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Development of E Waste Management System Using Machine Learning

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Abstract- Today, developments in technology have changed everyone's lifestyle. Although this innovation is beneficial, it creates serious effects on human health and environmental health. One of the main reasons for this is "e-waste" from electronic products. The use of electronic products worldwide has increased the amount of "e-waste" or electronic waste, which has now become a serious problem. Improper disposal of e-waste has now become an environmental and public health problem as these wastes have become the largest portion of water litter in the world's cities. Therefore, correct classification and management of e-waste requires the recovery of important information about waste. This growing waste is inherently hard and rich in metals such as neodymium, indium, palladium, tantalum, platinum, gold, silver, lead and copper, which can be recovered and brought back into the cycle of production and daily use. In this project, a deep learning model is used to identify e-waste and general waste using image processing. The design model, on the other hand, selects the waste with good accuracy and takes less time. Wastes are divided into two groups according to the amount or value in the waste. By using this model effectively, we can solve e-waste management problems, improve recycling and contribute to environmental sustainability.
View table

Contents - e-waste management, Internet of Things, machine learning, imaging, smart green city etc.

I. INTRODUCTION

A smart city is an advanced ecosystem that integrates information and communications technology (ICT) to improve environmental safety and citizens' quality of life. Smart city applications, including personal and home services such as remote patient care and utilities, as well as solutions such as smart grids, traffic management and waste management, help create a smart and safe city.

E-waste - also known as e-waste - is the disposal of unwanted, non-functional or unusable electronic products. E-waste has an impact on the environment. Every year, millions of tons of electronic waste are thrown into landfills, and some of it ends up in rivers and oceans. E-waste emits toxic substances such as mercury, lead, cadmium, polychlorinated biphenyls, benzene and dioxins, damages soil and water bodies, threatens water and air quality, and harms human health and the environment.

In this context, e-waste, one of the most important problems regarding the use of smart cities, negatively affects human and environmental health, making this field an important research area. Today, rapid advances in technology and increasing consumer demand have caused many electronic products to reach the end of their useful life after a period of use. E-waste is the abbreviation for electronic waste. This term applies to waste electrical equipment or electrical equipment that can no longer be used due to malfunction, repair or lack of spare parts, or equipment that is no longer used to do good work.

II. PROBLEM IDENTIFICATION

E-waste is one of the largest sources of waste in the world. Studies show that India produces approximately 3.3 million tonnes of e-waste every year and total e-waste generation is expected to reach 4.8 tonnes by 2011. In developing countries, WEEE accounts for 1% of total waste and is expected to grow. to 2% by 2010. Two major problems with WEEE production include large-scale e-waste and environmental safety waste.

TRAI report shows that there were approximately 113.26 million new mobile subscribers in 2008, with an average of 9.5 million new subscribers per month. The cellular market grew from 168.11 million from 2003 to 2004 to 261.97 million from 2007 to 2008. In 2006, the growth rate of microwave ovens and air conditioners was around 25%. From 2006 to

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2007, the sales volume of refrigerators reached 4.2 million units, and production increased by 17% compared to the previous year. Washing machines, which were growing poorly, showed reasonable growth in 2006. Color TV (CTV) sales tripled compared to 2007.

Of all e-waste products, only approximately 19,000 tonnes of e-waste are recycled, 95% of which consists of waste. recycled in illegal activities. E-waste contains precious metals such as silver, gold and copper, and utilizes renewable energy. This process involves the destruction of e-waste and the elimination of valuable items that could harm the environment and health if these activities are carried out illegally through illegal activities.

This is a bad idea because it compounds the importance of the problem with the industry, given the volume of e-products produced and the content of toxic and beneficial products within them. The content of iron, copper, lead, gold and other metals in e-waste is more than 60%, plastic is about 30%, and pollution is only about 2.70%. Since recycling and extraction processes are illegal in illegal activities, significant and very dangerous processes are used to process and extract recycled materials from e-waste.

