International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 1, 2025
https://www.theaspd.com/ijes.php

Reclaiming Resources With Iot And Cloud-Based E-Waste Management And Data-Driven Decisions

[1]Dr. S.Menaka, [2]Nisha M.Shrirao, [3]Harish L, [4]Dr.PALPANDI. S, [5]G. Vasundhara Devi, [6]Dr. R. Senthamil Selvan, [7]Dr. Sangeetham Rohini
[1]Professor, Department of Computer Applications,Nehru institute of information technology and management Coimbatore, Tamilnadu. Orcid id :0009-0005-4293-9969, niitmmenaka@gmail.com
[2]Assistant professor, Department of Electrical Engineering.Yeshwantrao Chavan College Of Engineering.Nagpur.Maharashtra, Sahu.nisha11@yahoo.in
[3]Assistant Professor,Department: Artificial Intelligence and Data Science, Global Academy of Technology, Bangalore, harishl@gat.ac.in
[4]Assistant professor-Senior Grade, Department of Computer science and Engineering, Vel Tech Rangarajan Dr Sagunthala R&D Institute of Science and Technology, Avadi,Chennai, sppecerdeee@gmail.com
Avadi
[5]Assistant professor, Department of Computer science & Engineering, Madanapalle Institute of Technology and Science, vasundharadevig@mits.ac.in
[6]Associate Professor, Department of ECE, Annamacharya Institute of Technology and Sciences (Autonomous),Tirupati,A.P, orcId: 0009-0008-6500-5255, selvasenthamil2614@gmail.com
[7]Associate Professor and Head of the Department, Department of ECE, Annamacharya Institute of Technology and Sciences (Autonomous),Tirupati,A.P, Orcid id 0000-0003-2889-0984, srohini512@gmail.com

Abstract
Internet of Things-based smart e-waste management is a new eco-friendly technology. Wasted electronics harm humans and the environment, making e-waste a worldwide concern. This study suggests a smart electronic garbage management technique. E-waste collection, sorting, and disposal are managed by this system using IoT devices and sensors. These sensors' real-time data may assist in the collection and disposal of electric waste. People typically see e-waste as a valuable resource due to its recycling potential. Machine learning has the potential to recycle metals from discarded electronics into solar cells, convert plastics into biofuel via pyrolysis, and create biochar. A sustainable waste management and material recovery alternative, they optimise utilisation and reduce environmental impact. The recommended method uses cloud-based systems to analyse data trends and patterns. A cloud-based autoregressive Integrated Moving Average can estimate garbage levels, which may assist in optimising waste collection schedules and processes.
Keywords: *Smart e-waste Management, Internet of Things, Long-Term Waste Management, Electronic Garbage, Machine Learning.*

1. INTRODUCTION

Refused electronic gadgets that are about to be used again are called e-waste. This includes things like computers, mobile phones, and other similar equipment [1]. Due to rapid technological advancement, more people are buying electronics. Asia is expected to generate the most electronic waste [2]. Only 15% of electronic garbage was recycled, therefore 85% was burnt or disposed of in dumps [3]. Discarded gadgets pose significant environmental harm [4]. These gadgets contain high levels of lead and mercury, which may damage landfill soil [5]. Electronic waste swiftly decomposes into hazardous compounds that affect the environment [6]. This mechanism increases air pollution by releasing hazardous chemicals [7]. E-waste's toxic chemicals, carried by rain and groundwater, may affect land and marine organisms [8]. Separating electronic waste from

