OPTIMIZING BIOMEDICAL WASTE MANAGEMENT THROUGH A HYBRID GENETIC ALGORITHM-FUZZY INFERENCE SYSTEM FOR SMART CITIES

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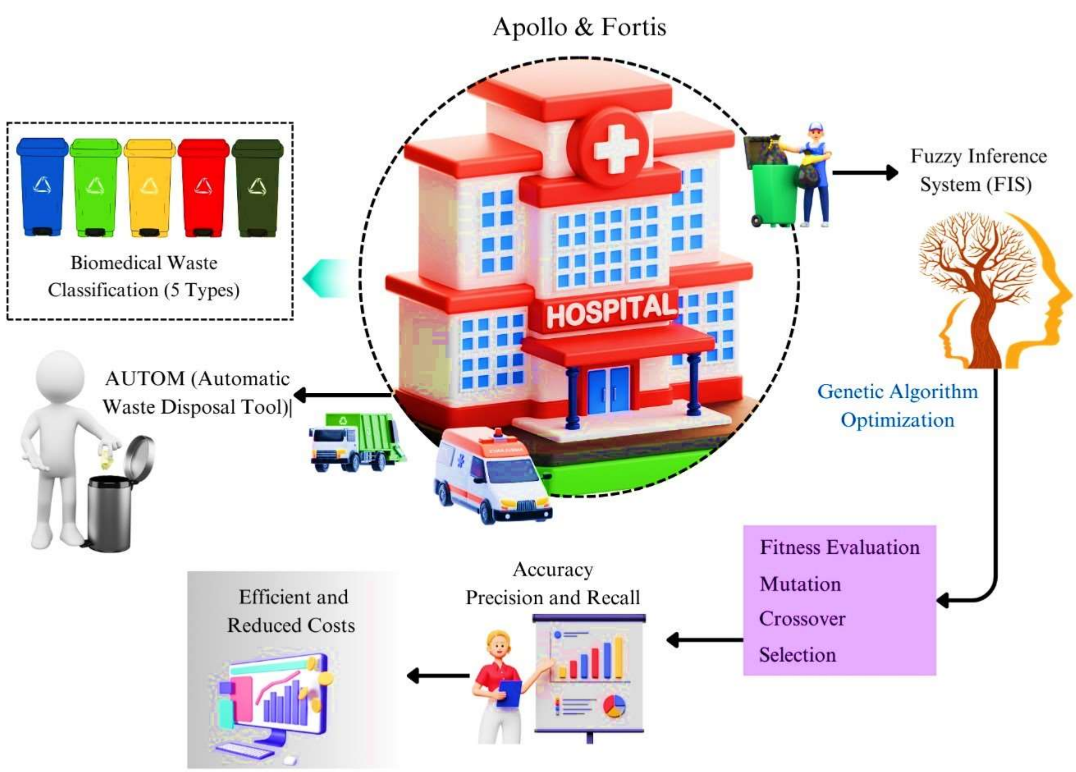
GRAPHICAL ABSTRACT



ABSTRACT

Efficient biomedical waste management is essential for hospital hygiene and public health, particularly within the context of smart city infrastructures. This study proposes an innovative hybrid model combining a Genetic Algorithm (GA) with a Fuzzy Inference System (FIS) to enhance waste classification accuracy and improve segregation efficiency. Leveraging six months of empirical data from Apollo Hospitals and Fortis Malar Hospital in Chennai, the model is tailored to classify five distinct types of biomedical waste effectively. A central component, AUTOM, employs fuzzy logic for automated decision-making, optimizing waste disposal and addressing challenges like the preservation of critical genetic information typically compromised in traditional GA approaches. This integration not only improves system interpretability but also enables precise waste classification using compact, cost-effective sensors that ensure scalability. Validation in the Proteus simulator demonstrates robust performance, with the model achieving a classification accuracy of 96.4%, precision of 96.8%, and recall of 94.8%. These results underscore the GA-FIS model's potential to elevate biomedical waste management practices, contributing to sustainable public health efforts and environmental protection within smart cities.