Fig. 1.E-Wastage

III. PROPOSED SYSTEM

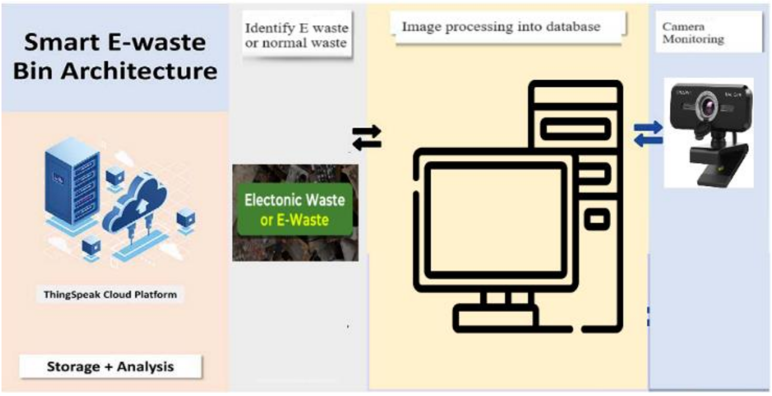

Fig. 2. Block Diagram of system

With the help of the suggested system, users will have a simple method to submit a request to the administrator and provide data about the waste from anywhere at any time. The suggested method requires no physical labour and saves a great deal of time.

With a camera installed, clients will be able to upload pictures of the places that need to be cleaned to the system. To manage file uploads, Image Field will be incorporated. We'll use server-side validation to make sure the submitted files fulfil the necessary requirements. The uploaded photos will be analysed, and a machine learning system trained to identify the kind of e-waste present will be used. By integrating the learned model, automated waste type categorization will be made possible.

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Advantages Of Proposed System

- Menu driven
- Eliminates manual intervention as far as possible
- Error free modification facilities
- On line error modification facilities
- Secured environment
- Immediate report generation for may given two dates
- To maintain security.

IV. FLOW DIAGRAM

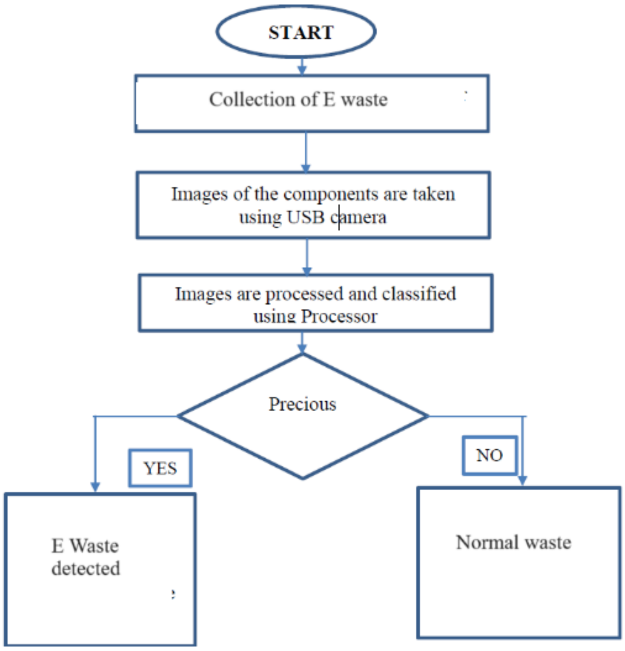

Fig. 3. Flow Diagram of system

V. REQURIEMENTS ANALYSIS

A. Product Overview

The E-waste application is a web-based tool designed to aid the organization RSC by facilitating the reporting and tracking of E-waste. Specifically, it allows general users to report E-waste to RSC and enables RSC members to track these reports as well as monitor E-waste donations.

Initially, the eMargin8 E-waste application will be freely available for use within Trinidad and Tobago. It operates on a web-based system utilizing a client-server model.

Key features of the eMargin8 E-waste application include:

- Cross-platform support: The application is compatible with various operating systems, ensuring accessibility through any web browser.
- User account creation: Users can create accounts based on their specific needs and purposes for using the application.
- Scalability: While the exact number is unspecified, the system is capable of accommodating a large volume of online users simultaneously.
- E-waste Reporting: Any user can submit reports regarding E-waste, whether they own it or have observed it.
- E-waste tracking: RSC users, including administrators and club members, have the ability to track and view reports on E-waste reporting and donation activities.