MSW is challenging yet vital, requiring a lot of time and labour [9]. Recycling e-waste involves specialized sorting and processing, which costs more [10]. The main research topics include machine learning-based e-waste sorting, pyrolysis-based plastic recycling, biochar applications, and metal-based solar battery production [11]. Time series data can be used to monitor cloud trash levels, ARIMA can forecast and analyse lifetimes, and e-waste metals can be changed into solar batteries to provide energy that is sustainable and renewable [12]. Cloud computing, IoT, and machine learning simplify and centralize the waste-to-asset procedure in garbage collection and sorting [13]. This system can continually inform the garbage level in the clouds and store information, making waste management more efficient and easier, promoting an environmentally friendly approach to trash removal by improving management while reducing bin overflow, and collecting and analysing waste patterns [14]. This might influence rubbish management strategies. Even though meagre countries may struggle to construct procedures, this system has limits that might hinder its success. Time series data, mode collapse, training instability, and picture evaluation [15].
Solar batteries and biofuels may operate differently owing to contaminants and chemical interactions. E-waste management efficacy is the study's main emphasis. The primary goal is to assess the advantages of e-waste management systems that use IoT and smart solutions hosted on the cloud [16]. These technologies would provide effective communication and connectivity between all electronics waste management system equipment and parties. The project examines machine learning for e-waste sorting. The system will identify e-waste without human interaction using machine learning. This increases recycling accuracy and efficiency while minimizing sorting labour [17]. Data-driven initiatives accelerate e-waste collection, maximise resource utilisation, boost operational efficiency, and enhance management. Data analysis and interpretation help stakeholders choose the collection of waste, recycling, and allocation of resources [18]. Research also reveals how to turn e-waste plastic into biofuels and charcoal. E-waste metals may also be used to build solar batteries [19]. Recycling electronic waste into solar batteries is an eco-friendly solution to address renewable energy needs [20]. The use of these metals converts environmental risk into resource. This research seeks sustainable and efficient e-waste management. They may evaluate pyrolysis as a recycling process, uncover new applications for e-waste metals, develop sustainable strategies, promote data-driven decision-making, and explore IoT and cloud-based systems. This helps us build a greener, healthier future.
The paper's main contributions are listed below:

1. Using these state-of-the-art technologies, may have improved the precision and efficiency of e-waste recycling, which should lead to better sorting and separation of costly components.
2. The training of a numerical copy processing camera to identify ideal waste components, and the seamless integration of devices and the cloud can analyse data and recycle garbage flawlessly.
3. With the support of the cloud a basic model of an Internet of Things (IoT) waste management system will automate the whole process.
4. Through the improvement of the waste management and recycling system are transforming trash into valuable assets.

2. Suggested Framework:

Efficient and automated collection of e-waste and shipment for recycling is the primary objective. They are utilizing a blend of IoT and machine intelligence to gather electronic waste for recycling purposes. Their strategy involves deploying a Field-Programmable Gate Array, along with the GAN algorithm, to differentiate electronic waste from other types of waste and properly dispose of the processing components in a dumpster. An intelligent trash that can autonomously track and update its contents is at the core of the suggested solution. The SIM900A module notifies the collectors by messages if the bin is filled to its utmost capacity. Systematically, sort the trash into plastic and metal after it's collected. The metal parts are recycled into solar panels and batteries, while the plastic parts are pyrolyzed to make biofuel.

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2.1. Step by step system framework:

Figure 1 depicts the suggested system for efficient e-waste management, the system employs several measures. In the first stage (step-1), machine learning is used to categorise wastes according to their kind and a smart bin is used to collect e-waste, depending on the garbage. In steps 2 and 3, a notice is issued to the garbage collector if the data on the trash level exceeds specified thresholds. This procedure begins by evaluating the trash level data against these levels.

In the background, the cloud-based technology is constantly checking the garbage level. The fourth step is to sort the electronic trash into metal and plastic bins. In the next step, the metal waste is prepared for use in solar series. After that use the pyrolysis process to convert the plastic trash into bio-char, with bio-fuel being a by-product. The last stage involves turning the recycled and reused materials into something valuable.

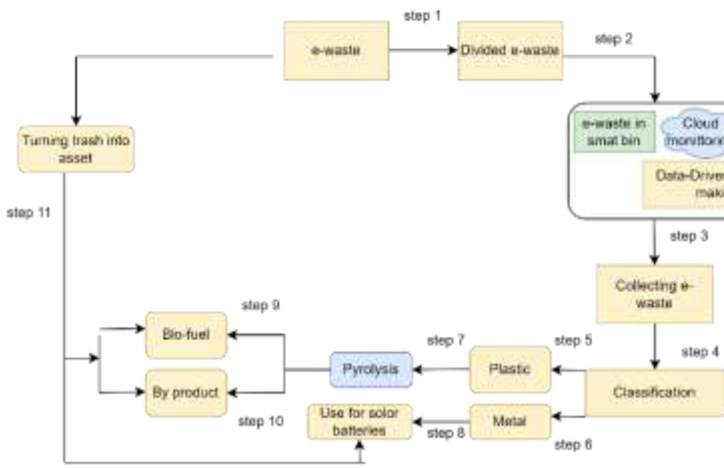

Figure 1: Proposed solution system architecture.

