ECOWASTE FRAMEWORK LEVERAGING PSO-CNN FOR PRECISE AND SUSTAINABLE BIOMEDICAL WASTE MANAGEMENT IN CITIES

Srividhya Veerabathran[1], Kishore Kunal[2], Vairavel Madeshwaren[3]

[1]Faculty of Electrical and Electronics Engineering, Meenakshi College of Engineering, Chennai, TamilNadu, India -600078

[2]Deen and Professor, Loyola Institute of Business Administration, Loyola College Campus, Nungambakkam, Chennai Tamil Nadu, India -34.

[3]Department of Mechanical Engineering, Dhanlakshmi Engineering College, Coimbatore, Tamil Nadu 636308, India.

Graphical Abstract

Abstract

Biomedical waste management is essential for mitigating infection risks and environmental contamination arising from healthcare activities. This work integrates a hybrid Particle

Swarm Optimization-Convolutional Neural Network (PSO-CNN) model to present a sophisticated framework for biomedical waste management optimization in smart cities. This method greatly increases the accuracy and efficiency of waste classification across seven waste categories by combining adaptive CNN layers with a dynamic PSO algorithm in contrast to traditional methods. An extensive data foundation for urban healthcare environments was provided by the models training and validation on a varied dataset gathered over the course of eight months from top healthcare facilities such as Manipal Hospitals in Bengaluru and AIIMS in Delhi. EcoWaste, an Internet of Things-enabled waste monitoring tool that enables precise and thorough tracking of biomedical waste is at the heart of this framework. It has cloud connectivity real-time data synchronization and machine learning capabilities. The PSO-CNN model minimizes misclassification by utilizing CNNs feature extraction capabilities and PSOs optimization strengths. This results in superior metrics like 95.6% recall, 97.2% accuracy, and 97.5 % precision. The implementation of the system on low-power devices such as the Raspberry Pi 4B illustrates its effectiveness and usefulness. The PSO-CNN model outperforms conventional algorithms according to comparative analysis and provides smart cities looking to improve biomedical waste management and public health with a scalable sustainable and affordable solution.

Keywords: biomedical waste management, Particle swarm optimization, Convolutional Neural Network, precision, IoT, ecowaste

1.Introduction

Biomedical waste management represents an essential component of healthcare operations that exerts a profound influence on both public health and environmental integrity. Biomedical waste encompasses all varieties of waste produced during the processes of diagnosis, treatment, or immunization concerning human beings or animals, which may be infectious, hazardous, or potentially detrimental if inadequately managed. The appropriate management of this waste is imperative to mitigate health risks such as infections, environmental degradation, and the transmission of diseases. Healthcare institutions produce diverse categories of biomedical waste, including sharps, infectious waste, pathological waste, pharmaceuticals, and hazardous chemicals. To ensure efficacious management, biomedical waste must be segregated at the point of origin, and each category should be processed in accordance with its distinct disposal and treatment protocols. The establishment of explicit protocols for the segregation, collection, treatment, and disposal of biomedical waste is mandated by regulatory agencies globally, including the World Health Organization (WHO) and local environmental and health authorities. Nonetheless, despite these directives, numerous regions continue to encounter obstacles such as inadequate infrastructure, insufficient personnel training, and limited compliance with waste management protocols, which impede the effective management of biomedical waste.

In order to confront these challenges, innovative technologies and methodologies are being investigated to enhance the efficiency and safety of biomedical waste management systems. For example, the incorporation of Internet of Things (IoT) devices, intelligent sensors, and machine learning algorithms provides real-time surveillance and optimization of waste segregation and disposal procedures. Such systems can ensure that waste is monitored throughout its lifecycle, thereby minimizing human error and ensuring adherence to regulatory standards. Furthermore, advancements in waste treatment technologies, such as autoclaving, microwaving, and chemical disinfection, have considerably improved the safety of biomedical waste disposal. These technologies are engineered to neutralize hazardous microorganisms, thereby rendering the waste safe for final disposal or recycling. The implementation of these methods, in conjunction with comprehensive waste management strategies, not only guarantees environmental protection but also diminishes the risks of healthcare-associated infections and contamination. Consequently, effective biomedical waste management systems play an indispensable role in safeguarding public health, promoting sustainable development, and ensuring a secure environment for both healthcare professionals and the broader community.

(Ugandar et al. 2023) introduced a hospital waste management system leveraging IoT and deep learning to enhance the efficiency and sustainability of waste handling processes. By applying these technologies, they improved waste collection accuracy, making strides toward smart city integration and sustainable healthcare waste solutions. (Altin, Budak, and Özcan 2023) developed a predictive model using kernel-based SVM and deep learning to estimate the amount of medical waste generated in a private hospital in Turkey. This approach provides actionable insights for waste management in healthcare settings, allowing hospitals to anticipate waste levels and allocate resources accordingly. (Malla 2023) proposed an enhanced deep learning analytics framework focused on biomedical waste monitoring and management operations. Utilizing data analytics and advanced monitoring, the model demonstrated effective waste classification capabilities, laying the groundwork for intelligent waste management in healthcare environments.