Keywords: biomedical waste, genetic algorithm (GA)–fuzzy inference system , environmental sustainability, Proteus simulator, AUTOM tool

1. Introduction

Biomedical Waste Management (BMW) is an important worldwide concern that needs to be addressed immediately. The production of biomedical waste has increased due to the quick expansion of the healthcare industry as well as the rise in hospital stays, doctor visits, and laboratory diagnostics. Manual sorting, handling, and disposal are examples of traditional

BMW procedures that are labor-intensive, prone to inaccuracy, and dangerous for one's health. At the forefront of resolving these issues is the incorporation of AI technologies. These technologies have the ability to completely transform the procedure, from the collecting of garbage to its disposal, with increased accuracy and efficiency. Biomedical waste may be precisely identified, sorted, and managed by automated systems, guaranteeing maximum safety and environmental compliance. In order to solve the issues and raise the general effectiveness of healthcare waste management, BMW must incorporate AI technologies. Because of its hazardous nature and various composition, biomedical waste management is a difficult issue that calls for sophisticated ways to assure environmental protection and public health safety. Biomedical waste is defined by the World Health Organization as materials produced during research operations or during the diagnosis, treatment, or immunization of humans or animals. Conventional waste management techniques are expensive, labor-intensive, and prone to mistakes. Effective waste treatment is further complicated by the dynamic nature of healthcare environments and the variety in waste composition. Fuzzy inference systems are one example of an advanced computational technology that has gained popularity recently for optimizing biomedical waste management procedures. Artificial intelligence systems known as fuzzy inference systems use fuzzy logic to simulate human decision-making processes while handling imprecise and uncertain input. This method can handle degrees of truth, which makes it ideal for difficult decision-making situations involving ambiguities and uncertainties.

Biomedical waste management is incorporating fuzzy inference algorithms to separate and classify trash according to factors including toxicity, infectiousness, and recyclable nature. Real-time decision-making on trash disposal techniques may be made by these systems, which also optimize resource allocation and lower operating costs. Additionally, they improve the precision and dependability of waste management procedures by constantly modifying the selection criteria in response to shifting operational and environmental circumstances. This flexibility is especially useful in settings involving smart cities, where linked systems need for clever management strategies. Fuzzy logic and genetic algorithms (GA) have been effectively combined in hybrid models to maximize system efficiency, reduce transportation costs, and plan the best routes for collecting waste. In order to increase system performance, the fuzzy rule base is optimized via genetic algorithms, which identify the optimal set of rules. Fuzzy inference systems in real-world scenarios can be experimentally validated and their performance evaluated with the help of sophisticated simulation tools such as the Proteus simulator.

The interval-valued fuzzy DEMATEL (Decision-Making Trial and Evaluation Laboratory) method to investigate sustainable healthcare waste management. It lists and assesses the most important variables affecting sustainability in the handling of medical waste. The authors offer a thorough framework for decision-making in the context of waste management strategies by using a fuzzy method to capture ambiguity and interdependencies among these aspects. Their conclusions provide useful information for enhancing sustainability and effectiveness in the handling of medical waste (Li et al., 2021). A multilayer hybrid deep learning technique intended for recycling and garbage sorting. The method improves garbage sorting and recycling systems' accuracy by combining multiple deep learning models. In an effort to increase recycling rates and waste management techniques, this technique makes use of cutting-edge neural network designs for the effective processing and classification of waste items. The suggested approach outperforms conventional techniques in terms of automation and efficacy (Chu et al., 2018)

Moreover, applying machine learning and IoT for waste management and air quality forecasting, developing a system that combines these technologies for real-time monitoring, improved waste management efficiency, and predictive environmental insights (Husain et al., 2020). Additionally, a hybrid decision-making framework is proposed for sustainable healthcare waste management, integrating operational and environmental considerations (Takur et al., 2021). Another study presents a fuzzy decision-making model for selecting eco-friendly healthcare waste treatment systems, focusing on emerging economies to aid in sustainable technology choices (Li et al., 2020).