An example of a procedure for making decisions based on data for collecting electronic waste is illustrated in Figure 2. The process is based on the analysis of data. A built-in ultrasonic sensor in the garbage can keeps track of the current trash level in real time. This information is gathered so that e-waste levels may be analyzed in real time. According to the results, Collectors of electronic garbage get notices to collect e-waste from designated containers. In response to the alerts, the collectors gather the e-waste and check that it was recycled correctly. By optimizing collection efficiency and facilitating timely and targeted e-waste collection, this data-driven strategy aids in effective e-waste management and contributes to environmental sustainability.

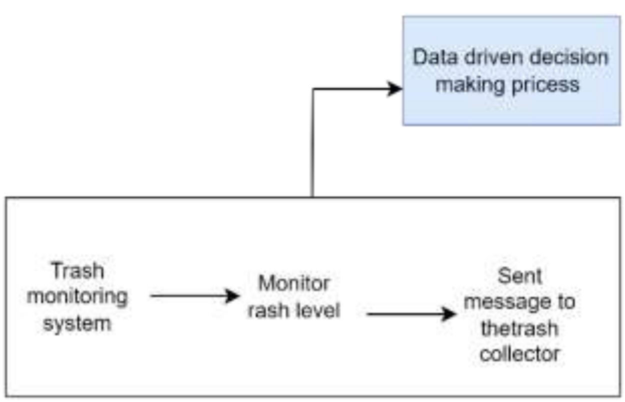

Figure 2: Database-driven decision-making

Three levels are shown in Figure 3. Ultrasonic garbage with intelligence is part of the sensor layer that keeps tabs on garbage accumulation. The ESP-8266 Wi-Fi Unit transmits sensor data to the cloud layer. The cloud layer receives information after the sensor layer and saves it in a database that contains period sequence information.

Temporal sequence databases manage data gained over time, such as garbage levels in bins. Users may query and analyse time series record data to make future predictions. Applying the Auto-Regressive Integrated Moving Average is a statistical analysis tool that is commonly used in finance and economics to analyze time series data. It is often abbreviated as RIMA.technique to the record predicts future garbage levels. The cloud layer enables real-time garbage level and other information viewing and transmission to the microcontroller. Users may access this interface via an online or mobile app. When garbage levels exceed a specific threshold, the microcontroller transmits a message to the application layer via the GSM module level of the application gets the notice, and the collector gathers data. The smart bin system collects and analyses waste-level data using sensors, cloud computing, and prediction algorithms. These data enhance trash management and notify users in real-time.