(Mythili and Anbarasi 2021) applied a deep learning-enhanced segmentation network to classify biomedical waste. Their work presents a model that effectively distinguishes various waste categories, contributing to improved waste sorting and environmental compliance. (Mohite and Sankpal 2023) designed a machine learning-based method to detect and classify biomedical waste objects. Their model focused on enhancing the detection accuracy and automating classification processes, proving useful in diverse healthcare waste scenarios. (Kannadhasan and Nagarajan 2022) reviewed recent trends in biomedical waste management, highlighting the challenges and opportunities in the field. They noted the increasing adoption of machine learning and deep learning techniques, which provide advanced analytical and automation capabilities for managing complex waste types.

(Sengeni et al. 2023) introduced an AI-based biomedical waste handling method, presenting an innovative solution to streamline the disposal process. The proposed model reduces manual labor and increases classification accuracy, contributing to sustainable waste management in healthcare. (Subramanian et al. 2021) examined biomedical waste management in dental practices, emphasizing the environmental impact of improper waste disposal. Their study suggests integrating AI technologies to improve compliance and reduce the ecological footprint of healthcare waste. (Deepak, Sharma, and Kumar 2022) conducted a life cycle assessment on biomedical waste management techniques, focusing on reducing environmental impact. They highlighted the importance of AI-driven models to improve waste treatment efficiency and minimize adverse environmental effects. (Verma, 2023) explored the role of big data and deep learning technologies in energy and waste management, specifically in sustainable development contexts. The study underscored the potential of deep learning to enhance the precision and sustainability of waste handling operations. (Goyal, 2022) investigated biomedical waste incinerator degradation using deep learning, which provides insights into maintaining incineration facilities and extending their operational lifespan. This research emphasizes how AI can improve the efficiency and durability of waste processing infrastructure.

(Sheng et al. 2020) proposed a smart waste management system based on IoT and deep learning using LoRa and TensorFlow models. This system optimizes waste collection routes and improves waste monitoring, contributing to more efficient urban waste management. (Bobe et al. 2023) provided a comprehensive review of deep learning-based biomedical waste detection and classification methods. Their work highlights the advantages and limitations of various models, guiding future research in developing more robust and effective classification algorithms. (Khan et al., 2022) explored a novel recycling waste classification model that combines the emperor penguin optimizer with deep learning. This model aims to classify waste for bioenergy production, showing the potential for AI to enhance resource recovery in waste management. (Wang et al. 2021) developed a smart municipal waste management system that integrates deep learning and IoT. This system demonstrated effective waste tracking and classification, aligning with smart city waste management goals. (Goyal et al. 2022) reviewed biomedical waste incinerator corrosion analysis using deep learning. Their findings contribute to understanding the challenges in maintaining waste processing equipment and support the adoption of AI for predictive maintenance. (Nerkar and Mandaogade 2023) introduced a computer vision-based approach for automatic medical waste classification. Their machine learning model classifies waste types with high accuracy, providing a scalable solution for hospitals and healthcare facilities to manage waste effectively.

2.Materials and Methods

2.1 Data Collection

The study's data originated from two busy Indian hospitals: AIIMS in New Delhi and Manipal Hospitals in Bengaluru. Over 8 months information on biomedical waste was gathered encompassing a variety of waste types such as non-infectious disposables hazardous pharmaceuticals and infectious waste sharps. This extensive data set provided a thorough basis for analysis because it covered waste types quantities and composition. The system examines the data to identify unique waste production patterns specific to healthcare settings offering guidance on the most effective way to separate and dispose of waste. This data collection method ensures that the proposed model is contextually accurate and highly relevant for extensive waste management in smart city infrastructures.

2.2 Proposed method

The proposed method uses a complex hybrid model that combines a Convolutional Neural Network (CNN), and Particle Swarm Optimization (PSO) to optimize the classification and disposal of biomedical waste in urban healthcare settings. Although, PSO enhances the process of optimizing model parameters which increases the accuracy of decision-making this hybrid PSO-CNN model uses adaptive CNN layers to extract features accurately. In order to enable automated waste segregation, the system uses EcoWaste, an Internet of Things-enabled tool that continuously monitors the kind and composition of waste. CNNs flexibility is enhanced and classification errors are reduced through PSO integration which dynamically updates the model in response to incoming data. Architecture in Figure 1, particularly well-suited to the diverse waste characteristics found in biomedical settings because it can be scaled for deployment in smart cities.