An interval-valued fuzzy model combined with a genetic algorithm optimizes waste collection and disposal, enhancing flexibility and efficiency (Ikram et al., 2023). During the COVID-19 pandemic, fuzzy logic has been used to manage the complexities of pandemic-related medical waste, ensuring efficient and safe treatment and disposal (Goodarzian et al., 2024). Additionally, an integrated Bayesian and type-2 fuzzy TISM approach assesses the risks of COVID-19 medical waste transportation, offering a robust framework to enhance safety (Tang et al., 2023).

The Pythagorean fuzzy-based decision framework for evaluating healthcare waste treatment choices is presented in this research. The framework takes into account uncertainty and different levels of membership in decision-making processes by utilizing Pythagorean fuzzy sets. The suggested model assesses many options for treatment, providing a strong instrument for choosing the most efficient and long-lasting waste management techniques. The framework facilitates a thorough evaluation of treatment methods in the healthcare industry by integrating qualitative and quantitative criteria (Rani et al., 2020). In order to improve waste management systems and guarantee the environment's and healthcare workers' safety and health, the research highlights shortcomings in present procedures, fills in those gaps, and makes recommendations for enhancements (Nosheen et al., 2022). However, to examine the obstacles and enablers that Malawian healthcare professionals face in attaining sufficient environmental health conditions and infection control. The writers highlight major obstacles like lack of training, infrastructural problems, and resource constraints through interviews and field observations. In environments with limited resources, the study offers suggestions for enhancing environmental health and infection control procedures (Tu et al., 2022).

In order to evaluate and forecast operational factors for physicians, this article uses an Adaptive Neuro-Fuzzy Inference System (ANFIS) approach to investigate the application of Industry 4.0 technologies in healthcare. The study shows how ANFIS may increase operational efficiency and adaptability in healthcare by combining data-driven insights with fuzzy logic to boost decision-making processes (Fatima et al., 2022). To reduce surgical site infections, the authors suggest using a fuzzy inference system to assess the indoor air quality in operating rooms. The technology helps to maintain a clean environment during surgeries by modeling and evaluating different air quality factors using fuzzy logic. Through improved air quality control in operating rooms, the study seeks to increase patient safety and reduce the incidence of infections (Colella et al., 2022).

Adaptive neuro-fuzzy algorithms are integrated into the MANFIS model to forecast e-waste levels while accounting for multiple affecting factors. Because the study increases forecast accuracy and facilitates better planning and resource allocation in waste management, it offers a useful tool for managing electronic trash (Khoshand et al., 2023). The integration of artificial intelligence (AI) into the modernization of biological waste management is the subject of this research. The authors offer cutting-edge methods for waste tracking, sorting, and disposal by utilizing AI technology. The paper demonstrates how artificial intelligence (AI) may improve biomedical waste management systems' efficacy and efficiency by tackling issues with operational efficiency, safety, and regulatory compliance (Sarkar et al., 2023). Better environmental and health results can be achieved by applying sustainable waste management solutions that can be tailored to the specifics of resource-constrained regions (Peter et al., 2023). It examines several bioremediation approaches, including enzyme-based procedures and microbial degradation, that are used to handle and recycle biomedical waste. The report provides insights into creative and sustainable solutions to the mounting problems associated with biomedical waste management by highlighting developments in bioremediation technology (Khan and Mohd Sajjad Ahmad 2024).

2. Proposed Methodology

2.1.Data collection

Data for biomedical waste was meticulously collected from two prominent healthcare institutions in Chennai, namely Apollo Hospitals and Fortis Malar Hospital, over a period of six months. The primary goal was to capture a detailed picture of the biomedical waste management practices employed within these healthcare settings. This involved not only the identification and classification of waste but also the quantification and composition analysis of various waste categories generated within the hospitals.