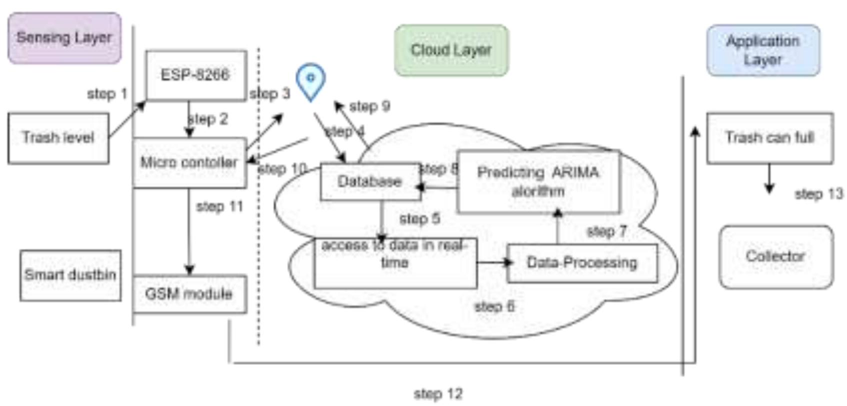

Figure 3: Garbage collection and monitoring system design via cloud and IoT

2.2 Methodology

The work procedure includes an e-waste container. The garbage will be transported on a conveyor belt, using a trained camera and Generative Adversarial Network (GAN) algorithm in the first portion. The GAN needs plenty of memory and processing. FPGAs are strong hardware platforms that compute well. The discriminator and generator comprise the GAN. The generator monitors waste and generates a picture if the generator and discriminator images match. The electronic waste smart bin is designated for garbage, while a separate pile is used for other types of rubbish. The smart bin uses an ESP8266 Wi-Fi module and an ultrasonic waste level sensor to transmit data to a cloud-based database. To predict waste levels, use the ARIMA model. Forecasting may optimise the system by estimating garbage level thresholds and scheduling pick-ups appropriately. Forecasting can optimise the system by anticipating waste levels and scheduling pick-up according to the threshold. It may improve productivity while reducing costs. The SIM900A GSM module will alert the garbage collector and send it for recycling if the trash level exceeds a certain edge. The process of recycling electronic trash involves pulverizing the material with a strong blade and then sorting it into metal and plastic pieces utilizing a magnetic arena.

Plastic components will be pyrolyzed. Pyrolysis has numerous steps:

Shredded plastic increases surface area for better pyrolysis. Plastic shreds enter pyrolysis reactors. Pyrolysis uses heat to break down complex organic molecules (plastic) into simpler ones without oxygen. Pyrolysis produces liquid fuel (bio-oil) and gaseous syngas, suitable for generating electricity and chemical manufacturing. Pyrolysis occurs without oxygen; hence the container is enclosed to prevent air entrance. The reactor temperature and pressure are precisely managed to effectively convert plastic into biofuel. Heat causes the plastic to degrade into gas, liquid, and char. Condensed gases and liquids become biofuel. Reactor cooling and biofuel recovery from the condenser follow pyrolysis. The gathered biofuel may need additional purification to eliminate contaminants like water and acids. To do this, use processes like filtering or distillation. Tanks or containers hold finished biofuels till use. Mixing organic materials like bio-solids with plastic garbage may produce bio-char, which can be recycled for improving the soil, storage of carbon, and energy generation. This solution significantly improves soil quality and eliminates contaminants from wastewater. Additionally, scrubbers and electrostatic precipitators reduce pollutants. Solar batteries may be made from metal scrap. Metal is shredded and treated with acids to eliminate impurities and extract pure metals. Electrolysis processes metals that are pure by infusing a current of electricity into a metal ion solution. Electrodes develop metal deposits when metallic ions receive or lose electrons during this process. Metal deposits are used to make solar battery anodes, cathodes, and electrolytes. These parts make a solar battery that stores and releases electricity. The technique of transforming metal roils into solar series varies based on the metal kind and the intended final result. In general, chemical and electrochemical methods are used to clean and refine metal and manufacture battery components.
The methodological parts of the procedure are:

- Method of information collection
- Machine learning and Camera: a trained camera system monitored and photographed conveyor belt garbage.
- The e-waste smart bin has a sensor that uses ultrasound to assess garbage levels.
- ESP8266 Wi-Fi module: ultrasonic sensor waste data were sent to a cloud database.
- The SIM900A GSM Module alerted the collector when trash levels surpassed the threshold.
- Data analysis: ARIMA model used to predict waste levels.

2.3 Flowchart representation

Garbage aggregation and classification using a GAN-trained camera is the first step in the process flow diagram for cloud and IoT-based e-waste management (Figure 4). This device uses visual processing to identify electronic garbage. If electronic waste is not present, it is placed in a separate pile. Otherwise, it is deposited in a smart bin. The disposal of e-waste tends to increase garbage levels, which are updated and monitored in the cloud using an ultrasonic sensor to ensure that the bin is full. If the bin is not full, the procedure continues or the collector is notified. Recycling begins after the e-waste has been collected. The initial process involves churning the e-waste, followed by magnetic separation. Two pieces result after separation: plastic and metallic churns. Plastic is converted into biofuel by pyrolysis, while metallic churns are used to make solar batteries. The technique produces bio-fuel, charcoal, and solar batteries, transforming e-waste into environmentally friendly and sustainable resources.

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Figure 4: Proposed System Flowchart.

