SSRG International Journal of Mechanical Engineering
ISSN: 2348-8360/ https://doi.org/10.14445/23488360/IJME-V11I12P104

Volume 11 Issue 12, 38-46, December 2024

Original Article

Smart Waste Revolution: AI-Powered Biomedical Segregation and Recycling with IoT Integration

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Received: 08 October 2024 Revised: 18 November 2024 Accepted: 05 December 2024 Published: 27 December 2024

Abstract *- The threat to the environment and health posed by biomedical waste requires a proper approach to its management and recycling. This study aims to develop an advanced smart waste management system that combines IoT sensors for real-time monitoring and an Extreme Learning Machine (ELM) to segregate waste. This system applies IoT sensors to get data from hospital ward dustbins that alert bins' fullness. The ELM uses the information received to categorize the waste as recyclable or non-recyclable. The sorted-out trash items are then directed either to disposal or recycling bins accordingly. Our method improves efficiency in handling biomedical wastes by utilizing state-of-the-art ELM algorithms, which exhibit superior performance over conventional methods in accuracy and computation speed, among others. Our simulation results show that our model has 95% classification accuracy compared with other AI-based approaches such as Cohort Intelligence Algorithm (CIA), Hesitant Fuzzy Weight and Rank Finding (HFWRF), and Deep Learning (DL). This new system not only contributes to efficient waste management but also supports environmental sustainability, promoting effective recycling plans.*

Keywords *- Use Segregation, Recycling, Extreme Learning Machine, Deep Learning, Waste management, IoT sensors.*

1. Introduction

Medical care and the removal and handling of biomedical waste (BMW) [1] should be viewed in tandem because it is a social responsibility to safeguard biodiversity and ecosystems from harmful substances. To assess the quality of medical facilities, the WHO (World Health Organization) and the National Health Insurance (NHI) have been working together to examine how healthcare facilities and labs eliminate diagnostic debris. The Influenza and the dengue epidemic alone claimed several lives this past year; this is what happens when garbage runs out. Healthcare [2] the leadership's top priority is the automaker; environmental disorders are the cause of numerous new illnesses that are spreading currently. Clinical trash removal particularly includes body parts, sickness, spores, microbial and infectious diseases, and circulatory cleaning instruments. Consequently, it is imperative to eliminate these calamities. Several illnesses will be brought on by bacterial, viral, and bacterial illnesses that harm human and ecological health if the waste cannot be disposed of appropriately.

Right now, the safety administration [3] is mostly concerned with manipulating contemporary disposal techniques. In particular, medical waste has an impact on the ecosystem and contains pathogens that harm other living things; waste usually has an impact on the surroundings. In addition to being an occupational danger, these healthcare wastes also carry a direct infection risk to healthcare professionals and other hospital personnel members. The release of medical supplies must be chosen with consideration for the current weather and the globalization of illnesses [4]; not only do these illnesses hurt people, but they also impact plants and animals. These days, numerous illnesses propagate in numerous manners; therefore, taking the appropriate precautions to avoid appropriate BMW garbage procedures is essential.

After being released from a healthcare facility, bacteria could grow and have an impact on people's lives. The primary purpose of BMW administration is to prevent infections from spreading from one individual to another, from patients to medical professionals, and from patients to other patients. The BMW technique ought to be an excellent means of preventing contagious ailments brought on by contagious microorganisms. Additionally, composting and repurposing garbage reduce the demand for extracting commodities and lessen the risk of pollution, both of which are good for the environment. In addition to raising the risk of water and atmospheric contamination, faulty disposal raises the risk of fatal infections. Discharging waste outside can result in contamination of creatures and explorers, which can disperse garbage and propagate diseases.

The roadmap of the work is in Section 2, where the relevant works are reviewed, including their merits and demerits. The system model of the proposed work is presented in Section 3. The proposed work for the classification and recycling is deliberately explained in Section 4. The experimental investigation is enclosed in Section 5. The summary is presented in Section 6.