The data collection process included a thorough categorization of biomedical waste into distinct types, such as sharps (e.g., needles, scalpel blades), infectious materials (e.g., contaminated gauze, surgical waste), pharmaceuticals (e.g., expired or unused medications), and non-hazardous waste (e.g., general hospital waste). The quantities of each waste type were recorded, providing a quantitative assessment of the waste generated in both hospitals. Additionally, the study focused on understanding the variability in waste production over time, including factors such as seasonal trends, hospital activities, and patient volume, which could influence waste generation patterns. This data was crucial in identifying trends and patterns that could inform more effective waste management strategies tailored to the specific needs of healthcare facilities. The collected data also considered the waste segregation and disposal methods already in place, highlighting areas where improvements could be made to ensure compliance with environmental and health safety standards. The comprehensive nature of this dataset allowed for an in-depth evaluation of existing waste management practices and served as the foundation for proposing more efficient, sustainable solutions for biomedical waste disposal. In summary, the data collected from Apollo Hospitals and Fortis Malar Hospital provides a comprehensive empirical basis for evaluating and improving biomedical waste management practices in healthcare settings. It offers critical insights into waste types, quantities, and disposal methods, with the goal of enhancing operational efficiency, ensuring regulatory compliance, and promoting sustainable environmental practices in the healthcare sector.

2.2.Proposed method

The proposed methodology includes the following process, figures 1 show the proposed model's high-level overview as well as its intricate operations. When an object is placed in the middle of the bin, it comes into contact with a load cell that detects the impact weight. After collecting the initial impact weight, the weight is measured again until it stabilizes. In this case, thirty consecutive weight readings are recorded in total. The measurements are divided into two groups:

1. The impact and rebound measurements, which show variations when the object bounces off the load cell, are included in the first group. The highest weight value is determined from this group.
2. Readings when the object's weight has stabilized make up the second group. The maximum value from the first group is divided by the average weight from this stable group.

The system causes the servo motor to rotate 90 degrees from its initial position if the ratio of these two numbers is greater than a predefined threshold. In contrast, the motor rotates 270 degrees if the ratio is below the threshold. By precisely measuring and sorting waste items on the smart garbage board used in healthcare settings, this adjustment aids in calibrating the waste segregation system.