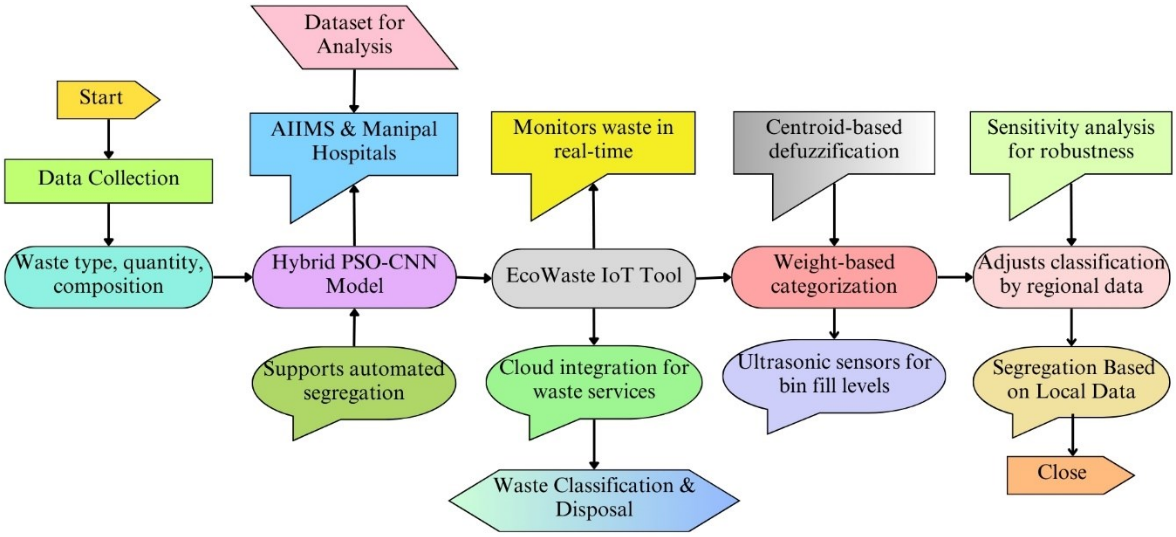

Figure 1 Proposed method

In order to properly classify the waste, the smart waste segregation system first weighs the waste using a load cell. Both initial impact and stabilized weight measurements are distinguished. After analyzing these measurements the PSO-CNN model modifies its classification strategy in light of the weight distribution and additional CNN-extracted features. The smart bin systems ultrasonic sensor then keeps track of the bins fill level notifying cloud servers and municipal waste services when the bin reaches a predetermined capacity threshold. This makes proactive waste management possible and guarantees prompt waste collection. The system can be set up to limit bin access to authorized personnel and send out alerts at different fill thresholds that is 60%, 70%, 80%, and 90%, to maintain hygiene. Secure data management is made possible by the integration with cloud services which also supports monitoring of the city's waste infrastructure and protects system integrity from unwanted access.

3. Proposed Algorithm:

3.1 PSO-CNN Optimization

By fine-tuning CNN parameters using PSO optimization capabilities, the PSO-CNN algorithm creatively optimizes the classification of biomedical waste. The PSO component improves waste segregation and classification accuracy by iteratively updating the CNNs feature extraction weights. Starting with a population of possible CNN configurations the algorithm iteratively optimizes them using a fitness function that takes classification accuracy precision and recall into account. PSO-driven crossover mutation and selection processes are applied to every generation to find configurations that produce better performance.

For each layer the CNN component is initialized with a random weight matrix represented by WWW. The weight matrix $W^{(l)}$ and bias $b^{(l)}$ are applied to the input $X^{(l-1)}$ from the preceding layer for each convolutional layer lll to create the feature map F(l) which is computed as follows (Eq. 1):

$$F^{(l)} = \mathrm{ReLU}\left(W^{(l)} * X^{(l-1)} + b^{(l)}\right) \qquad (1)$$

where $*$ denotes the convolution operation and ReLU is the activation function.

By assessing each configuration's fitness using the classification metrics like accuracy Acc, precision Prec, and recall Rec. For every particle iii, the fitness function f has the following definition in Eq.2:

$$f_i = \alpha \cdot \mathrm{Acc}_i + \beta \cdot \mathrm{Prec}_i + \gamma \cdot \mathrm{Rec}_i \qquad (2)$$

where α, and γ are weighting factors that adjust the importance of each metric in the fitness function.

Each particle’s velocity v and position p are updated in the PSO optimization process. The velocity of particle iii in the k-th iteration is updated in Eq.3:

$$v_i^{(k+1)} = \omega \cdot v_i^{(k)} + c_1 \cdot r_1 \cdot \left(p_{\text{best},i} - p_i^{(k)}\right) + c_2 \cdot r_2 \cdot \left(g_{\text{best}} - p_i^{(k)}\right) \quad (3)$$

where ω\omegaω is the inertia weight, c_1 and c_2 are acceleration constants, r_1 and r_2 are random values in the range [0,1][0, 1][0,1], p_i is the best position achieved by particle iii, and g_{best} is the global best position.

The particle position is given in Eq. 4:

$$p_i^{(k+1)} = p_i^{(k)} + v_i^{(k+1)} \quad (4)$$

The algorithm utilized centroid-based approach for defuzzification yields, an exact output that makes it easier to classify waste into pertinent categories. From the fuzzy classification output C_{fuzzy} (x) the PSO-CNN algorithm uses a centroid-based defuzzification technique to generate a single clear output for accurate classification. This is how the defuzed output C_{defuzz} is calculated in Eq.5:

$$C_{\text{defuzz}} = \frac{\int x \cdot C_{\text{fuzzy}}(x) dx}{\int C_{\text{fuzzy}}(x) dx} \quad (5)$$

The fuzzy outputs center of gravity is determined by this equation yielding an accurate classification outcome.