2. Literature Survey

Kumar et al. [5] have presented an Artificial Intelligence (AI) based on an autonomous system that separates COVID-related medical material sources from different garbage kinds while guaranteeing informed data recycled selections within the framework of circular economy (CE). Based on image-texture sensitive elements, the waste kind is classified, allowing for precise separation and identification prior to the commencement of the reuse procedure. The suggested decision-level merged features technique is applied to merge the attributes. Regarding garbage category categorization in the framework of symmetrical production, it demonstrates the ability to handle transformed medical waste associated with COVID-19. If there is any kind of interruption, it will impact the entire procedure.

Agrawal et al. [6] described the Cohort Intelligence algorithm (CIA) for Biomedical Waste organizations as one considering human vulnerabilities. This approach might also help determine the best pathway for transporting learners. Additionally, it can be used in medical professions such as emergency dispatching, delivering blood to medical facilities, and transportation handling scenarios involving goods collection and transport. It can support the promotion of a harmless, nutritious way of life. However, there were certainly some cases that the additional synthesis alone could sort out.

Narayanamoorthy et al. [7] implemented a bio-medical waste disposal method using a hesitant fuzzy weight and rank finding technique (HFWRF). The process of choosing the optimal course of action in the BMW hierarchy following its disposal may result in multi-criteria decision-making (MCDM) procedures involving ambiguous analytical judgments. These individuals hesitate a little bit before offering a suggestion. The selected five medical-grade BMW destruction techniques in today's environment and their equivalents are as follows: Furthermore, there is a lack of clarity in this pattern while discussing medical and biological therapies.

Liu et al. [8] method employs conversational computational technology to examine footage captured by sensors positioned in populated regions, to find large amounts of rubbish waste in inappropriate places and notify the local government of the issue. The suggested approach starts by creating a software design that detects large amounts of useless information. The security system issues an advisory to the community to stop discharging rubbish. The suggested approach offers both a wholesome atmosphere and a clever garbage disposal technique. Additionally, it is inadequate to determine the issue of stopping illegal dumping in smart communities.

Govindan et al. [9] highlighted a bi-objective mixed-integer linear programming model for the COVID-19 outbreak's administration of waste from medicine. The suggested bi-objective system is solved using an imprecise target programming technique, and the effectiveness of the hypothesis and response technique is evaluated with the use of information from 13 clinical waste-generating regions; the suggested framework concurrently reduces the hazards and general expenses associated with the public's interaction with contamination. Furthermore, if such materials are not handled correctly, they should be a threat to ecosystems and creatures that live, which is dangerous.

From the detailed literature survey, the following research gaps are identified. Exploring research gaps in the application of Extreme Learning Machines (ELM) for biomedical waste segregation and recycling using IoT sensors could involve examining several areas:

Data Quality and Preprocessing: Biomedical waste data gathered from IoT sensors can be noisy or incomplete. Investigating techniques for improving data quality before feeding it into ELM could be a gap. There might be a need for advanced preprocessing methods tailored specifically for biomedical waste data.

Real-Time Processing: ELM is known for its speed, but integrating it effectively for real-time applications in IoT environments, where decisions must be made on the fly, could present challenges. Research could focus on optimizing ELM for real-time biomedical waste segregation.

Scalability of ELM Models: While ELM is efficient, scaling it for large-scale IoT networks with numerous sensors and varied data could be challenging. Identifying methods to enhance scalability while maintaining performance could be an important research gap.

Integration with IoT Architectures: How ELM integrates with existing IoT architectures for biomedical waste management might not be fully explored. This includes how it communicates with different layers of IoT systems (sensing, network, processing) and how it can be optimized for such architectures.

Energy Efficiency: Given the resource-constrained nature of many IoT devices, there could be a gap in developing energy-efficient ELM models that can run effectively on low-power devices while still delivering accurate results.

Security and Privacy Concerns: Implementing ELM in IoT systems for biomedical waste segregation raises data security and privacy concerns. Research could explore how to secure the data being processed and how ELM models can be designed to be robust against cyber-attacks.

Multi-Class Segregation: Biomedical waste often involves multiple categories that need precise segregation. There might be a gap in optimizing ELM for handling complex, multi-class classification tasks, ensuring high accuracy across all categories.

Comparative Analysis with Other Techniques: While ELM is popular for its speed and simplicity, comparing its performance against other machine learning models in the context of biomedical waste segregation could reveal gaps. Research could focus on benchmarking ELM against deep learning models or other advanced algorithms.