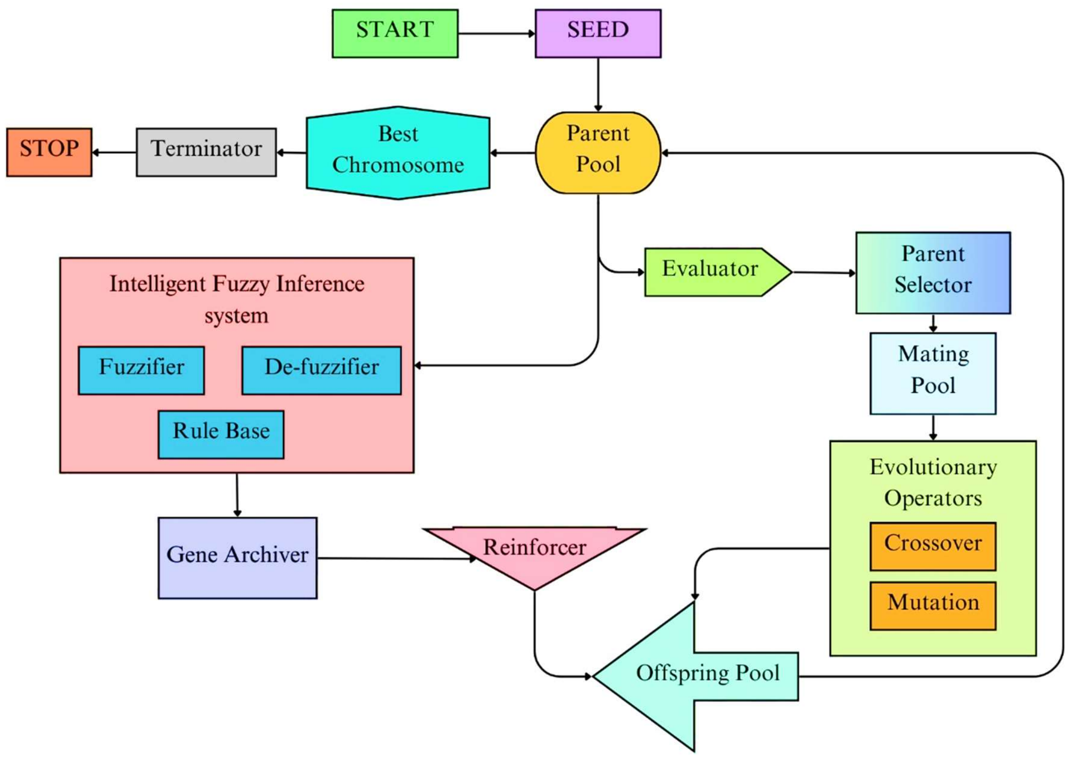


Figure 1 Architecture of the proposed methodology

The smart bin system works by first measuring and determining the weight of the garbage that is deposited into the bin using a load cell. The system then separates the waste. An ultrasonic sensor keeps track of the bin's fill level. The information is sent to the cloud when the bin fills up more than half the way, alerting the municipal authorities (referred to as customers) and causing them to empty the bin. By utilizing cutting-edge technology, this system improves waste management by increasing the effectiveness of waste collection, segregation, and notification procedures. To further avoid any hygienic problems, managers can set the system to sound an alert when the bin fills up to 60%, 70%, 80%, or 90% of its capacity. The smart bin system limits access to authorized individuals exclusively, ensuring ongoing, effective service. In addition to promoting operational dependability, cloud computing secures the infrastructure of the city, preventing illegal access and guaranteeing functional integrity.

2.3.Proposed algorithm

2.3.1. GA-fuzzy inference system

The proposed GA-fuzzy inference system combines Genetic Algorithms (GA) with Fuzzy Inference Systems (FIS) to present a novel approach to biomedical waste management optimization in smart cities. With the help of this hybrid strategy, waste segregation decision-making will be more effective, resulting in lower operating costs, less environmental impact, and more efficiency. Genetic Algorithms (GA) are sophisticated optimization methods derived on the concepts of natural selection and evolution. They work well for traversing intricate search environments and finding the best answers according to predetermined standards. In order to determine the best rules for categorizing and handling different kinds of biomedical waste, GA is used in biomedical waste management to improve and optimize the fuzzy inference system's rule set.

Conversely, fuzzy logic is used by fuzzy inference systems (FIS) to handle ambiguous or uncertain data. Fuzzy logic is superior to binary logic in situations when decisions need to be made using human-like thinking or when data is ambiguous. Fuzzy logic permits more nuanced interpretations. FIS is crucial to this system because it helps understand sensor data, classify various waste types, and dynamically modify waste management plans in response to operational requirements and environmental changes. Data from sensors and waste management facilities, either real or simulated, is used to evaluate and apply the hybrid GA-FIS model. Metrics like accuracy, precision, and recall are used to evaluate the system's performance and determine how well it works for managing and classifying trash. Furthermore, scenario testing and sensitivity analysis are carried out to make sure the system is resilient and flexible in a variety of operational and environmental settings.

A single value y* is the result of defuzzification, while the input is a fuzzy set2 that represents the aggregate output fuzzy set. To defuzzify, the centroid approach is applied. The output is extracted using the defuzzification procedure described in Equation (1) as follows:

$$y^* = \mathrm{def}\ uzz(B_0) = \frac{\int_y y_n \cdot \sum_{r=1}^{n} \mu B_r(y)dy}{\int_y \sum_{r=1}^{n} \mu B_r(y)dy} \qquad (1)$$

Acceptable value of GA parameters is the defuzzified rate, such as: The power to choose tournaments is output#1, while the likelihood of bit-mutations is output#2.

(y1* = 2) = The binary tournament selection is denoted

(y2* = 0.03) = 3% mutation probability is indicated

To produce local minima, a test function is integrated with cosine modulation. The function is multimodal and extremely continuous. Minimization is facilitated by reaching a global minimal standardization to a zero value of the objective function. The following is the function in equation (2):

$$f_1(\vec{x}) = A \cdot n + \sum_{i=1}^{n} \left(x_i^2 - A \cdot \cos(2\pi \cdot x_i)\right),\ \vec{x} \in [-5.12{,}5.12]; \min f_1(\vec{x}) = 0, \mathrm{n} \ldots \ldots \mathrm{dinensionality}, \mathrm{A} = 10 \qquad (2)$$

Accompanying defuzzification, the final biological waste segregation shown in Equation (3) is determined using the coefficient of the following equation.

$$\mathrm{Totalwaste}\ = \sum_{i=1}^{m} a_i x_i + \sum_{j=1}^{n} b_{iy} y_{ij} \qquad (3)$$

where ai is a representation of the local population, i; The defuzzification process yields the entire area of activity j in the area i, which is represented by bij. xi is the daily waste production value per person in the region i. Furthermore, n denotes the activities in each zone, and m designates the various regions. The waste production is constructed using the estimates (xi and yij coefficients), and forecasts are made for additional study. trash products can therefore be estimated to improve trash planning and management. Two FIS inputs—FIS and fuzzy-rule-based singleton values—are introduced by this method.