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B. Functional and Non-Functional Requirements

Functional Requirements:
The application aims to digitize the processes of:

- Allowing individuals to schedule the collection of their e-Waste.
- Identifying and categorizing e-waste in images uploaded by the public and club members.
- Permitting users to capture photos of e-Waste they encounter, along with its geographical location.
- Sending notifications to school clubs regarding posted e-Waste.
- Alerting RSC about e-Waste collected by clubs.
- Monitoring the recycling journey of e-Waste, including whether it was refurbished, donated, or recycled.
- Facilitating the efficient distribution of donated equipment to beneficiaries.
- Providing educational videos to raise awareness about the hazards of e-Waste.

Non-Functional Requirements:

- Providing a highly scalable, fluid, and responsive application with an intuitive interface and satisfactory user experience.
- Ensuring compatibility with all browser platforms.
- Employing machine learning techniques for accurate identification of e-Waste images.
- Implementing robust security measures to protect against various attacks, including Cross Site Scripting and SQL injection attacks.
- Ensuring scalability to handle up to 10,000 simultaneous users accessing the site.
- Accommodating the enrollment of all existing, new, and past users into the system.
- Ensuring information availability with restricted access to each user's data.
- Maintaining fast response times, even during periods of high user activity, with a maximum delay of 15 seconds.
- Guaranteeing cross-platform functionality across all devices.
- Presenting confirmation checks, screen prompts, and alerts within 10 seconds.
- Ensuring consistency and currency of system information.

C. Model Processing

This research investigates an image recognition method aimed at identifying and categorizing waste electrical and electronic equipment from images. The primary objective is to facilitate the sharing of information regarding the waste intended for collection from individuals or waste collection points. The system revolves around a central computer unit that processes a machine learning (ML) model utilizing a Convolutional Neural Network (CNN) algorithm. The waste type is detected through a camera module positioned within a container. Figure 4 illustrates the training process of the Machine Learning (ML) model.

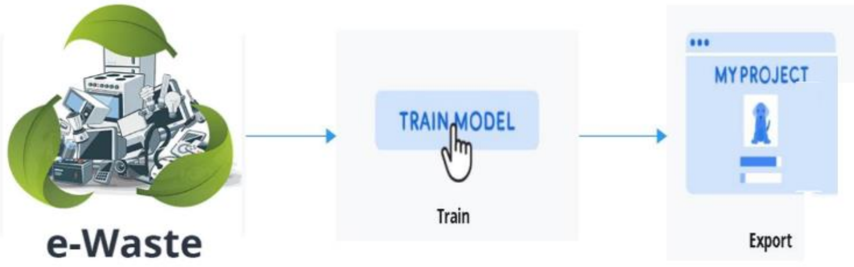

Fig. 4. Model Processing

D. Use Case

As seen on Figure 1, there are currently 5 main user groups:

- Administrator: This user holds the authority to approve various transactions conducted by other users within the system.
- Club Members: Individuals affiliated with specific clubs, with Club Administrators having the ability to authorize requests made by club members.

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• Contributors: Both individuals and companies can act as contributors. They have the capability to submit donation requests, detailing the electronic waste they intend to donate. Administrators then have the authority to confirm whether the waste is accepted and/or collected.

• Recipients: Recipients, who may be individuals or companies, have the option to request refurbished units. Administrators can then indicate whether the request is approved and/or fulfilled.

• General Users: All users possess the capability to report observed or collected electronic waste for collection. Administrators or club members can then confirm the collection status of this waste.

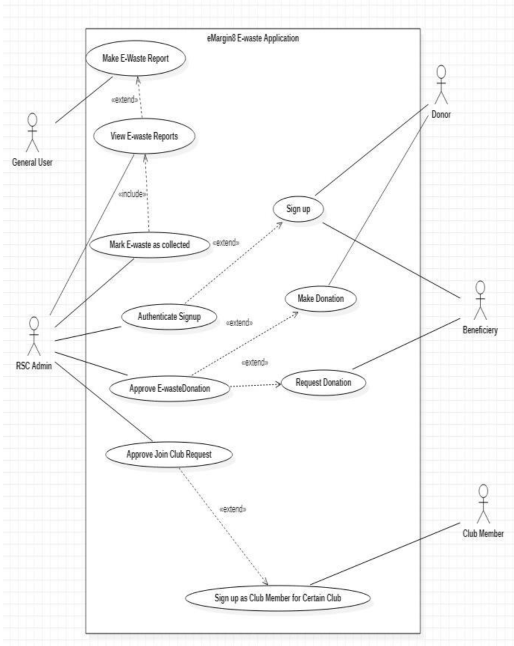

Fig. 5. Use Case Diagram of E-waste project

VI. CONVOLUTIONAL NEURAL NETWORKS

A convolutional neural network, abbreviated as CNN or comp net, is an artificial neural network primarily utilized for image analysis. While image analysis remains its predominant application, CNNs can also be employed for various other data analysis or classification tasks. In essence, a CNN can be conceptualized as an artificial neural network equipped with specialized features for pattern detection, enabling it to effectively identify and interpret patterns within data. This capability for pattern detection renders CNNs particularly valuable for image analysis purposes.