2.4 Algorithm

GAN, a high-level algorithm, processes images. GAN image processing accuracy depends on the use case and model training and optimisation methods. This GAN training will use real-life e-waste photos to inform the machine's decision-making. Below is the GAN pseudo code:

Generator and discriminator networks are initialized with random weights in Algorithm 1. Initialise β, α, and γ hyper-parameters. For a certain amount of training iterations, the following steps are carried out: a mini-batch of m sample of noise from a distribution; a sample of m photographs from the dataset was taken; and for each generator update, a given number of discriminator updates are carried out. Generator network G creates fake pictures. Minimizing the binary cross-entropy loss among actual and false pictures and computing gradients via back-propagation updates the discriminator network D. Noise distribution mini-batch samples are taken.

Gradient steps on the harm purpose which exploits the binary loss of cross-entropy across produced and actual pictures are calculated using back-propagation to update generator network G. To update hyper-parameters β and α, a decline factor γ is used. Returns qualified generator network G.

Algorithm 1 Image classification using Generative Adversarial Networks

```
Initialize the generator network G wih random weights
Initialize the discriminator network D wih random weights
Initialize the hyper-parameters α, β, and γ
for number of training iterations do
  for number of discriminator updates per generator update do
    Sample a mini-batch of m real images from the data-set
    Sample a mini-batch of m noise samples from a noise distribution
    Generate fake images using the generator network
     Update the discriminator network.
end for
  Sample a mini-batch of noise samples from a noice distribution
   Update the generator network by taking a gradient step on the loss function
    Update the hyper-parameter
   α ← γα
     β ← γβ
End for
Return the trained generator network G
```

Discriminator and generator neural networks train on actual e-waste pictures. Training the generator network to make pictures that look like actual ones and the discriminator network to discriminate between them is the aim. In training, the generator creates pictures to mislead the discriminator, while the discriminator improves at discriminating actual and created images. After training, the generator may produce new pictures that can be compared to genuine ones. Similar rubbish may be thrown in the right trashcan. Algorithm 2 detects when a smart trashcan is nearly full of e-waste and alerts the garbage collection. This algorithm has three inputs: n (iterations), x (echo), and y (trip). A smart trashcan can identify e-waste at a maximum distance of 4. E-waste is placed in the smart trashcan and the programme loops until n is not 0. The starting point of y is set to 0 or Low inside the loop. The procedure then sets y to 1 or High after 10 repetitions. Y returns to 0 after 10 repetitions. Set x to 1 or High.

Algorithm 2 An algorithm for calculating the e-waste level in a smart dustbin

```
  Require: n ≥ 0
    x= echo Pin
    y= trig Pin
    n=iteration
 thresholdDistance = 4
Put e-waste in Smart dustbin
While n ≠ 0 do
    y ← 0 or low
     For number of 10 iterations do
        y ← 1 or High
     End for y ← 0
   x ← 1 or High
      distance ← (time×0.034)/2
      garbagelevel=totalDustbinDistance - distance
     If distance ≥ thresholdDistance then
        Sent notification to garbage collector
     Else
       Smart dustbin collects the e-waste
     End if
     End while
```

The algorithm uses time and sound speed to compute the smart dustbin-e-waste distance. Distance minus dustbin distance equals rubbish level. ESP8266 sends data to the cloud. If the distance exceeds the threshold, the algorithm notifies the trash collector via the SIM900A GSM module. Otherwise, smart dustbins gather e-waste.

3. EVALUATING RESULTS

3.1. Cloud E-Waste Level Updates Graphical Analysis

Figures 5–6 show the smart waste bin's empty area and the processes of informing cloud information over time. The gap between the trash can's contents and the top signifies vacant space. The greater distance equals more vacant space.

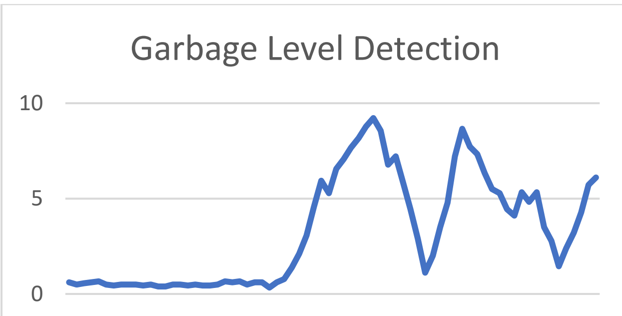

Figure 5: Cloud e-waste level updates.