The first input, which is represented by Equation (4), gives the separation between an individual and the world average.

$$is_i = \sqrt{\sum_{d=1}^{N} \left(x_i^d - GB^d\right)^2} \tag{4}$$

If GBd indicates the dth dimension of GB, the dimension d th of the i th individual is described as xid, and the distance between the global best and i th individual is supplied by Disi. The other input, an error of diversity (Errdiv), is provided below in equation (5),

$$Err_{\mathrm{div}} = D_g - D_{\mathrm{goal},g} \tag{5}$$

Since these inputs' magnitude order alters when the evolutionary methodology is being carried out, the inputs are changed prior to applying the FIS in the suggested manner. The equations below are shown in (6).

$$Dis_{std,j} = \left\{ \begin{array}{cc} 0, & Dis_{max} - Dis_{min} = 0, \\ \frac{Dis_i - Di_{\ min}}{Dis_{max} - Dis_{min}}, & Others \end{array} \right\} \tag{6}$$

The system classifies data with different degrees of membership using three fuzzy sets for the first input and five for the second. This structure transforms hazy input data into explicit actions, facilitating correct interpretation and decision-making in biomedical waste management.

Algorithm 1. GA-fuzzy inference system.

```
Algorithm GA-FuzzyInferenceSystem
Input:
  - Population size (pop_size)
  - Number of generations (num_generations)
  - Crossover rate (crossover_rate)
  - Mutation rate (mutation_rate)
  - Fuzzy Inference System (FIS) model
  - Evaluation function (fitness_function)
Output:
  - Best FIS parameters after optimization
1. Initialize the population
  - For i from 1 to pop_size:
    - Generate a random individual (solution) with fuzzy parameters
    - Evaluate the fitness of the individual using the fitness_function
2. Repeat for each generation from 1 to num_generations:
  a. Selection
    - Select individuals from the population based on their fitness (e.g., using roulette wheel or tournament selection)
  b. Crossover
    - For each pair of selected individuals:
    - With probability crossover_rate:
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- Perform crossover to create new offspring
- Each offspring inherits traits from both parents

c. Mutation
- For each individual in the population:
- With probability mutation_rate:
- Mutate individual’s parameters (e.g., modify membership functions or rule weights)

d. Evaluate the new population
- For each individual in the new population:
- Evaluate its fitness using the fitness_function

e. Replacement
- Replace the old population with the new population based on fitness (e.g., generational replacement or elitism)

3. Return the best individual from the final population