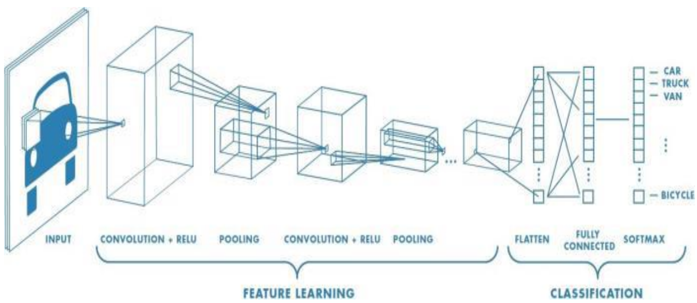

Fig. 6. Convolutional Network: Layers and Learning

If a CNN is essentially a type of artificial neural network, what sets it apart from a standard multi-layer perceptron or MLP? The distinctive feature of a CNN lies in its inclusion of hidden layers known as convolutional layers (refer to Figure 6). These layers are the fundamental components that define a CNN. While CNNs may also incorporate additional non-convolutional layers, it is the presence of convolutional layers that forms the basis of their architecture.

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VII. METHODOLOGY

The architectural design of a system encompasses various elements, including the application type and architectural style or pattern employed. In this project, the solution falls within the realm of web-based information systems, utilizing web browsers to access user interfaces and process user requests for querying and posting information to a database.

Performance, security, and modularity are key factors in assessing the suitability of a system architecture. Performance considerations involve optimizing critical operations, while security focuses on authentication and authorization mechanisms for accessing sensitive information. Modularity ensures the separation of the system into independent modules.

The chosen architectural style plays a crucial role in defining interactions between software components and subsystems. In this project, two architectural patterns are considered: the Layered pattern and the Model-View-Controller (MVC) pattern.

For this project solution, the need to support the presentation of database information in multiple views and to separate presentation and interactions from system data led to the selection of the Model-View-Controller (MVC) pattern as the architectural style. Figure 7 illustrates the application of this system architecture within the project's domain.

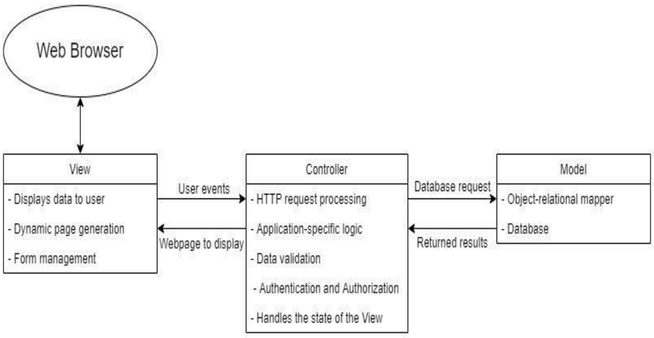

Fig. 7. System Architecture of E-waste project

Considering the system's web-based architecture, all users are required to employ a web browser for accessing the user interface, which presents different web pages and facilitates input via forms. The Controller component is tasked with overseeing the state of the View component and handling the transmission and reception of HTTP (Hypertext Transfer Protocol) requests and responses, encompassing application-specific logic and data validation. Lastly, the Model component comprises the system's database along with the Object-Relational Mapper (ORM) [18], serving as the Application Programming Interface (API) for database communication.

An alternative option for the project's architectural design was the Layered architectural pattern, which structures the system into distinct layers, each offering specific services. When implemented effectively, lower layers (core services) can utilize various higher layers, and modifications within one layer will not impact others. Figure 8 depicts an illustration of this system architecture applied within the project's domain.