Sustainability and Lifecycle Impact: The overall impact of implementing ELM-based systems on the sustainability of biomedical waste management practices could be under-researched. This includes looking at the long-term benefits and potential drawbacks of using ELM for recycling and segregation processes.

User Interaction and Feedback Mechanisms: In many IoT systems, human feedback plays a critical role in improving system performance. Exploring how ELM models can be integrated with user feedback to improve segregation and recycling outcomes continuously could be a gap worth exploring.

Focusing on these areas could provide a more comprehensive understanding of the limitations and opportunities in applying ELM to biomedical waste segregation and recycling within IoT ecosystems.

3. System Model

Smart bin technology comprises IoT-based sensors that collect the data and forward the signals used for segregation, transportation, and recycling [10]. The proposed system model is designed in Figure 1. The waste bin data from various wards of the hospitals are collected via the sensors with the association of a wireless network. The wireless network is linked to the hospital's routers and forwarded to the central monitoring station. The wastes collected are removed periodically to avoid the spillage.

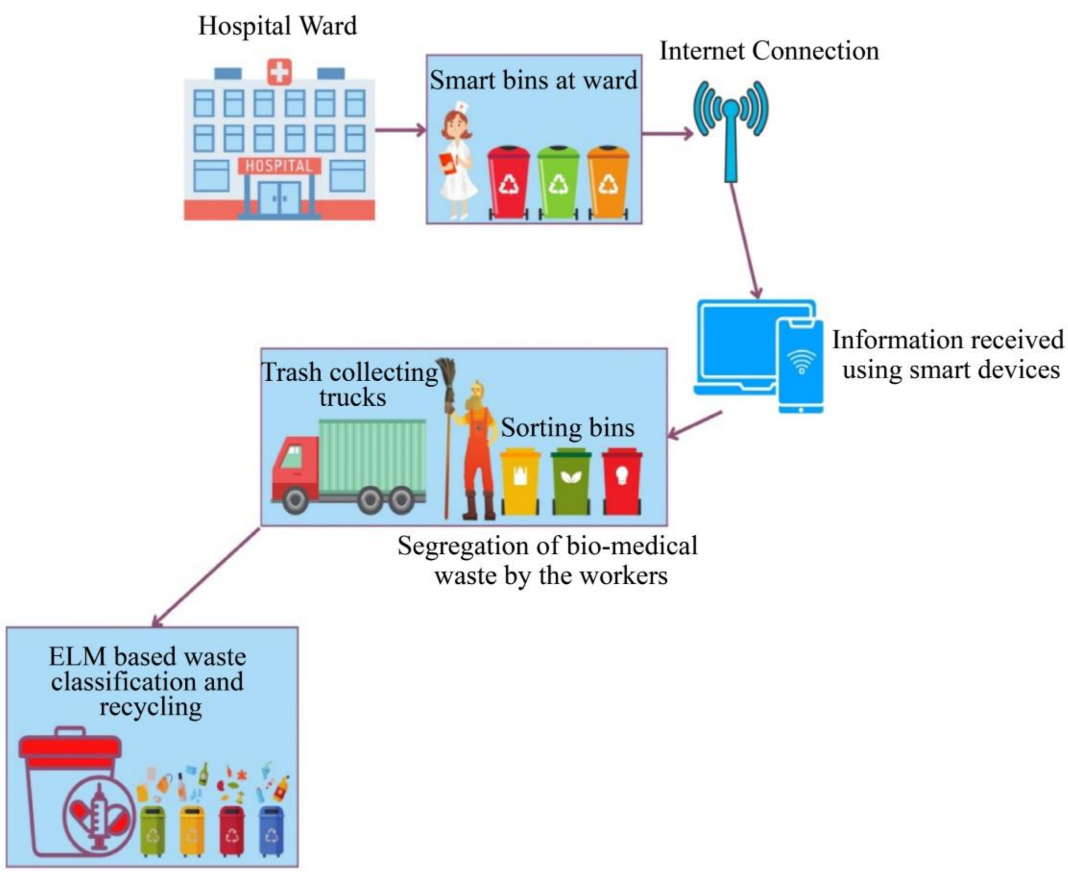

Fig. 1 System model for the proposed Bio-medical waste management

Figure 1 illustrates a smart waste management system for handling biomedical waste generated in hospital wards. The process begins with waste disposal into smart bins located within the hospital ward. These bins are designed to segregate different types of waste, such as recyclable and non-recyclable items, and are connected to an internet network. The smart bins transmit real-time data to a central monitoring system through an internet connection, allowing waste management personnel to monitor the bin status using smart devices like tablets and smartphones. This real-time data enables efficient waste collection scheduling by trash-collecting trucks, ensuring timely removal and reducing overflow risks.

Once collected, the biomedical waste is transported to sorting facilities, where workers further segregate the waste into appropriate categories using designated sorting bins. This manual sorting step ensures that any errors made during initial disposal are corrected, enhancing the effectiveness of the waste management process. The waste then undergoes an ELM (Extreme Learning Machine)-based classification and recycling process, which uses advanced machine learning techniques to accurately identify and categorize different waste materials for recycling and safe disposal. This integrated approach combines smart technology, real-time data monitoring, and machine learning to improve hospitals' efficiency, safety, and sustainability of biomedical waste management.

3.1. Bio-Medical Waste Management System

