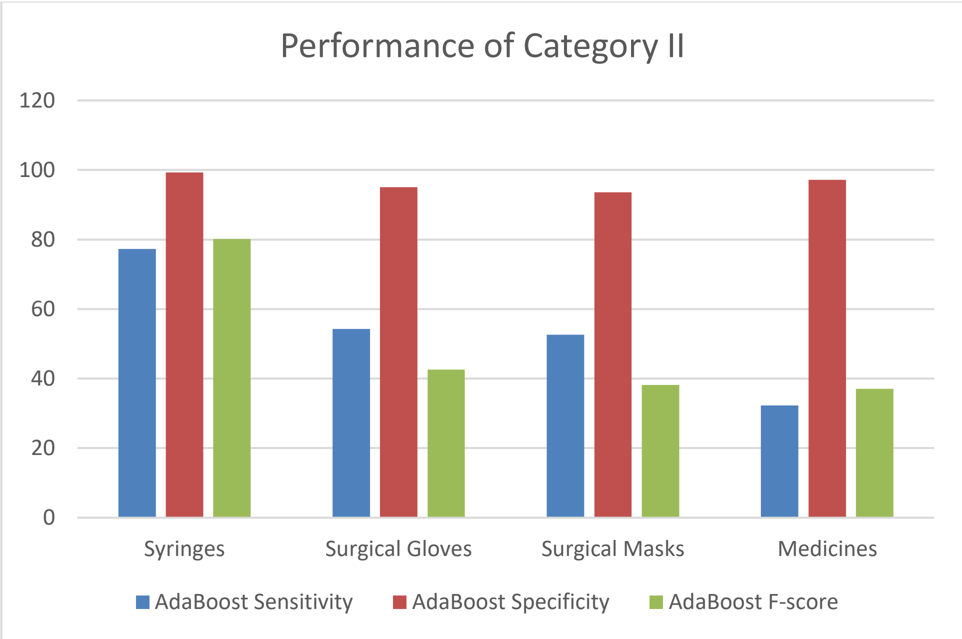

Figure 5. 18: Performance of Category II using AdaBoost

Table 5. 6: Classification Report Performance for Category III

Output Classes	**Classification Algorithms**					
	MK-SVM			**AdaBoost**		
	Sensitivity (%)	**Specificity (%)**	**F-score (%)**	**Sensitivity (%)**	**Specificity (%)**	**F-score (%)**
Electronic chips	82.05	96.75	78.81	79.48	94.58	69.50
Laptops and Smartphones	80	98.28	80	92	96.56	73.24
Appliances	97.36	99.64	97.36	100	99.64	97.93
Electric wires	53.33	100	85.10	60	100	88.23
Cords and cables	78.94	100	94.93	63.15	99.66	84.50