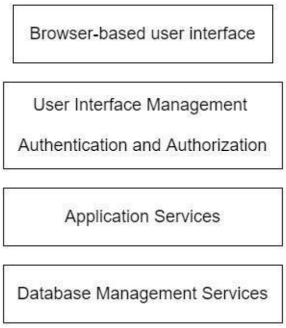

Fig. 8. Applied Architecture on Domain of E-waste project

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VIII. TESTING

For the application, two main types of testing would be done.

1. Usability Testing:
To conduct the testing, various tasks were assigned to different users [4]. Testers then utilized the application to complete these tasks. Additionally, a talk-aloud analysis was conducted, wherein testers verbalized their observations and feedback regarding the application. Subsequently, testers were interviewed to provide quantitative ratings on task difficulty and qualitative suggestions for enhancing task ease.
The data gathered from these tests included:

Quantitative Data:
Time taken to complete each task.
Number of errors encountered during task completion.
Testers' ratings of task difficulty.

Qualitative Data:
Insights and concerns expressed during the talk-aloud recordings.
Suggestions for improvements offered by testers.

2. Functionality Testing:
To ensure the application's functionality aligns with both the functional and non-functional requirements, various features will undergo testing.

The following features will be tested:
- E-Waste Reporting by General Users.
- Sign up and Login for all User Types, including Club Member Join Requests.
- Creation and Requesting of Donations by Donors and Beneficiaries, respectively.
- Approval of all types of requests by Admin users.

Communication and testing will predominantly occur online. Screen-sharing applications will enable observation of user actions, while communication platforms like Zoom or Discord [13] will facilitate interaction with participants. Each user will complete a survey comprising closed-ended questions based on their application usage. Additionally, quantitative data from the usability study and survey will be recorded and analyzed to test hypotheses regarding ease of use for both user groups. A report incorporating qualitative insights will complement the quantitative findings.

All users will engage with all listed application features as per the test plan. The test will be deemed successful if all features operate as intended, adhering to specified requirements. A verification matrix will document the tested features. For functionality testing of the Machine Learning Classification, each user will submit one picture for each device type, with classifier accuracy recorded for analysis.

Fig .4. Detected Components

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A pre-trained model has been developed to classify wastes into eight categories. Utilizing a pre-trained network to train on 1000 images demands minimal GPU resources and consumes less time compared to building a network from scratch. The process predominantly relies on CNN, which proves to be an efficient tool for both machine learning and deep learning tasks.

IX. ADVANTAGES

- Improved Accuracy: Machine learning algorithms can learn complex patterns and features from data, leading to higher accuracy in detecting and classifying e-waste items compared to traditional methods.
- Efficiency: Automated e-waste detection using machine learning can significantly reduce the time and effort required for manual sorting and inspection, leading to increased operational efficiency.
- Cost-Effectiveness: While initial development may require investment, in the long run, automating e-waste detection with machine learning can reduce labor costs associated with manual sorting and inspection.
- Scalability: Machine learning models can be trained on large datasets and easily scaled to handle increasing volumes of e-waste, making them suitable for both small-scale and large-scale waste management operations.
- Real-Time Monitoring: Machine learning-based e-waste detection systems can provide real-time monitoring of waste streams, enabling timely intervention and decision-making to optimize waste management processes.
- Customization and Adaptability: Machine learning models can be customized and adapted to specific waste streams, environments, and requirements, allowing for greater flexibility and optimization.
- Environmental Impact: By improving the efficiency and accuracy of e-waste detection and sorting, machine learning systems can contribute to reducing the environmental impact of improper disposal and recycling of electronic waste.
- Overall, implementing an e-waste detection system using machine learning offers numerous benefits, including improved accuracy, efficiency, scalability, and environmental sustainability in waste management practices.

X. CONCLUSION

The development and implementation of an e-waste detection system using machine learning present promising solutions to tackle the challenges associated with managing electronic waste. By leveraging machine learning algorithms such as convolutional neural networks (CNNs) and support vector machines (SVMs), the system can accurately identify and categorize various types of electronic waste items in real-time. This automation reduces the need for manual sorting, thereby minimizing the risks of human error and ensuring consistent detection performance. Moreover, the benefits of deploying an e-waste detection system using machine learning extend beyond enhancing operational efficiency to promoting environmental sustainability and conserving resources. Through the system's capability to identify and segregate valuable materials from e-waste streams, it encourages recycling, resource recovery, and adherence to the principles of a circular economy.

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