IoT-based sensors are used to sort and collect waste, which are elucidated in this section. The state-positioning dust bins associated with the sensors are placed in different hospital wards and departments. The collected data are stored in the cloud storage, processed and analysed for further segregation and recycling. The sensor in the bin sends an alert to the central waste management cloud system when it gets filled [11]. Henceforth, the segregation and recycling of waste are made with the centralized waste collection facility (Figure 2).

Biomedical waste management starts with collecting data via the smart bins from various wards of the hospitals. The wastes from different wards are different, so segregation is important [12]. The experts from the waste collection weigh the waste, followed by the segregation. Henceforth, the wastes are classified as recycled wastes and disposal wastes with the association of ELM, and they act accordingly.

Key points of the proposed system model are,

Feedback: The real-time feedback is obtained by the LED indicators or other buzzing sounds. This is used to update the users promptly on further actions.

Waste Sorting: To sort the waste, we proposed the novel ELM approach and classified it as recyclable or disposable waste by classifying and grouping the different wastes.

Integration of mobile app: Integrating mobile apps can help front-end workers access waste management data to keep the environment clean.

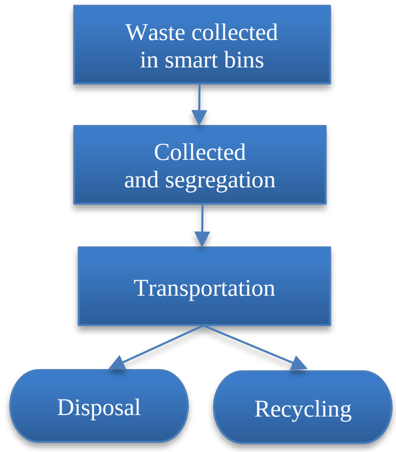

Fig. 2 Process involved in biomedical waste management

Smart sensor: The cutting-edge technology is combined with the proposed system and helps in automatic sorting. This work discerns the difficulties of manual sorting and helps maintain a clean environment.

Scalability: With the perseverance of artistic look, the system is maintained in various cities without intricate works.

Information Collection and Analysis: This can be effectuated by gathering information about the waste and volumes. The gathered information is forwarded to the centralized system or cloud system for further analysis. Based on the decision like recycling rates and disposal rates, this help in attaining a sustainable environment.

Monitoring and management remotely: The bins are monitored remotely to mitigate operational costs and collection routes and significantly reduce environmental impacts.

Customizability: This is to align the trash categorization based on the rules and regulations. With the perseverance of the artistic look, waste management is followed in different cities.

Figure 2 outlines a systematic waste management process, starting with waste collection in smart bins. Using smart bins allows for efficient initial sorting and waste monitoring, leveraging technology to facilitate better waste categorization from the point of origin. After waste is collected, it goes through a collection and segregation stage, where different types of waste are separated based on their characteristics—such as recyclables, hazardous materials, and general waste. This segregation step is crucial for ensuring that different waste streams are treated appropriately in subsequent stages.