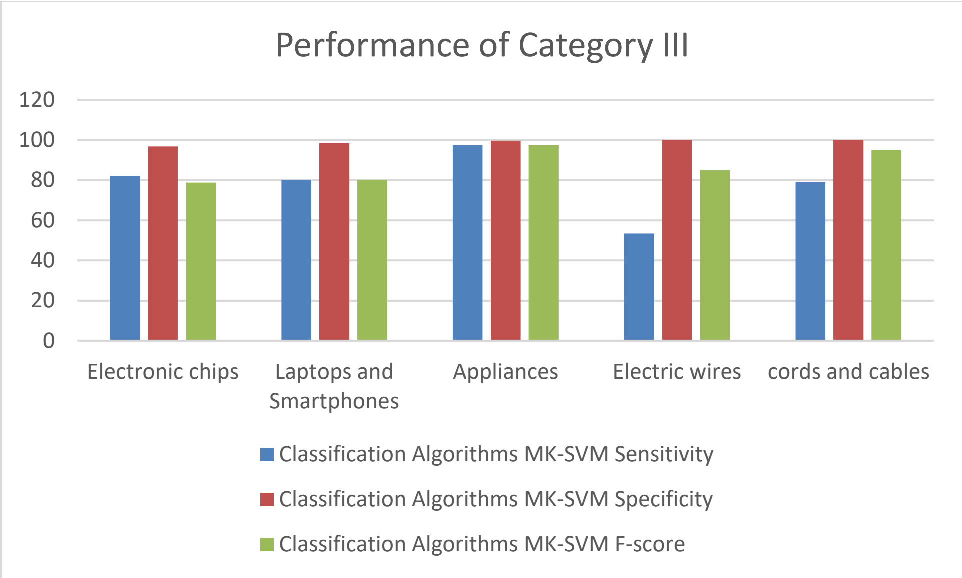

Figure 5. 19: Performance of Category III using MK-SVM

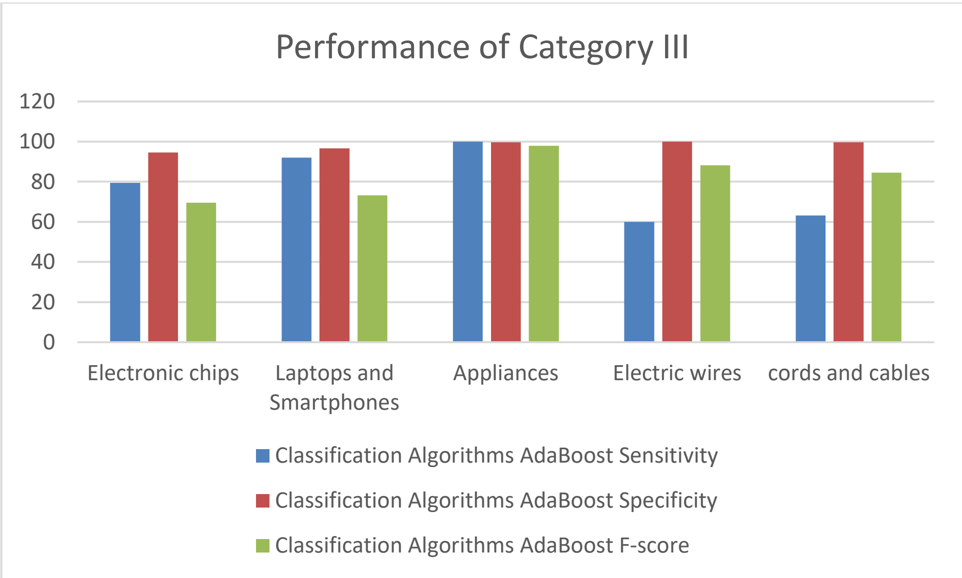

Figure 5. 20: Performance of Category III using AdaBoost

The proposed system framework is also validated on another standard benchmark dataset, TrashNet [145]. The dataset consists of six distinct categories: glass, paper, cardboard, plastic, metal, and rubbish. The dataset has a total of 2527 pictures. The photographs were captured by positioning the object on a white posterboard and utilizing natural sunshine and/or artificial room lighting. The images have been reduced in size to 512 × 384 pixels. The devices utilized were the Apple iPhone 7 Plus, Apple iPhone 5S, and Apple iPhone SE. The result evaluation on this dataset using the best classification model, MK-SVM is shown in Table 5.7 in terms of confusion matrix-based parameters.

Table 5. 7: Result evaluation of classification model on TrashNet Dataset

Output Classes	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Precision (%)**	**F-score (%)**
Glass	98.50	98.01	99.18	96.73	96.98
Paper	99.21	97.76	99.65	98.87	98.64
Cardboard	98.81	95.04	99.53	97.45	96.96
Plastic	98.95	97.29	99.34	97.29	97.29
Metal	98.81	96.74	99.21	95.96	96.12
Trash	98.95	92.5	99.30	88.09	88.94

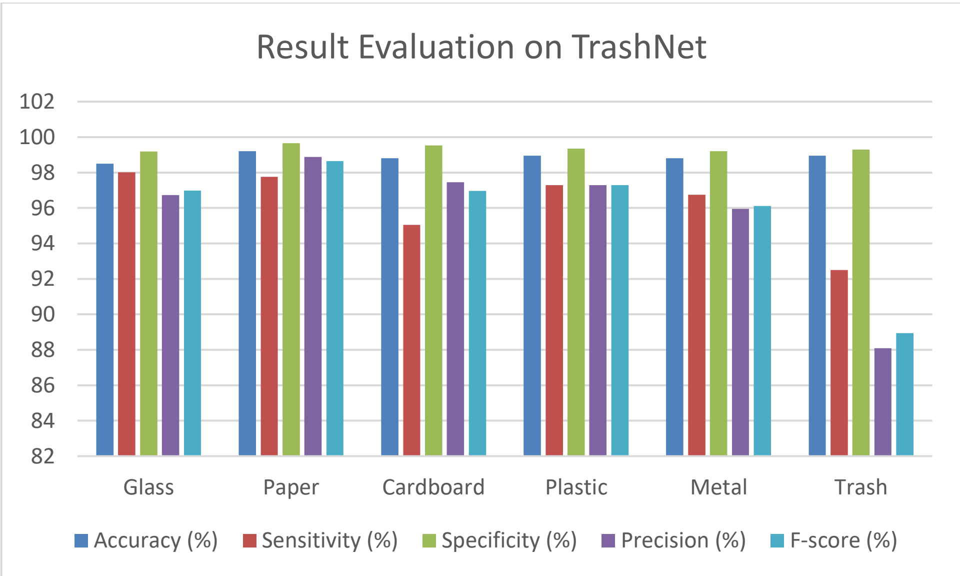

Figure 5. 21: Result Evaluation on TrashNet Dataset

5.5 PERFORMANCE ANALYSIS OF SENSOR BASED SYSTEM

A prototype hardware-based system is used to implement the suggested experimental architecture, and this system has undergone extensive testing. Two nodes' odour (in ppm), air quality (in ppm), smart dustbin weight (in gramme), and smoke levels (in ppm) are among the feature attributes included in the collected data set. The dustbin status and the presence of toxic waste serve as the actuator control for the dustbin at node 1. The presence or absence of dust and toxic gases, respectively, serve as actuator controls for node 2's trash can. This dataset includes hourly readings recorded over the course of many days and under a variety of weather situations. The average daily value for each sensor's characteristic. Building a sensor net for smart waste management with the use of supervised machine learning algorithms, and developing fundamental models embedded systems for successful waste management, are the two main stages of experimentation. The effectiveness of the system is measured using a confusion matrix. The model was trained and tested with MATLAB's built-in statistics and machine learning tools, and two supervised machine learning models, KNN and Decision Tree Bagger (DTB) classifier.