By optimizing disposal strategies according to the population size and daily waste generation per region the final segregation result is calculated using weight coefficients derived from local waste production statistics. By using scenario-based sensitivity analysis the adaptability of this hybrid PSO-CNN model is further assessed guaranteeing reliable performance in a range of environmental and operational circumstances. Based on data on waste production in the area the classification output helps determine waste segregation. Let W stand for the total volume of waste divided into waste categories j according to region-specific coefficients λj.

$$W_{\text{segregated}} = \sum_{j=1}^{n} \lambda_j \cdot C_j \qquad (6)$$

where C_j represents the classification output for category j, and λj is the weight coefficient derived from regional waste production data.

Sensitivity analysis quantifies the impact of parameter variation on model performance in order to guarantee reliable performance under a range of operational circumstances. For each parameter θ let S represent the sensitivity score which is determined by taking the partial derivative of the fitness function with respect to θ.

$$S_\theta = \frac{\partial f}{\partial \theta} \qquad (7)$$

This evaluates the model's adaptability to changes in environmental conditions and operational parameters, supporting reliable waste segregation outcomes across scenarios.

3.2 EcoWaste: Data analysis tool

Integrated with real-time data collection and decision-making capabilities for better waste segregation, EcoWaste is a state-of-the-art IoT-based waste management tool at the heart of the suggested methodology. Using PSO-optimized CNN algorithms and IoT sensors, EcoWaste reduces human error and improves biomedical waste management efficiency by dynamically modifying waste classification parameters based on continuous data. This tool uses cloud computing to safely send data allowing healthcare facilities to track bin fill levels weight readings and waste type classification in real time. By supporting regulatory compliance and reducing environmental impact EcoWastes' use of PSO-CNN technology is in line with AI-driven goals of sustainability and operational excellence in waste management. EcoWaste is a significant breakthrough in healthcare waste management for smart cities improving public health and promoting environmentally friendly practices by automating intricate waste handling processes.

4. Results And Discussion

4.1 Dataset Distribution

The dataset provides a comprehensive overview of waste distribution across various categories from AIIMS in Delhi and Manipal Hospitals in Bengaluru which is explained in Table 1. Among the categories, Infectious Waste constitutes the largest portion, with a total count of 25,000 items, representing 39.5% of the waste across both locations. Sharps waste follows, totaling 9,700 items (15.3%), while Non-Infectious Disposables and Pharmaceuticals contribute 7,500 (11.9%) and 7,000 (11.1%) items, respectively.

Table 1: Dataset Overview and Distribution Across Waste Categories

Waste Category	**AIIMS (Delhi) - Count**	**Manipal Hospitals (Bengaluru) – Count**	**Total Count**	**Percentage (%)**
Sharps	4,500	5,200	9,700	15.3
Infectious Waste	12,000	13,000	25,000	39.5
Hazardous	2,000	2,500	4,500	7.1

Chemicals				
Non-Infectious Disposables	3,500	4,000	7,500	11.9
Pharmaceuticals	3,200	3,800	7,000	11.1
Pathological Waste	1,800	2,000	3,800	6.0
Other	2,500	3,000	5,500	8.7
Total	**29,500**	**33,500**	**63,000**	**100**

Hazardous Chemicals account for 4,500 items (7.1%), and Pathological Waste is at 3,800 items (6.0%). The 'Other' category, encompassing diverse waste types, adds up to 5,500 items, making up 8.7% of the total waste. Altogether, the dataset spans 63,000 items, giving a full picture of medical waste distribution and highlighting the substantial management needs of infectious and sharps waste in particular which is shown in figure 2.