Following segregation, the waste is transported to designated facilities where it undergoes further processing. At this stage, the waste stream diverges into two main pathways: disposal and recycling. The disposal path involves safely eliminating waste that cannot be reused or recycled, following strict regulatory guidelines to prevent environmental harm. On the other hand, the recycling path focuses on recovering valuable materials from the waste, which can be reprocessed and used in manufacturing new products. This dual approach not only helps reduce the volume of waste directed to landfills but also promotes resource conservation and environmental sustainability. The figure presents a streamlined waste management workflow that integrates technology, proper segregation, and sustainable waste-handling practices.

4. Proposed ELM-Based Waste Classification and Recycling

This section presented the ELM-based waste classification to help identify the wastes that need to be recycled and disposed of. It is deliberately explained in the following section.

4.1. Extreme Learning Machine based Classification

ELM is a feedforward neural network designed for single-layer or multi-layer networks. It randomly assigns input weights and biases for hidden neurons and then determines the output weights analytically to achieve optimal classification.

Input weights: Randomized, initialized uniformly.

Number of hidden nodes (K): Determined experimentally to balance complexity and performance.

Activation function: Sigmoid or radial basis function (RBF), selected based on the nature of the data.

Output weights: Calculated using Moore-Penrose generalized inverse.

The ELM technique is utilized to classify biomedical wastes. With robust generalization, this approach provided 1000 times more maximized performances than the neural network and backpropagation. For the considered K hidden nodes, the ELM provides 1 D layer products [13].

$$F_K = \sum_{l=1}^{K} \rho_l g_l\, y \tag{1}$$

The hidden node outcome is $F_K$with the Kth node. The weight connected to the hidden nodes of K is implied asρ.

$$O_\gamma = MO \times \rho \tag{2}$$

The output matrix of the hidden layer isO_γ. Without considering the input data, the weights and bias values are allocated randomly with the ELM layer [14]. It is also used to define the output weight when the time is t.

$$\vec{\rho} = \overrightarrow{MO} \times t \tag{3}$$

Based on the layers, the weights of the biomedical weights are trained and classified as waste. The framework of the proposed ELM is shown in Figure 3.

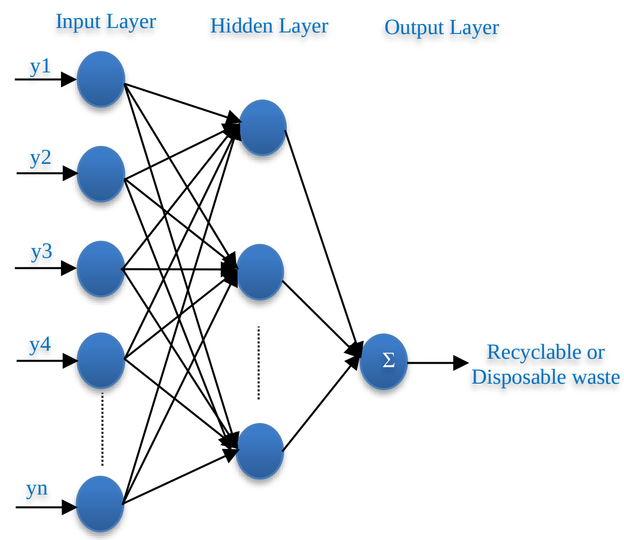

Fig. 3 Framework of ELM for the classification of waste

4.2. ELM based Recycling

The biomedical wastes that are collected from the hospitals contain numerous valuable substances that are to be recycled. Recycling is a process of converting waste into useful products with the association of some advanced techniques. This will reduce the environmental impacts and help in maintaining positive climatic conditions. Practically, the recycling materials are classified by some AI techniques and in our approach, we utilized our proposed ELM work [15]. The proposed approach is used from the beginning to the end of the recycling process. The materials are forwarded to the Material Recovery Facility (MRF) to separate, clean, and process into useful raw materials for future usage, such as motor oils, cereal boxes, aluminium cans, etc. The important step in waste management is waste segregation and classification to avert the contamination of the products. The recycling rate is further improved by separating materials such as paper, metal, plastics, and glass. The proposed ELM-based approach enhances the recycling rate, mitigates environmental pollution, and more.