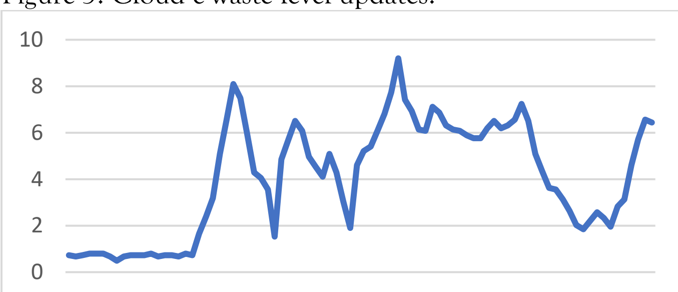

Figure 6: Cloud e-waste level updates with timestamps.

3.2. GAN Algorithm Accuracy Chart

The dataset is separated into training, validation, and testing sets using the GAN technique. The training set trains the model, its validation set tunes its hyper-parameters, and its performance on unknown data is tested. Table 1 illustrates a GAN-based e-waste identification system's accuracy chart. The graphic displays the accuracy, F1-score and recall for every type of e-waste the system can recognize: TVs, cellphones, monitors, laptops, and others.

Table 1: GAN Algorithm E-waste Recognition Accuracy Chart.

Category	Accuracy (%)	Recall (%)	F1-Score (%)
Cellphone	96	98	97
Laptop	91	86	88
TV	86	92	89
Monitor	93	90	91
Other	81	76	78
Overall	91	89	90

Figure 7 shows precision, a performance parameter that assesses a system's relevance detection accuracy. It measures the percentage of system-identified things correctly. Precision is the ratio of actual positives to true

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positives plus false positives. High accuracy means the system properly identifies relevant things. It indicates that the system seldom misidentifies unrelated things as the target. An accuracy of 96% means the algorithm seldom misidentifies non-smartphone goods as cell phones.

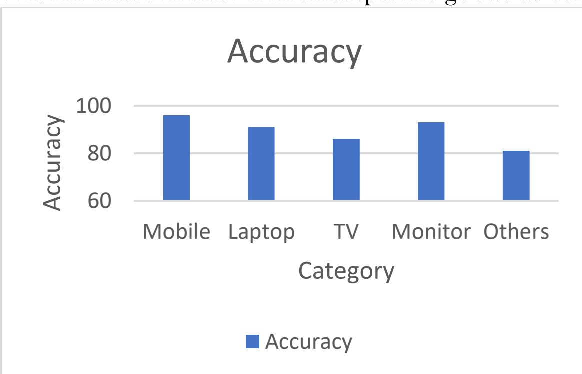

Figure 7: Individual category precision.

Precision simply may not reveal the system's performance. To assess the system's relevance detection ability, it should be assessed with recall and the F1-score. For instance, a system that distinguishes cell phones from other objects. The technology accurately classified 96% of smartphones as phones. The remaining 4% may be misclassified smartphones. Recall, shown in Figure 8, measures a system's ability to detect relevant objects. Divide the number of actual positives by the total of true positives and false negatives. Recall is crucial when false negatives have serious effects. By increasing memory, the approach reduces the probability of missing important items and improves recognition. Consider a laptop identification system between items. A system with an 86% recall accurately recognized 86% of the computers in the sample. The other 14% were laptops that the operating system failed to recognize. A greater recall score indicates that the system captures more relevant items. It means the algorithm misses fewer target category items due to fewer false negatives. The example's 91% recall indicates that the system can recognize and identify TVs.