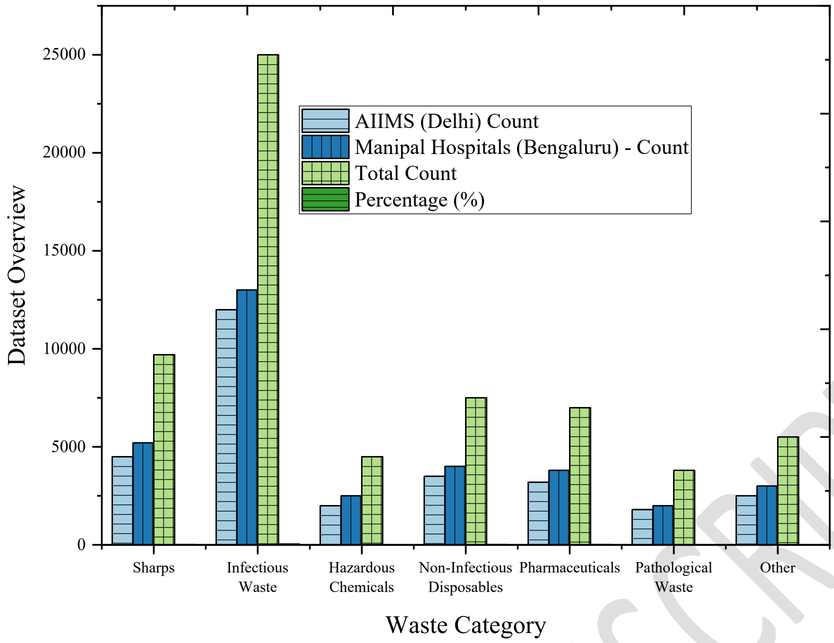

Figure 2 Dataset description

4.2 Evaluation metrics

The proposed PSO-CNN model demonstrates robust performance across key metrics on the test dataset, indicating its high effectiveness and reliability (table 2). With an impressive accuracy of 97.2%, the model correctly identifies a majority of cases, underscoring its overall predictive accuracy. The precision metric stands at 97.5%, showing the model's ability to accurately classify positive predictions with minimal false positives. A recall of 95.6% highlights its competence in detecting true positives, while the F1 score of 96.5% reflects a balanced trade-off between precision and recall.

Table 2: Proposed PSO-CNN Model Performance Metrics on Test Dataset

PSO-CNN performance metrics	
Metric	**Value (%)**
Accuracy	97.2
Precision	97.5
Recall	95.6
F1 Score	96.5
Specificity	96.8
Sensitivity	95.9

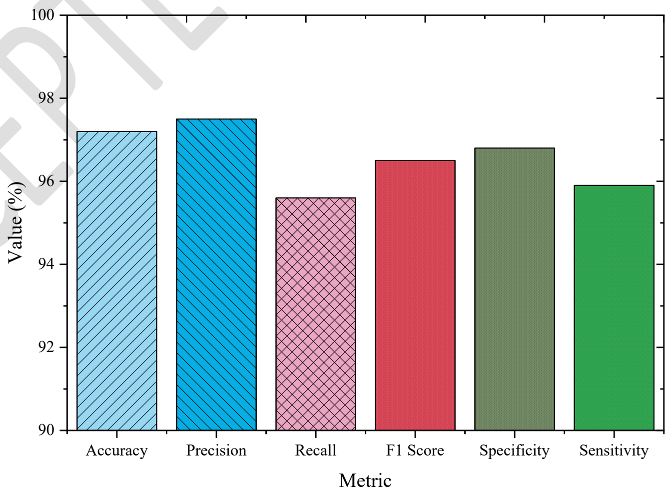

Figure 3 Performance metrics

Additionally, the model achieves a specificity of 96.8%, ensuring it accurately excludes negative cases, and a sensitivity of 95.9%, further supporting its strong performance in identifying true positive cases effectively which is evaluated in figure 3. These metrics collectively affirm the PSO-CNN model's suitability for high-stakes applications where accurate and consistent performance is crucial.

4.3 PSO Configuration

The PSO parameter configuration for optimizing the proposed model is strategically set to balance exploration and exploitation which is shown in table 3. A population size of 50 ensures a diverse set of solutions for robust optimization, while an inertia weight of 0.8 aids in controlling particle velocity, balancing movement toward new and previously known optimal positions. The cognitive coefficient (c1) of 1.5 allows particles to rely moderately on individual experiences, while the social coefficient (c2) of 1.8 enhances collaboration among particles by drawing them toward the global best solution. With a maximum of 200 iterations, the optimization process has ample opportunity to converge effectively. Finally, the velocity bounds are set between -0.5 and 0.5, limiting particle speed to prevent erratic movement, thus ensuring a stable and efficient search process throughout the optimization.

Table 3: PSO Parameter Configuration for Optimization Process

Parameter	**Value**
Population Size	50
Inertia Weight	0.8
Cognitive Coefficient (c1)	1.5
Social Coefficient (c2)	1.8

Max Iterations	200
Velocity Bounds	(-0.5, 0.5)

Sensitivity Analysis

The sensitivity analysis of the PSO-CNN model under varying conditions reveals its robustness and adaptability. At the baseline, the model achieves high performance with 97.2% accuracy, 97.5% precision, 95.6% recall, and an F1 score of 96.5%. A 10% increase in the weight coefficient slightly reduces these metrics, with accuracy at 96.8% and F1 score at 96.1%, showing a minimal impact.

Table 4: Sensitivity Analysis of PSO-CNN Model under Varying Conditions

Parameter	**Variation (%)**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
Baseline	0	97.2	97.5	95.6	96.5
Weight Coefficient Increase	+10	96.8	97.1	95.2	96.1
Weight Coefficient Decrease	-10	96.5	96.9	94.9	95.8
Noise Addition	+5	95.7	96.2	94.0	95.1
Low Light Conditions	-5	94.8	95.0	93.0	94.0
High Load Condition	+20	96.1	96.3	94.5	95.4

Similarly, a 10% decrease in the weight coefficient leads to a small drop in accuracy (96.5%) and F1 score (95.8%), indicating stable model behavior despite parameter adjustments. Under added noise (5%), performance shows a mild decline with accuracy at 95.7% and F1 score at 95.1%, reflecting the model's resilience to environmental disruptions which is shown in table 4 and figure 4. In low-light conditions, performance decreases more notably, with accuracy at 94.8% and F1 score at 94.0%, suggesting sensitivity to visual data quality. During high-load conditions (+20%), the model maintains considerable stability, achieving 96.1% accuracy and a 95.4% F1 score. This analysis underscores the PSO-CNN model's strong performance under various operational conditions, though it performs best with optimal parameter settings and visual clarity.