5. Experimental Results and Discussion

Sources: Data collected via IoT sensors installed in hospital smart bins, categorized into recyclable and non-recyclable waste.

Preprocessing: Data underwent normalization to a range of [0,1] to align with the ELM's input requirements.

Noise Handling: Outlier detection and removal techniques applied to mitigate sensor anomalies.

The proposed work efficiency is illustrated and discussed in this section, and it is compared with comparative methods like AI [5], CIA [6], HFWRF [7], and DL [8]. MATLAB software implements the whole work, and the experimental outputs are plotted and illustrated in the following section.

Depending upon the number of smart bins delivered, several hospitals' efforts for waste management are outlined in Table 1. The response time of the average waste collector and the number of signals received depend upon numerous hospitals with waste management efforts. In hospitals, the number of smart bins is determined by the number of departments or wards provided by hospitals that differ in services.

Table 1. Smart bins-based response received

Smart bin location	Name of the hospital	Average response time for waste collectors in minutes	How many smart bins are delivered
Delivery, dental, services, gynaecology, obstetrics, paediatrics and surgical wards	BDT	11	6
Particular clinical services, medical and surgical wards	PDC	3	3
Delivery, special clinical services, gynaecology,	DSC	8	6
Special clinical services, gynaecology, obstetrics, a medical ward	BPH	7	2
Delivery, special clinical services, gynaecology, obstetrics and surgical wards	FH	9	4
Delivery, dental, special clinical services, gynaecology, obstetrics and surgical wards	ACM	12	6
Delivery, dental, special clinical services, gynaecology, obstetrics, paediatrics and surgical wards	GH	8	7
Delivery, special clinical services, gynaecology, obstetrics, paediatrics and surgical wards	KGH	11	6
Delivery, dental, special clinical services ward, gynaecology, obstetrics, paediatrics, medical and surgical wards	YDM	14	7
Eye clinic and surgical wards	NEC	5	2

Table 2 presents data on implementing smart bins in various hospital settings, focusing on locations, average response times for waste collectors, and the number of smart bins delivered. Each row represents a different hospital, with a variety of ward types involved, such as delivery, dental, clinical services, gynaecology, obstetrics, paediatrics, surgical, and speciality wards. The hospitals, identified by abbreviations, show variation in the average response time for waste collection, which ranges from as short as 3 minutes (PDC) to as long as 14 minutes (YDM). The data highlights differences in efficiency across the facilities, possibly due to the size of the hospital, layout, or waste management practices.

The number of smart bins delivered also varies, with some hospitals, such as YDM and GH, receiving 7 bins, whereas NEC, which serves eye clinics and surgical wards, received the fewest, with 2 bins. The variability in the number of bins could reflect different levels of waste generation, the capacity of the wards, or specific waste management needs. For example, hospitals with diverse services like BDT and KGH have 6 and 7 smart bins, respectively, indicating a broader demand for waste management in their multi-service environments. The table provides insights into the response time efficiency and resource allocation for smart bin implementation across different hospital contexts, indicating room for optimizing waste management strategies.

The comparative results of segregation based on accuracy are plotted in Figure 4. The existing models, such as AI, CIA, HFWRF, and DL, with the proposed method segregate the hospital wastes. The proposed methodology provides 95% segregation accuracy and superior results when compared with the previous AI, CIA, HFWRF and DL models.

Figure 5 plots the evaluation based on solid waste generated by different hospitals. Based on various hospitals like BDT, PDC, DSC, BPH, FH, ACM, GH, KGH, YDM and NEC, we compute the generated solid waste per day belonging to biomedical solid waste and overall solid wastes are plotted. The segregation error rates are tabulated in Table 2. The existing model like AI, CIA, HFWRF and DL with the proposed method segregates hospital wastes. The proposed methodology provides 0.25% error and minimum results compared with the previous AI, CIA, HFWRF and DL models.