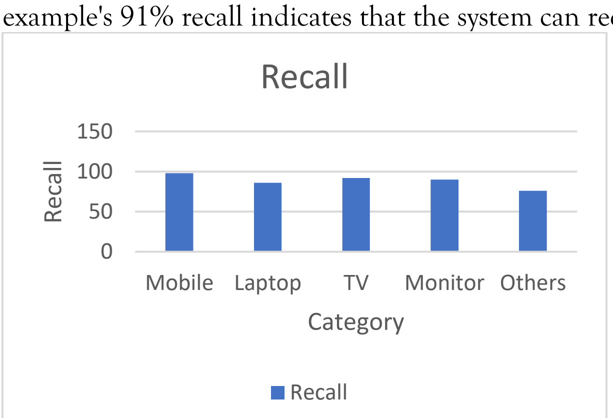

Figure 8: Individual category recall

The F1-score, shown in Figure 9, evaluates classification models based on accuracy and recall. Such models' efficacy depends on precision and recall. A balanced metric, the F1-score takes the harmonic average of accuracy and recall.

$$F1 - Score = \frac{2\ (Precision - Recall)}{Precision + Recall}$$

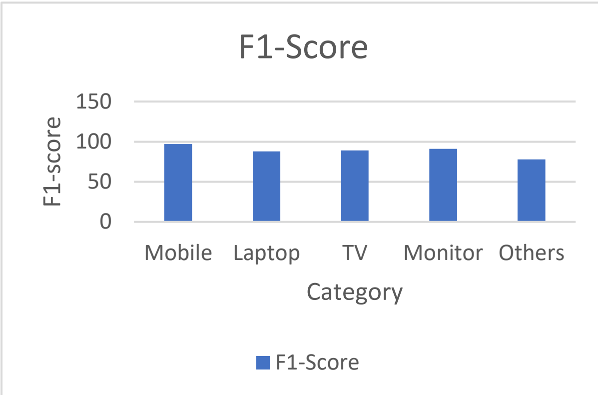

Figure 9: Individual category F1-Score (%)

Choosing the harmonic mean gives smaller numbers more weight, ensuring accuracy and recall are equal. In the F1-score, accuracy and recall are combined to measure performance. It balances accuracy and recall by detecting important objects accurately and recording their entire range. When there is no discernible pattern to the class delivery or when recall and accuracy are identical, the F1-score might be useful. To make comparisons and decisions easier, it gives a single figure for the effectiveness of classification models. Table 3's "Overall" row shows system performance in Figure 10. Precision, recall, and F1-Score are P, R, and F. Performance parameters including accuracy, recall, and F1-score are shown here. The system has 91% accuracy,90% F1-score, and 89% recall, according to the table. All aspects of system performance are assessed using these measures. The technology accurately identifies e-waste with 91% precision. The method collects a considerable part of the sample's e-waste, as shown by its 89% recall.

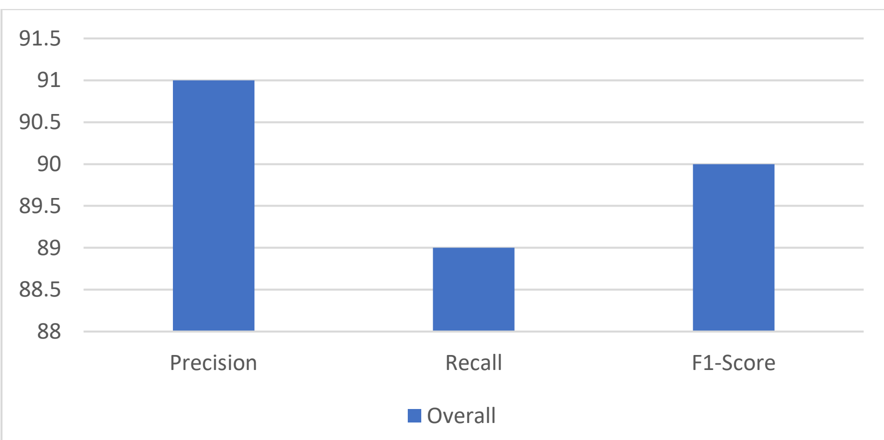

Figure 10: Category performance overall.

The 90% F1 score strikes a good mix of recall and precision. The system's performance is evaluated using both metrics. The system consistently identifies e-waste goods, with an acceptable balance of accuracy and recall. However, it may make a few minor errors in certain categories, as shown by this score.