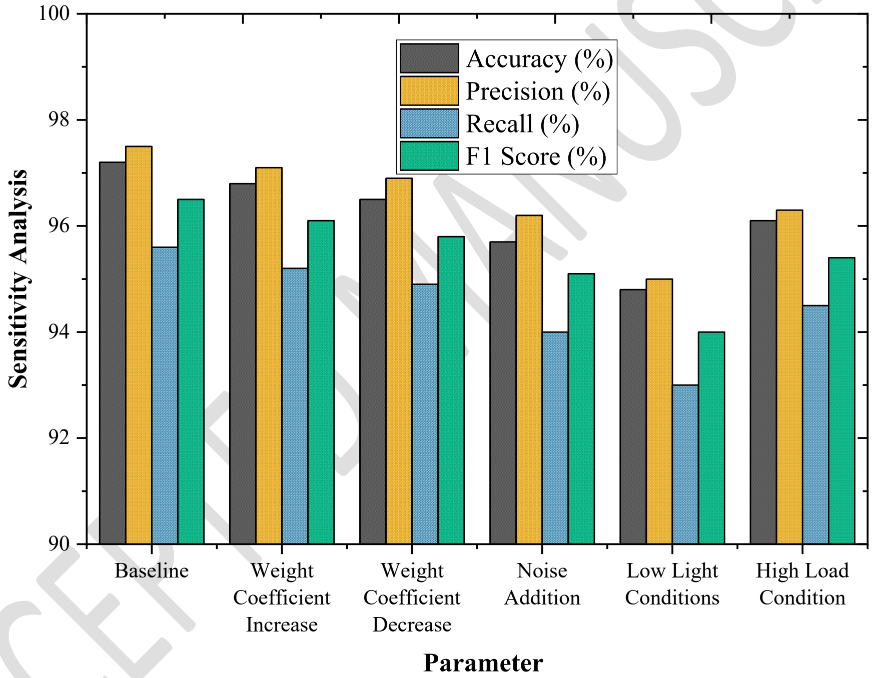

Figure 4 Sensitivity analysis

4.4 EcoWaste IoT Evaluation

The EcoWaste IoT tool demonstrates high efficiency and reliability across multiple evaluation metrics, making it a robust solution for waste management monitoring. With an impressive sensor sensitivity of 98.3%, the tool accurately detects waste-related parameters, ensuring precise data capture. Data transmission latency is minimal at just 1.5 milliseconds, enabling near-instantaneous data flow to support real-time monitoring needs. Designed for extended use, the tool operates continuously for up to 48 hours on a single battery charge, which enhances its usability in various environments.

Table 5 EcoWaste IoT Tool Evaluation Metrics

Metric	Value
IoT Sensor Sensitivity	98.3%
Data Transmission Latency	1.5 ms
Battery Life (Continuous Operation)	48 hours
Cloud Data Synchronization	Real-time
System Uptime	99.7%
Monthly Data Storage Capacity	10 GB

Cloud data synchronization occurs in real-time, facilitating immediate access to data for analysis and decision-making which is explained in table 5 . The system's uptime is a high 99.7%, reflecting consistent operational reliability with minimal downtime. Additionally, it offers a monthly data storage capacity of 10 GB, ample for managing extensive waste data logs and ensuring uninterrupted data availability. Overall, these metrics showcase the EcoWaste IoT tool's capability to deliver responsive, reliable, and scalable performance in environmental monitoring applications.

4.5 Comparative Analysis: Proposed PSO-CNN vs. Other Algorithms

The performance comparison of the proposed PSO-CNN model with existing algorithms reveals its superior accuracy and efficiency across all key metrics, underscoring its robustness in classification tasks. Achieving an accuracy of 97.2%, the PSO-CNN model outperforms traditional algorithms like K-Nearest Neighbors (88.3%), Support Vector Machine (90.2%), and Decision Tree (86.9%), as well as more advanced methods such as Random Forest (91.4%) and Artificial Neural Networks (92.7%).