For optimal model training, both techniques necessitate the best possible hyper-parameters, which may be found through a grid search. Tables 5.8 and 5.9 show the results of running the classification model on both nodes of the system. Figure 5.22-5.25 depicts the results of a comparison of the accuracy, sensitivity, specificity, and f-score of two different classifiers applied to two different actuator controllers.

Table 5. 8: Performance evaluation of classification model for Node 1 System

Attributes	**Accuracy (%)**		**Sensitivity (%)**		**Specificity (%)**		**F-score (%)**	
	DTB	**KNN**	**DTB**	**KNN**	**DTB**	**KNN**	**DTB**	**KNN**
Actuator 1	86.66	76.66	81.81	77.27	100	75	95.74	86.73
Actuator 2	96.66	70	100	89.47	90.90	36.36	95.95	73.91

Table 5. 9: Performance evaluation of classification model for Node 2 System

Attributes	Accuracy (%)		Sensitivity (%)		Specificity (%)		F-score (%)	
	DTB	KNN	DTB	KNN	DTB	KNN	DTB	KNN
Actuator 1	84.50	72.85	79.81	74.80	98.5	76.15	92.90	84.45
Actuator 2	93.75	71.15	98.60	85.45	87.30	38.05	93.35	71.80

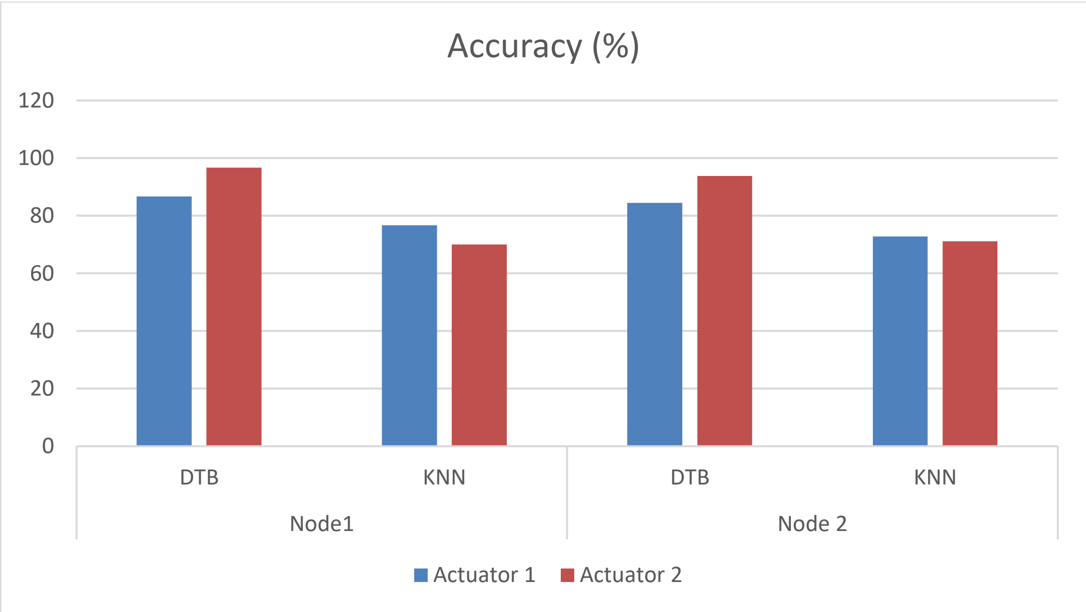

Figure 5. 212: Accuracy Performance Statistics

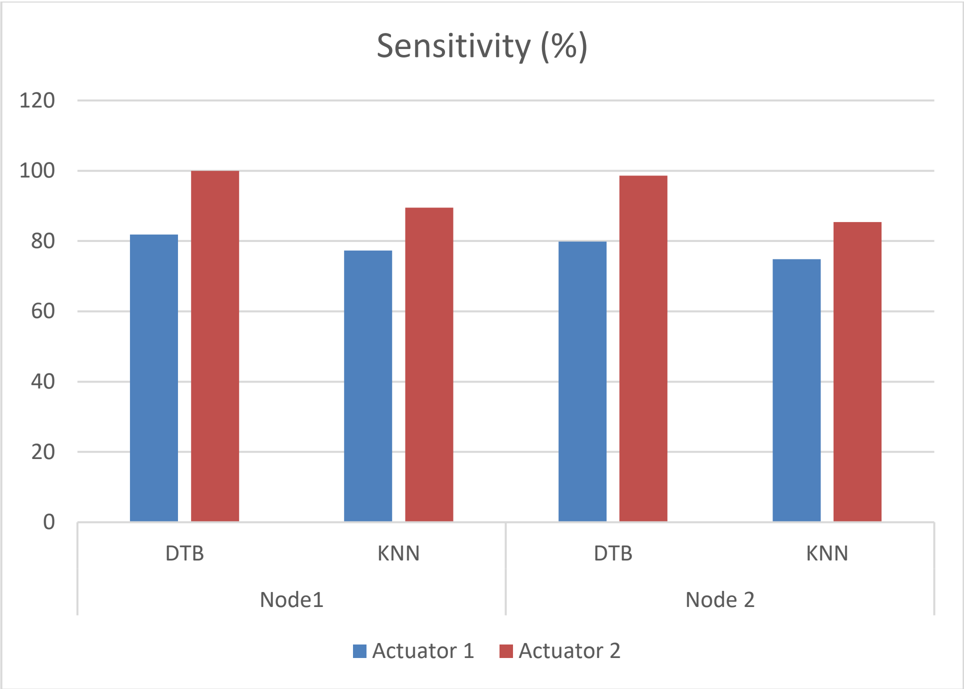

Figure 5. 223: Sensitivity Performance Statistics

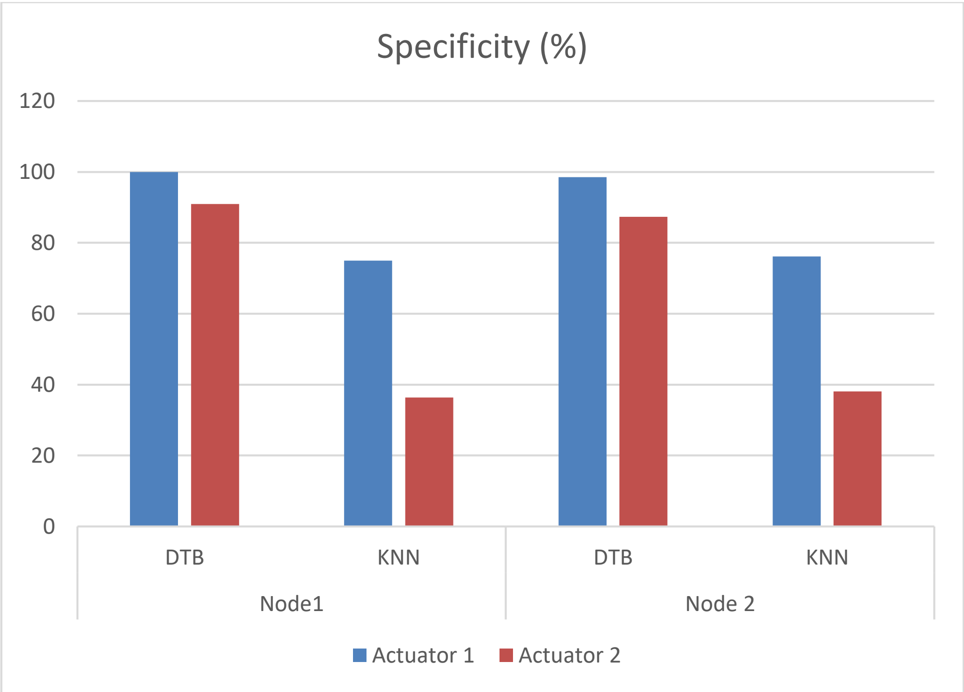

Figure 5. 234: Specificity Performance Statistics

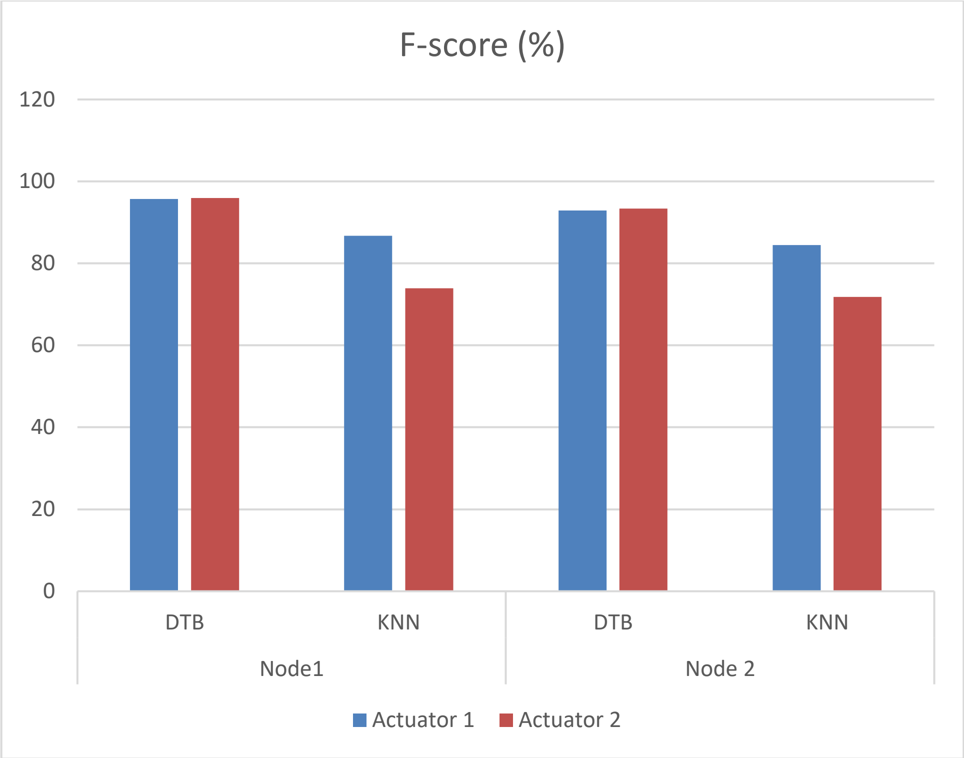

Figure 5. 245: F-score Performance Statistics

5.6 COMPARATIVE ANALYSIS

As compared to existing work developed by various researchers, formulated in table 5.10, based on the sensor used for development and technology used to build the system, our proposed model is much superior in all aspects.