- This individual represents the optimized FIS parameters

End Algorithm

2.4.Data analysis tool

The Automatic Waste Disposal Master Tool, or AUTOM, is a state-of-the-art biomedical waste management system that integrates a fuzzy model based on genetic algorithms to maximize operational efficiency. The correct classification and disposal of various biomedical wastes are crucial in medical laboratories and clinical settings, which is why this system was created especially for them. The AUTOM's GA-based fuzzy model improves decision-making by dynamically modifying waste treatment plans in response to real-time data inputs. Genetic algorithms find the best possible combinations of rules to efficiently classify and handle various kinds of biomedical waste by optimizing the fuzzy rule base. This integration lowers operating costs and lessens environmental effect while increasing trash segregation accuracy and guaranteeing adherence to strict regulatory criteria. Thus, AUTOM is a major step forward in the management of biomedical waste, utilizing AI-driven strategies to improve sustainability, efficiency, and safety in healthcare settings.

3. Results And Discussion

3.1. GA-FIS result analysis

Table 1 summarizes the experimental settings used for the proposed GA-FIS. The crossover rate was set at 0.8, and the dimensions (N) were tested with values of 10 and 30. The algorithm ran for 55 independent iterations. The mutant factor (F) was set to 0.7, and a population size (PS) of 50 individuals was employed during the experiments. These parameters were chosen to evaluate the performance and effectiveness of the GA-FIS approach under controlled conditions.

Table 1 Experimental configuration of the proposed GA-FIS model

Parameter	Values
Crossover rate	0.8
Dimensions (N)	10/30
Independent iterations	55
Mutant factor (F)	0.7
Population size (PS)	50

Figure 2 presents the diversity curves for ten generations comparing the Traditional Genetic Algorithm (GA) and the Proposed GA-Fuzzy Inference System (GA-FIS). Initially, both algorithms start with a diversity of 12 individuals at generation 0. As the generations progress, the diversity decreases in both approaches. By generation 2000, the Traditional GA exhibits a diversity of 1, whereas the Proposed GA-FIS achieves a diversity of 1 earlier, by generation 2000. This comparison highlights the evolution of diversity over time, showcasing how the Proposed GA-FIS method maintains higher diversity for most generations compared to the

Traditional GA, indicating potentially improved performance in preserving genetic diversity during the evolutionary process.