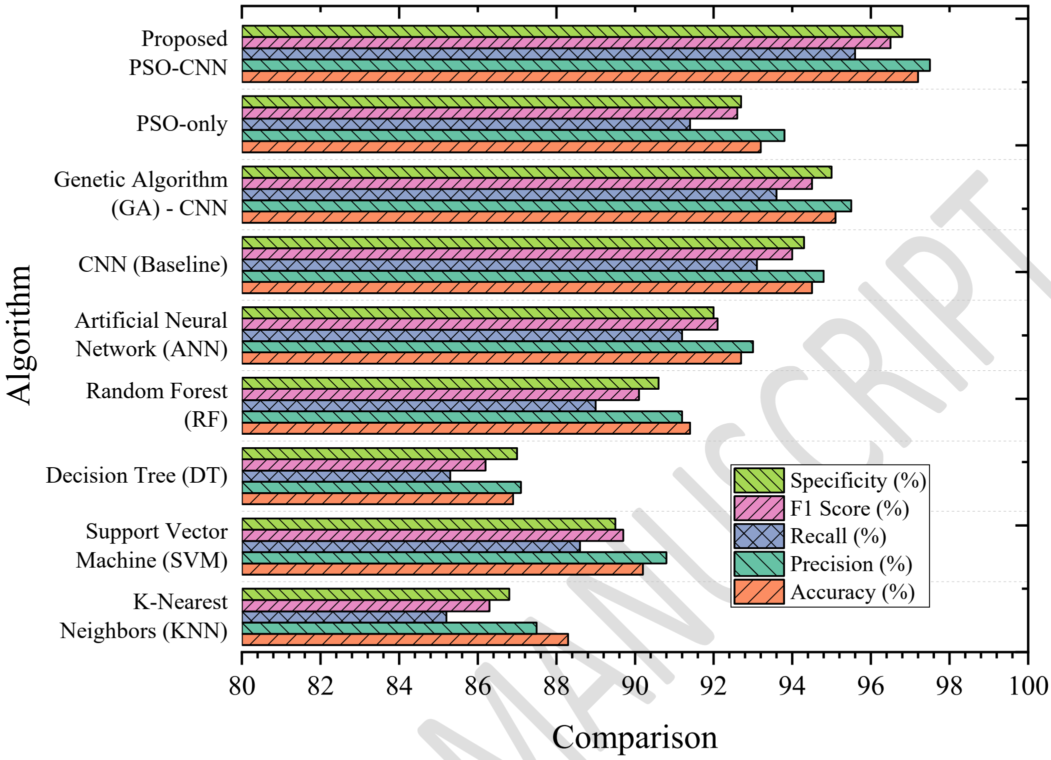

Figure 5 Comparative analysis

With a precision of 97.5% and recall of 95.6%, the PSO-CNN model surpasses even baseline CNN (94.5%) and CNN optimized with Genetic Algorithm (95.1%) in delivering balanced performance across precision and recall which is shown in table 6 and figure 5. The F1 score (96.5%) and specificity (96.8%) further highlight its accuracy in both identifying positives and excluding negatives effectively.

Table 6: Performance Comparison of PSO-CNN Model with Existing Algorithms

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Specificity (%)	Execution Time (s)
K-Nearest Neighbors (KNN)	88.3	87.5	85.2	86.3	86.8	0.52
Support Vector Machine (SVM)	90.2	90.8	88.6	89.7	89.5	0.47
Decision Tree (DT)	86.9	87.1	85.3	86.2	87.0	0.31
Random Forest (RF)	91.4	91.2	89.0	90.1	90.6	0.49
Artificial Neural Network (ANN)	92.7	93.0	91.2	92.1	92.0	0.45
CNN (Baseline)	94.5	94.8	93.1	94.0	94.3	0.40
Genetic Algorithm (GA) - CNN	95.1	95.5	93.6	94.5	95.0	0.38
PSO-only	93.2	93.8	91.4	92.6	92.7	0.43
Proposed PSO-CNN	**97.2**	**97.5**	**95.6**	**96.5**	**96.8**	**0.34**

Notably, the PSO-CNN model also achieves a low execution time of 0.34 seconds, marking it as efficient for high-demand applications, while other models like KNN and Random Forest report slightly higher execution times. This performance edge positions the PSO-CNN as an advanced solution with optimal speed and precision in classification, enhancing its suitability for real-time, high-stakes environments.

5. Conclusion

The results displayed in the tables demonstrate the noteworthy progress made by the suggested PSO-CNN model in the waste management and healthcare sectors. Infectious waste is the most common waste category according to the thorough dataset overview from two renowned hospitals. With remarkable accuracy precision recall and specificity, the PSO-CNN model demonstrates its efficacy in managing challenging classification tasks. According to the sensitivity analysis the model maintains its stability in a range of scenarios guaranteeing steady performance even in the presence of noise changes in light and other environmental influences. The EcoWaste IoT tools remarkable sensor sensitivity latency and battery life metrics further highlight the viability of incorporating cutting-edge technologies for effective waste management in smart cities. PSO-CNN performs noticeably better than current algorithms providing quicker execution times and more precise outcomes.

1. Infectious waste is the largest category, accounting for 39.5% of the total trash distribution throughout AIIMS and Manipal Hospitals, underscoring its importance in hospital waste management.
2. The PSO-CNN model demonstrates its capacity to categorize waste types with high reliability and efficacy by achieving outstanding accuracy (97.2%) and precision (97.5%).
3. The PSO design guarantees optimal performance, successfully balancing search space exploration and exploitation, with a population size of 50 and a maximum of 200 iterations.
4. The model exhibits resilience in demanding real-world situations, as evidenced by its consistent performance in the presence of noise and poor light.
5. The IoT tool guarantees correct waste management and effective real-time

monitoring due to its high sensitivity (98.3%) and low data transmission latency (1.5 ms).