3.3. Pyrolysis Method Graphical Analysis

Pyrolysis yields biofuel from plastic waste (Figure 11). The x-axis temperature in degrees and the y-axis shows biofuel yield as a percentage. The temperature-biofuel yield link is shown in blue. Temperature boosts biofuel output. Yield is 21% at 300 °C and 51% at 500 °C. This graph demonstrates that pyrolysis may produce biofuel from plastic trash and that greater temperatures provide more biofuel. The red line shows biofuel output, according to the caption. In Table 2, elements analysis of combined recyclable plastic pyrolysis liquid models from thermal and catalyzed procedures is shown. The table displays sample carbon, hydrogen, nitrogen, and Sulphur weight percentages. The findings show that catalyzed pyrolysis had more carbon and less hydrogen than thermal pyrolysis. Both procedures had identical nitrogen and Sulphur levels in pyrolysis liquid samples.

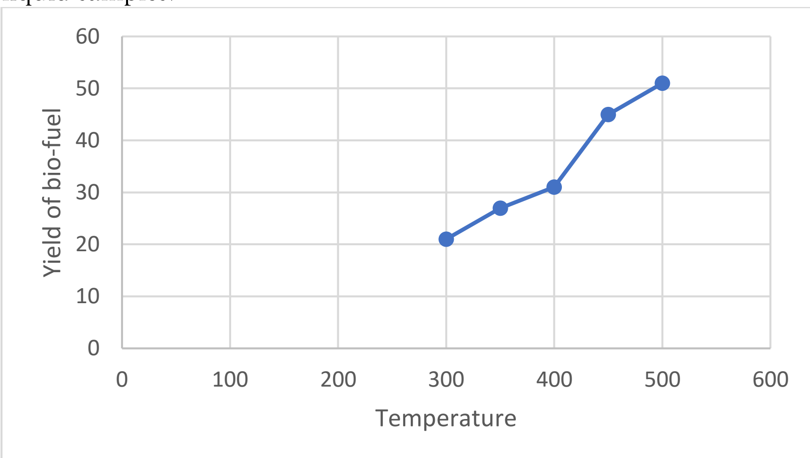

Figure 11: Pyrolysis yields biofuel from plastic trash.

Table 2: Mixture waste plastic pyrolysis liquid elemental analysis.

Weight (%)	**Thermal Pyrolysis**	**Catalyzed Pyrolysis**
C	95.25	98.12
H	12.74	11.13
N	0.62	0.29
S	5.9	5.37

4. Future Work and Limitations

Pyrolysis plant structures vary by feedstock, demands, products, and needs. Plastic recycling's future is pyrolysis. Pyrolysis will be mitigated by the following measures:
- Health and environmental dangers from emissions
- Inputs of energy
- Release of contaminants

The suggested system will mitigate all pyrolysis risks. The method may have these big drawbacks:
- Variability in feedstock
- Impurities and contaminants
- Emissions of pollutants

E-waste pyrolysis must be tested, developed, and researched to improve emission characterization and monitoring for safety and sustainability. The research paper should optimise the pyrolysis process, improve data-driven decision-making by using advanced technologies, analyse waste streams for easy reprocessing, manage and control solar batteries to maximise performance and lifespan and optimise the recycling process to train recycling facilities on various recycling processes.

5. CONCLUSION

IoT- and cloud-based trash management and recycling solve the e-waste problem. IoT, machine learning, and cloud computing were utilized to efficiently separate and dispose of e-waste. The study showed better efficiency, cost savings, monitoring, and sustainability. Real-time data analysis optimised rubbish collection routes, reduced environmental impact, and created biofuel and solar batteries. IoT and cloud-based trash management increased garbage monitoring, streamlined collection routes, and produced bio-fuel from pyrolysis and solar batteries from e-waste metal. The study's results match the primary research aims, showing that the system can overcome conventional waste management issues. IoT devices and cloud services provide security and privacy risks that must be handled with strong data protection procedures. Mode collapse, when the generator generates restricted output, stability while training and difficulties assessing produced pictures may also impair GAN algorithm performance. In conclusion, waste management solutions that are cloud-based and IoT-based have the potential to revolutionise the industry. Streamlined data gathering, optimisation of operations, distribution of resources, and production of recycled goods all contribute to reduced environmental effects, cost savings, and increased sustainability. Future deployment of such systems requires resolving security issues and undertaking further research to achieve general acceptance.

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