Table 5. 10: Technological Comparative Analysis

Parameters		References				
		Gunawan T. et.al. [52]	T. Bakhshi et al. [142]	Dev V. Savla et.al. [143]	Shamin.N et.al. [144]	Proposed Model
Sensors Used	Ultrasonic/IR	Yes	Yes	Yes	Yes	Yes
	Odour	No	No	Yes	No	Yes
	Air Quality	No	No	Yes	Yes	Yes
	Weight	Yes	No	No	No	Yes
	Smoke	No	No	Yes	No	Yes
Technology Used	IoT	Ye	Yes	Yes	Yes	Yes
	LoRa	No	No	No	No	Yes
	Fog Intelligence	No	Yes	Yes	Yes	Yes
	Real-Time Statistics	Yes	Yes	Yes	Yes	Yes
	Notification / Alert System	No	No	No	No	Yes

Table 5.11 analyses power consumption requirements for different embedded boards, namely Arduino Mega, Arduino Uno, and the proposed Node MCU ESP 32 system. It includes voltage levels, current consumption and DC supply for the 3.3V pin. The proposed ESP 32 system operates at a lower voltage level of 3.3V. It exhibits considerably lower current consumption than the Arduino boards, with 15 μA during normal operation and 5 μA during deep sleep mode. The DC supply for the 3.3V pin is 40 mA. Based on the analysis, it is evident that the proposed Node MCU ESP 32 system has the lowest power consumption requirements among the three boards. It consumes significantly less current during both normal operation and deep sleep mode.

Table 5. 81: Comparative power consumption analysis

Embedded MCU Board	**Voltage Level**	**Current Consumption**	**DC Current for 3.3V pin**
Arduino Mega	5V	50 mA	150 mA
Arduino Uno/Nano	5V	45 mA	150 mA
Node MCU ESP-32 (Proposed MCU)	3.3V	15 µA	40 mA

At the last, the performance of the proposed algorithm is compared with another standard existing work shown in Table 5.12 in terms of sensitivity, specificity, precision, f-score and computation time. Also, an accuracy-based comparison is shown in Table 5.13.

Table 5. 12: Comparative result analysis performance

References	Dataset	Output Classes	Sensitivity (%)	Specificity (%)	Precision (%)	F-score (%)	Computation Time (sec)
EnCNN-UPMWS [56]	TrashNet	glass, paper, cardboard, plastic, metal and trash	92.69	98.67	93.75	93.15	NA
YOLOv5x [1]	1) COCO dataset, 2) VOC2007 dataset, and 3) Garbage image data set	hazardous garbage, recyclable garbage, kitchen waste, and other garbage.	92.2	96.5	95.9	95.13	265 (hrs)
DNN [3]	Trash Dataset (Kaggle)	Organic, recyclable	94.37	92.8	88.7	89.77	2225 (sec)
mCNN [16]	Trash Dataset (Kaggle)	organic and recyclable.	95.0	96.5	95.5	94.5	NA
CNN [14]	TrashNet	glass, paper, cardboard, plastic, metal, and trash	95.16	98.44	94.24	94.39	1695 (sec)
Proposed Method	TrashBox	glass, plastic, metal, e-waste, cardboard, paper, medical waste	97.69	98.9	98.08	98.01	138.36 (sec)
	TrashNet	Glass, paper, cardboard, plastic, metal, trash	96.23	99.37	95.74	95.83	102.54 (sec)

Table 5. 13: Comparative Accuracy based Result Analysis Performance

References	Dataset	Output Classes	Number of Classes	Accuracy (%)
Recycle Net [138]	TrashNet	glass, paper, cardboard, plastic, metal and trash.	6	81
EnCNN-UPMWS [56]	TrashNet	glass, paper, cardboard, plastic, metal and trash	6	93.50
SVM [120]	Trash Image Dataset	Glass, metal, paper, plastic	4	87
YOLOv5x [1]	1) COCO dataset, 2) VOC2007 dataset, and 3) Garbage image data set	hazardous garbage, recyclable garbage, kitchen waste, and other garbage.	4	92.6
DNN [3]	Trash Dataset (Kaggle)	Organic, recyclable	2	94.53
mCNN [16]	Trash Dataset (Kaggle)	organic and recyclable.	2	94.96
DeepWaste [117]	Trash Dataset	Trash, Recycle and Compost	3	88.1
VGG19 [81]	TrashNet	plastic, metal, paper, cardboard and glass	5	87.9
CNN [14]	TrashNet	glass, paper, cardboard, plastic, metal, and trash	6	95.312
YOLOv5 [145]	TrashBox	e-waste	1	82.32
Proposed Method	TrashBox	glass, plastic, metal, e-waste, cardboard, paper, medical waste	7	98.2
	TrashNet	glass, paper, cardboard, plastic, metal, trash	6	98.95

5.7 SUMMARY

In this chapter, considering the prototype model environment, the proposed system is developed, simulated and analysed based on various conditions for an effective smart waste management environment. Initially, the prototype hardware system is analysed and performed several test cases. Later, the two predictive models are developed and analysed for two types of data, camera-based and sensor-based data to perform classification using supervised machine learning algorithms and are interpreted for the best accuracy with a particular algorithm. Also, the performance of the proposed model is compared with existing work, and it is found that the proposed model is much more capable in every aspect.