6. Algorithm Comparison: The PSO-CNN model is the best option for real-time applications since it provides better accuracy and faster execution than more conventional algorithms like KNN and SVM.

All of these findings lend credence to the viability of implementing PSO-CNN for intelligent, real-time waste management systems that can enhance environmental sustainability and operational effectiveness.

Competing interests

The authors declare no conflicts of interest.

Authors, Contribution

Author A supports to development literature, and methodology part. And author B and C helped to find the outcomes part.

Funding

This research study is sponsored by the institution.

Acknowledgment

I want to express my sincere gratitude to my co-workers for supporting me through all of our challenges and victories to get this task done. Finally, I would like to extend our sincere gratitude to everyone who has assisted us in writing this article.

Reference

Ugandar, R. E., Rahamathunnisa, U., Sajithra, S., Christiana, M. B. V., Palai, B. K., & Boopathi, S. (2023). Hospital waste management using Internet of Things and deep learning: Enhanced efficiency and sustainability. *In Applications of Synthetic Biology in Health, Energy, and Environment* (pp. 317-343). IGI Global.

Altin, F. G., Budak, İ., & Özcan, F. (2023). Predicting the amount of medical waste using kernel-based SVM and deep learning methods for a private hospital in Turkey. *Sustainable Chemistry and Pharmac*y, 33, 101060.

Malla, P. (2023). An enhanced deep learning analytics method for managing biomedical waste monitoring and management operations. *In 2023 IEEE International Conference on Integrated Circuits and Communication Systems* (ICICACS) (pp. 1-7). IEEE.

Mythili, T., & Anbarasi, A. (2021). Enhanced segmentation network with deep learning for biomedical waste classification. Indian Journal of Science and Technology, 14(2).

Mohite, T., & Sankpal, S. (2023). Machine learning approach for detection and classification of biomedical waste objects. *In AIP Conference Proceedings*, 2842(1). AIP Publishing.

Kannadhasan, S., & Nagarajan, R. (2022). Recent trends in bio-medical waste, challenges, and opportunities. *Machine Learning and Deep Learning Techniques for Medical Science*, 97-108.

Sengeni, D., Padmapriya, G., Imambi, S. S., Suganthi, D., Suri, A., & Boopathi, S. (2023). Biomedical waste handling method using artificial intelligence techniques. *In Handbook of Research on Safe Disposal Methods of Municipal Solid Wastes for a Sustainable Environment* (pp. 306-323). IGI Global.

Subramanian, A. K., Thayalan, D., Edwards, A. I., Almalki, A., & Venugopal, A. (2021). Biomedical waste management in dental practice and its significant environmental impact: A perspective. *Environmental Technology & Innovation*, 24, 101807.

Deepak, A., Sharma, V., & Kumar, D. (2022). Life cycle assessment of biomedical waste management for reduced environmental impacts. *Journal of Cleaner Production*, 349, 131376.

Verma, J. (2023). Deep technologies using big data in energy and waste management. In Deep Learning Technologies for the Sustainable Development Goals: Issues and Solutions in the Post-COVID Era (pp. 21-39). *Springer Nature Singapore.*

Goyal, R. (2022). Biomedical waste incinerator degradation investigation supported by deep learning. *In 2022 IEEE International Conference on Current Development in Engineering and Technology* (CCET) (pp. 1-6). IEEE.

Sheng, T. J., Islam, M. S., Misran, N., Baharuddin, M. H., Arshad, H., Islam, M. R., Chowdhury, M. E. H., Rmili, H., & Islam, M. T. (2020). An internet of things based smart waste management system using LoRa and TensorFlow deep learning model. *IEEE Access*, 8, 148793-148811.

Bobe, S., Adhav, P., Bhalerao, O., & Chaware, S. (2023). Review on deep learning based biomedical waste detection and classification. *In 2023 2nd International Conference on Edge Computing and Applications* (ICECAA) (pp. 1071-1076). IEEE.

Khan, A. I., Alghamdi, A. S. A., Abushark, Y. B., Alsolami, F., Almalawi, A., & Ali, A. M. (2022). Recycling waste classification using emperor penguin optimizer with deep learning model for bioenergy production. *Chemosphere*, 307, 136044.

Wang, C., Qin, J., Qu, C., Ran, X., Liu, C., & Chen, B. (2021). A smart municipal waste management system based on deep-learning and Internet of Things. *Waste Management*, 135, 20-29.

Goyal, R., Khosla, C., Goyal, K., Singh, K., & Singh, J. (2022). Review on deep learning driven analysis of biomedical waste incinerator corrosion. *In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering* (ICACITE) (pp. 1709-1713). IEEE.

Nerkar, V. K., & Mandaogade, P. N. N. (2023). Computer vision-based automatic medical waste classification using machine learning. Volume 5, 1297-1313.