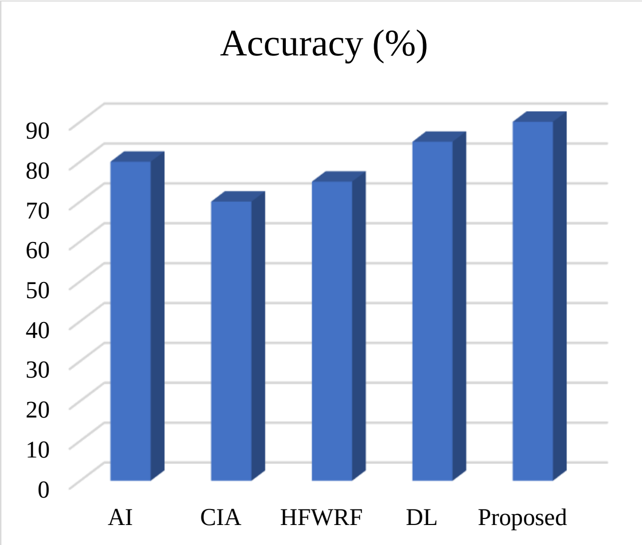

Fig. 4 Comparative results of segregation based on accuracy

The authors have experienced the following practical impacts of using ELM for biomedical waste segregation and recycling based on IoT sensors across different dimensions of waste management.

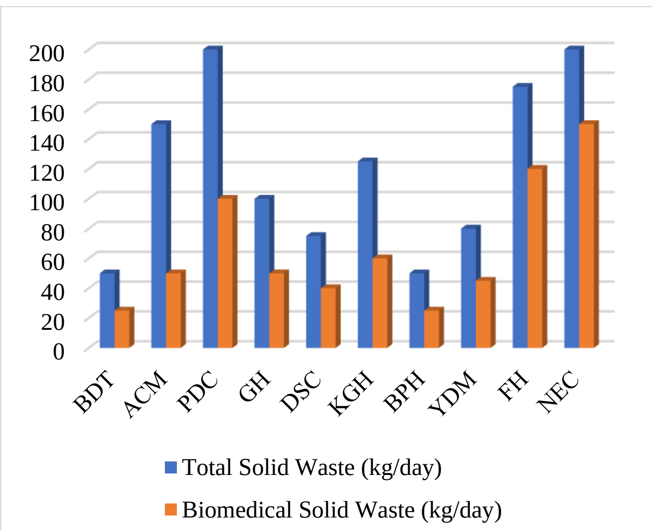

Fig. 5 Performance based on generated solid wastes from different hospitals

Table 2. Segregation error rates

Methods	Error (%)
AI	2.98
CIA	3.72
HFWRF	3.14
DL	2.13
Proposed	0.25

Table 2 compares the performance of five different methods based on their error percentages. These methods include AI, CIA, HFWRF, DL, and the "Proposed" method. Each method is evaluated in terms of its error rate (percentage of incorrect segregations), with lower values indicating better performance.

AI: This method has an error rate of 2.98%, which is relatively moderate compared to other methods in the table.

CIA: Showing the highest error rate of 3.72%, this method seems to have the lowest performance among the five.

HFWRF: With an error rate of 3.14%, HFWRF also exhibits a higher error percentage, indicating it has room for improvement.

DL (Deep Learning): This method has a significantly lower error rate of 2.13%, suggesting it performs better than AI, CIA, and HFWRF.

Proposed Method: Notably, this method achieves an extremely low error rate of 0.25%, which is by far the best among all the methods listed. This suggests that the proposed method offers substantial improvements in segregation performance compared to the others. The authors have experienced the following limitations.

Potential Biases: Dependence on IoT sensor accuracy. Limited generalizability due to specific hospital environments.

Challenges: Real-time integration posed latency issues in high-load environments. Resource constraints in scaling to larger facilities.

ELM Limitations: Suboptimal handling of imbalanced datasets without additional preprocessing.

5.1. Improved Segregation Accuracy

Efficient Classification: ELM's ability to handle multi-class classification with high accuracy can lead to better sorting biomedical waste into appropriate categories (e.g., sharps, infectious waste, non-infectious waste). This ensures that hazardous materials are correctly identified and managed, reducing the risk of contamination.

Reduced Human Error: Automated segregation using ELM minimizes the reliance on manual sorting, which can be prone to errors, especially in high-pressure environments like hospitals.