CHAPTER 6 CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION

Waste management grows in importance for a number of reasons, including ensuring the long-term viability of urban environments, maximizing the effectiveness of public spending, increasing the accessibility of metropolitan areas, and protecting the planet's finite natural resources. Waste management in the modern day might benefit from the correct technological implementation. Every city on Earth will be ultra-modern and efficient thanks to the Internet of Things, a revolutionary invention. The rapid expansion of "smart cities" has coincided with an increase in garbage output. One of the most pressing problems with the IoT is how to deal with trash. Garbage collection and disposal is a traditional urban responsibility, but it requires a lot of manpower. In addition, it contaminates personality features, economic development, and the natural world. The proposed paradigm emphasises the usage of a standard Internet of Things (IoT) layered architecture for garbage collection. The suggested architecture is primarily composed of four layers: perception, network, middleware, and application. In the perception layer, physical characteristics, toxic gas levels, rubbish levels, garbage images captured by the camera, etc. are all detected using specialised sensors, and item identification data is collected as a byproduct. The measured data is transmitted from the perception layer to the middleware layer, where the expert services are set up, through the network layer, which makes use of Wi-Fi and LoRa. In the middleware layer, a data analytics system is implemented using a machine learning approach. Finally, at the application layer, sensed data is visualised and interpreted.

A proposed system was developed using the ThingSpeak cloud platform to collect raw garbage data in real-time across the Internet of Things, as was intended. It was also proposed in this work that garbage cans be tracked using LoRa in areas without cell service. The testing of the suggested system validated that the given solution met all of the requirements. In addition, the suggested four-layer architecture includes a middleware layer where the data analytics system is executed through periodic data collection. Waste segregation and management are perennial problems that have had far-reaching effects on the natural worldThis research demonstrates that hybrid learning approaches are useful for addressing the problem of garbage image classification. When comparing and analysing the performance with the existing systems the overall accuracy was found to be 98.2% as compared to the existing methods Recycle Net[138] is 81%, EnCNN UPMWS [56] is 93.50%, SVM[120] is 87, YOLOv5x [1] is 92.6% , DNN [3] is 94.53% , mCNN[95] is 94.96% , Deep Waste[117] is 88.1, VGG19[81] is 87.9 and CNN[14] is 95.3%.

6.2 FUTURE SCOPE

Further, the future scope involves numerous opportunities for advancement and innovation, driven by emerging technologies, increased urbanization, and the need for sustainable practices. However, further improvisation of the proposed data analytics system is implemented by refining the deep learning algorithm moving forward with advanced approaches. Also, expanding the sensor parameters related to the acquisition of waste materials to obtain more versatile and accurate data, and lending a hand to the AI system in its prediction efforts. In addition, by strengthening and weatherproofing the proposed experimental model, it may be applied in practical scenarios. Future systems can also utilize more sophisticated learning algorithms like deep learning, reinforcement learning, and hybrid AI models to predict waste generation patterns with greater accuracy and efficiency. This can help in optimizing collection schedules and resource allocation. The integration of computer vision, robotics, and AI can lead to automated waste sorting at the source, improving the segregation of recyclables, organics, and general waste. This reduces manual labor and increases the efficiency of recycling processes. Autonomous robots can be developed for the sorting and segregation of waste, leading to more accurate waste categorization and recycling, particularly in areas where human labor is less effective. Smart waste management systems can be extended to monitor and minimize the carbon footprint of waste processing and transportation, contributing to greener and more sustainable city planning. By connecting waste management systems with public health, environmental monitoring, and city planning departments, authorities can collaborate to create more comprehensive sustainability initiatives and cleaner urban environments.

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List of Journal/Conferences/Book Chapter Publication

- Journal Publication

1. Belsare K, Singh M, Gandam A, Malik PK, Agarwal R, Gehlot A."An integrated approach of IoT and WSN using wavelet transform and machine learning for the solid waste image classification in smart cities". Trans Emerging Tel Tech. 2023;e4857. doi: 10.1002/ett.4857
2. Belsare Karan, Singh Manwinder, Gandam Anudeep, F. Soliman Naglaa, D. Algarni Abeer" Wireless sensor network-based machine learning framework for smart cities in intelligent waste management" Heliyon Volume 10, Issue 16, e36271, August 30, 2024 doi: 10.1016/j.heliyon.2024.e36271

- Conferences Publication

1. Belsare, K.S., Singh, M." Various Frameworks for IoT-Enabled Intelligent Waste Management System Using ML for Smart Cities". In: Shakya, S., Ntalianis, K., Kamel, (eds) Mobile Computing and Sustainable Informatics. Lecture Notes on Data Engineering and Communications Technologies, vol 126. Springer, Singapore. https://doi.org/10.1007/978-981-19-2069-1_55

2. K. Belsare and M. Singh, "An Intelligent Internet of Things (IoT) based Automatic Dry and Wet Medical Waste Segregation and Management System," *2022 International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)*, Trichy, India, 2022, pp. 1113-1119, doi: 10.1109/ICAISS55157.2022.10010913.

3. Belsare K, Singh M, " Data Acquisition and Monitoring Framework for Waste Management using Intelligent Sensors and Thing Speak IoT Analytics for Health Monitoring in Smart Cities", 5th International Conference on Intelligent Circuits and Systems (ICICS- 2023), LPU, Pagwada, Punjab, India 2023.

- Book Chapter Publication

1. Karan Belsare, Manwinder Singh, Anudeep Goraya," Data Acquisition and Monitoring Framework for Waste Management Using Intelligent Sensors and Thing Speak IoT Analytics for Health Monitoring in Smart Cities" Intelligent Circuits and Systems for SDG 3 – Good Health and well-being 1st Edition, 2024, CRC Press,Pages11, eBook ISBN9781003521716.

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(54) Title of the invention : MACHINE LEARNING BASED MULTI-CLASS WASTE CLASSIFICATION AND IOT ENABLED WSN FOR WASTE MONITORING SYSTEM

(51) International classification	:G06N0020000000, G06F0009500000, H04L0067120000, H04W0004380000, H04W0084180000	(71)**Name of Applicant :** **1)LOVELY PROFESSIONAL UNIVERSITY** Address of Applicant :JALANDHAR-DELHI G.T. ROAD, PHAGWARA, PUNJAB-144 411, INDIA. ----------- ----------- **Name of Applicant : NA** **Address of Applicant : NA** (72)**Name of Inventor :** **1)KARAN SANJAY BELSARE** Address of Applicant :LOVELY PROFESSIONAL UNIVERSITY, JALANDHAR-DELHI G.T. ROAD, PHAGWARA, PUNJAB-144 411, INDIA. ----------- ----------- **2)DR. MANWINDER SINGH** Address of Applicant :LOVELY PROFESSIONAL UNIVERSITY, JALANDHAR-DELHI G.T. ROAD, PHAGWARA, PUNJAB-144 411, INDIA. ----------- ----------- **3)DR. ANUDEEP GORAYA** Address of Applicant :LOVELY PROFESSIONAL UNIVERSITY, JALANDHAR-DELHI G.T. ROAD, PHAGWARA, PUNJAB-144 411, INDIA. ----------- -----------
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(62) Divisional to Application Number Filing Date	:NA :NA	

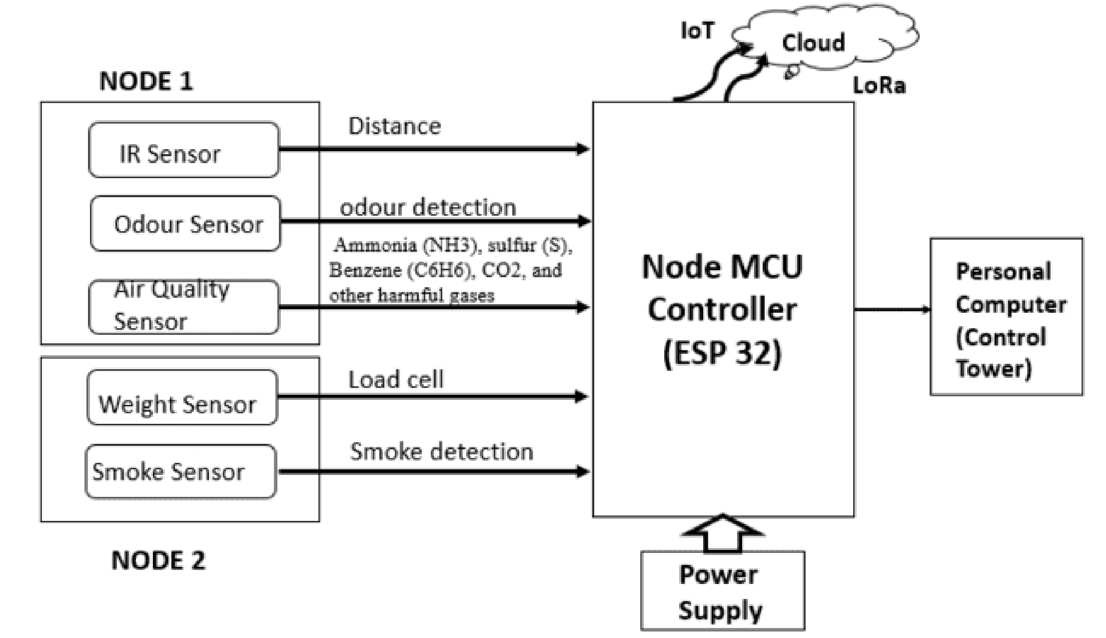
(57) Abstract :

MACHINE LEARNING BASED MULTI-CLASS WASTE CLASSIFICATION AND IOT ENABLED WSN FOR WASTE MONITORING SYSTEM Disclosed herein a machine learning based multi-class waste classification and IOT enabled WSN for waste monitoring system comprises IoT based WSN framework for data collecting and monitoring of waste materials, complete with an efficient and trustworthy data monitoring system and three nodes, capable of real-time waste and type monitoring via a cloud server infrastructure under a variety of conditions. The framework is divided into four primary layers: the application layer, the middleware layer, the network layer, and the perception layer. The sensed data is monitored for sensors nodes on a ThingSpeak cloud server platform and visualize the data on the IoT cloud platform using MQTT protocol with its data interpretation.The data analytics model is developed using supervised machine learning for two types of data from prototype hardware system with classification system, camera based and sensor's-based data analytics model.