5.2. Enhanced Operational Efficiency

Real-Time Decision Making: ELM's fast learning capability allows real-time data processing from IoT sensors, enabling immediate waste categorization and processing decisions. This improves the overall efficiency of waste management operations.

Scalable Solutions: ELM's simplicity and speed make it scalable across multiple waste management facilities, providing consistent performance even with large volumes of waste data.

5.3. Resource Optimization

Energy Efficiency: By optimizing the processing power required for segregation tasks, ELM can contribute to energy savings in IoT devices, which is particularly important in resource-constrained environments.

Cost Reduction: The automation of segregation and recycling processes using ELM can lead to significant cost savings by reducing labor costs and minimizing the need for manual intervention.

5.4. Environmental Impact

Reduction in Landfill Waste: Accurate segregation of recyclable materials from biomedical waste ensures that more waste is diverted from landfills, contributing to environmental sustainability.

Better Recycling Outcomes: ELM can help identify materials that can be recycled more effectively, thereby improving the recycling rates of biomedical waste and reducing the environmental footprint.

5.5. Compliance with Regulations

Adherence to Standards: Biomedical waste is heavily regulated, and accurate segregation is essential for compliance. ELM can help ensure that waste is categorized correctly according to regulatory requirements, reducing the risk of legal penalties.

Traceability and Reporting: IoT sensors combined with ELM can provide detailed records of waste segregation and recycling processes, which are essential for auditing and reporting purposes.

5.6. Safety and Public Health

Minimization of Health Risks: Proper segregation of hazardous biomedical waste reduces the risk of exposure to pathogens and dangerous materials, protecting healthcare workers and the public.

Enhanced Waste Handling Protocols: ELM's precision can lead to the development of better waste handling protocols, minimizing the chances of accidental contamination.

5.7. Innovation in Waste Management Practices

Integration with Smart Waste Management Systems: ELM can be a critical component in developing smart waste management systems that use IoT to monitor and optimize the entire waste lifecycle, from generation to disposal.

Support for Circular Economy Initiatives: By improving the recycling of biomedical waste, ELM supports circular economy initiatives, where waste materials are repurposed, reducing the demand for new resources.

5.8. Data-Driven Insights

Predictive Maintenance: Data from IoT sensors processed by ELM can be used to predict when waste processing equipment might fail or need maintenance, reducing downtime and ensuring continuous operation.

Continuous Improvement: The data collected and analyzed through ELM can provide insights into the waste management process, identifying areas for continuous improvement and optimization.

5.9. Scalability and Flexibility

Adaptable to Different Environments: ELM can be adapted to different waste management environments, from small clinics to large hospitals, providing flexibility in deployment.

Ease of Integration: The simplicity of ELM models makes them easier to integrate with existing IoT infrastructure, facilitating quicker adoption and implementation.

5.10. Social Responsibility

Public Awareness and Education: Implementing advanced waste management systems using ELM can raise public awareness about the importance of proper biomedical waste disposal, fostering a culture of responsibility.

Support for Health Initiatives: Effective management of biomedical waste is critical for public health initiatives, especially in regions where improper disposal is a significant problem. ELM can play a role in supporting these initiatives by ensuring safer waste management practices.

These practical impacts highlight the potential of ELM to transform biomedical waste segregation and recycling, leading to more efficient, cost-effective, and environmentally friendly waste management practices.

6. Conclusion

In this work, we presented a robust biomedical waste management system for segregating and recycling waste collected from the smart bins installed in hospitals in various parts of the city. In hospitals, the waste is collected in smart bins, composed of IoT-based sensors for the collection of data and notification of users. The users will then collect the waste periodically to avoid congestion. For the segregation and classification, our work proposed ELM based technique that effectively classifies the wastes as paper, plastics, metals, etc., from the classified data; the wastes are recycled and disposed of based on the material kind, and our proposed approach is utilized for recycling. This approach helps maintain the sustainability of the environment and prevents pollution. Further simulations are made to analyse the effectiveness of the proposed work, thereby providing 95% accuracy, which is higher than that of previous AI, CIA, HFWRF, and DL techniques.

Acknowledgments

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

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