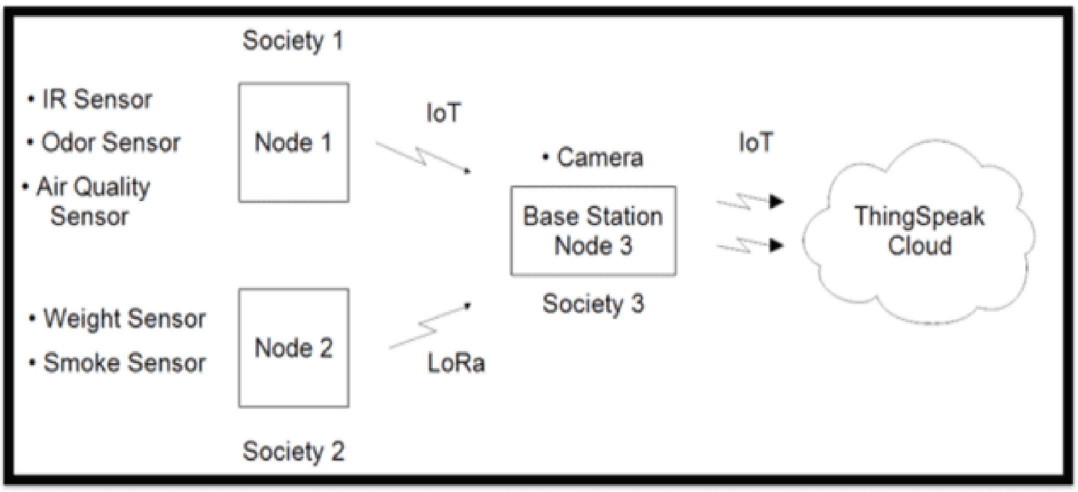
No. of Pages : 20 No. of Claims : 6

Annexure I

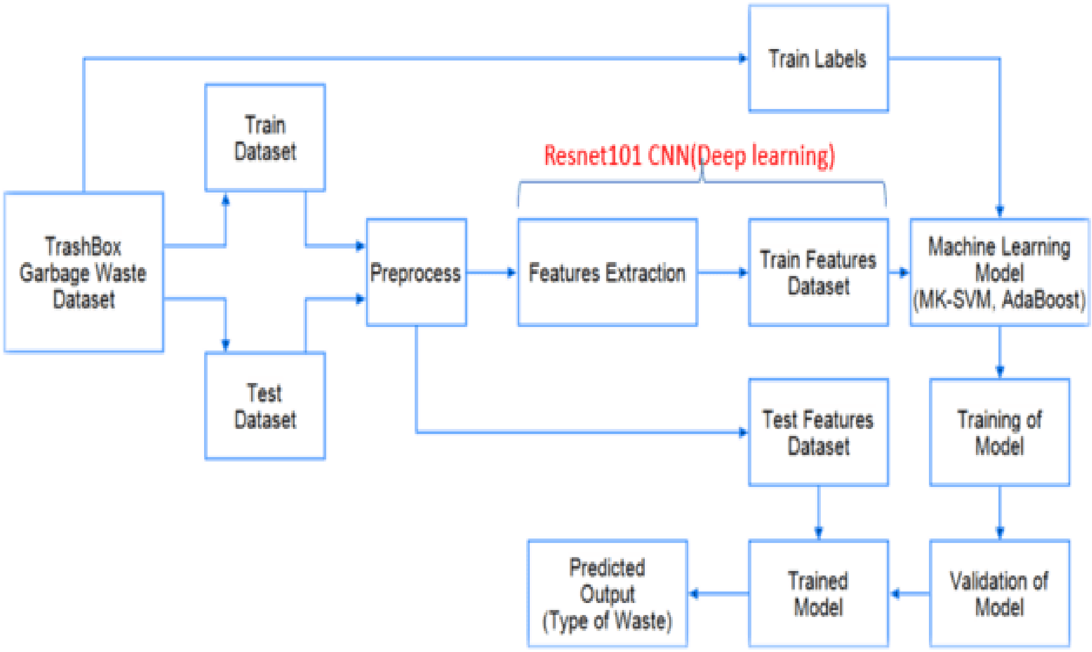
Circuit Diagram: Proposed experimental model with sensor specifications.



Proposed Hardware Model



Proposed Architectural Model



<u>**Proposed Classification System**</u>

Annexure II

- **Certificate of Field Visit.**

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जा.क्र./अमनपा/शअ/बावि/ 685 /2022

दि. 18/04/2022

CERTIFICATE

It is to certify that Karan Sanjay Belsare, PhD Scholar from School of Electrical and Electronics Engineering of Lovely Professional University, Phagwara, Punjab bearing Reg. No. 42000155 has interacted with the professionals on his PhD Topic "IOT ENABLED MACHINE LEARNING BASED INTELLIGENT WASTE MANAGEMENT SYSTEM" under the guidance of Dr. Manwinder Singh, Associate Professor, School of Electrical and Electronics Engineering of Lovely Professional University, Phagwara, Punjab.

The steps enforced for waste assortment along with methodology and techniques used for waste segregation were discussed and Primary Data for the same has been given to the PhD Scholar.

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City Engineer
AMC

CENTRAL RAILWAY

मध्य रेल

OFFICE OF JE SIGNAL
MURTIJAPUR

No. JE/SIG/MZR/213

Date: 19-03-2022

CERTIFICATE

It is to certify that Karan Sanjay Belsare, PhD Scholar from School of Electrical and Electronics Engineering of Lovely Professional University, Phagwara, Punjab bearing Reg. No. 42000155 has interacted with the professionals on his PhD Topic "IOT ENABLED MACHINE LEARNING BASED INTELLIGENT WASTE MANAGEMENT SYSTEM" under the guidance of Dr. Manwinder Singh, Associate Professor, School of Electrical and Electronics Engineering of Lovely Professional University, Phagwara, Punjab.

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