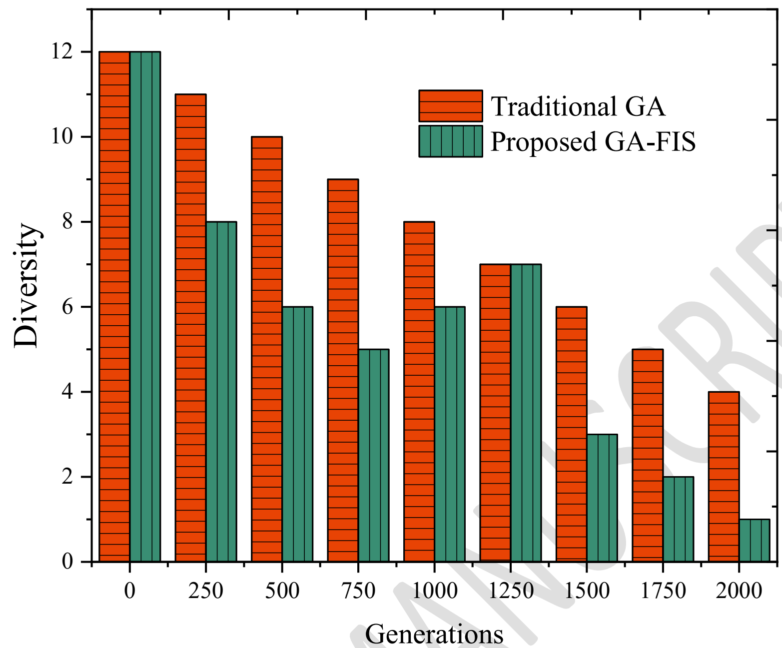

Figure 2 Diversity progression across 10 generations

Figure 3 illustrates the diversity curve over thirty generations for both the Traditional Genetic Algorithm (GA) and the Proposed GA-FIS. Initially, at generation 0, both approaches start with a diversity level of 40. As the generations progress, a gradual decline in diversity is observed in both methods, albeit with slight variations. By generation 250, the Traditional GA shows a diversity reduction to 36, while the Proposed GA-FIS maintains a slightly lower diversity at 35. This trend continues until generation 1000, where the Traditional GA records a diversity of 24 compared to 30 in the Proposed GA-FIS. Notably, from generation 1250 onward, the Proposed GA-FIS demonstrates a consistent improvement in diversity compared to the Traditional GA. By generation 2000, the diversity levels are markedly lower in both methods, with the Traditional GA at 8 and the Proposed GA-FIS at 10. Overall, Figure 3 highlights the comparative diversity trends between the Traditional GA and the Proposed GA-FIS across the thirty generations, showcasing the latter's potential for maintaining diversity more effectively in later generations.

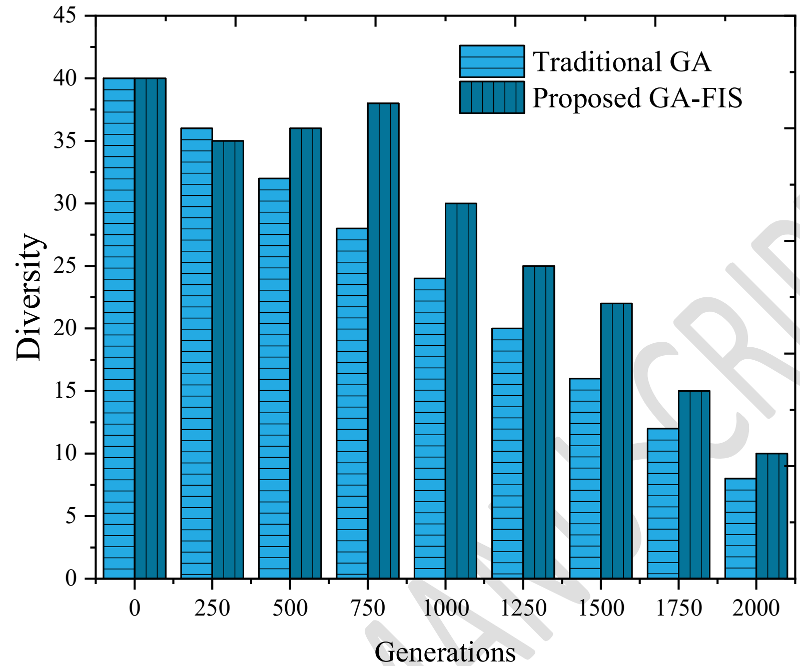

Figure 3 Diversity progression across 30 generations

Figure 4 presents the experimental analysis of waste distribution within a smart bin based on the distance from the inner lid. Three conditions are examined: "Nearly full" when waste is closest to the lid at 3 cm, "Half full" at 8 cm, and "Empty" at 15 cm distance from the inner lid. This analysis aims to understand how waste accumulates relative to the lid's position, providing insights into optimal filling levels and distribution patterns within the smart bin

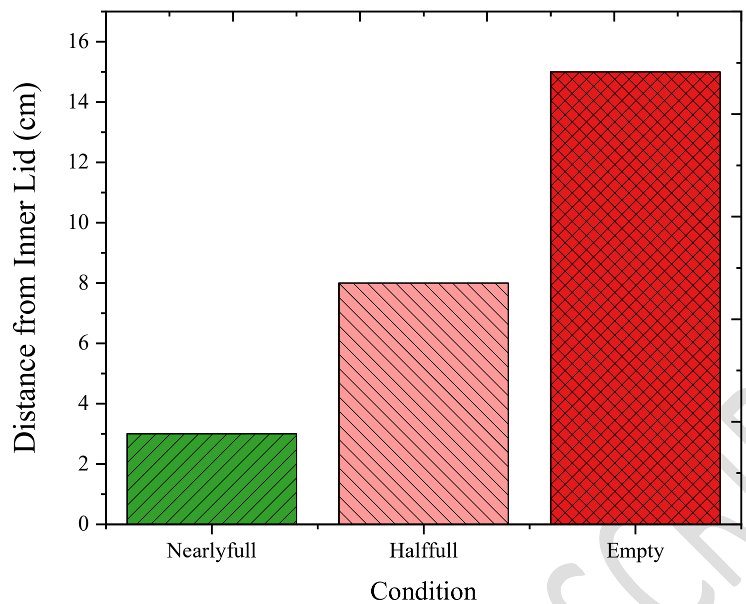

Figure 4 An experimental study of the garbage in the smart bin.

Figure 5 presents the performance metrics of the proposed model across different states of the smart bin: Empty, Partial, and Full, along with an Overall evaluation. The accuracy of the model is highest for the Full state at 98.6%, followed closely by Empty at 96.2% and Partial at 93.5%. Precision values show similar trends, with the Full state achieving the highest precision of 99.9%, Empty at 97.8%, and Partial at 93.6%. Recall rates indicate effective performance across all states, with Full achieving the highest at 99.5%, followed by Empty at 96.8% and Partial at 91.5%. Overall, these metrics underscore the robustness of the proposed model in accurately classifying the operational states of smart bins, demonstrating strong performance across diverse conditions.

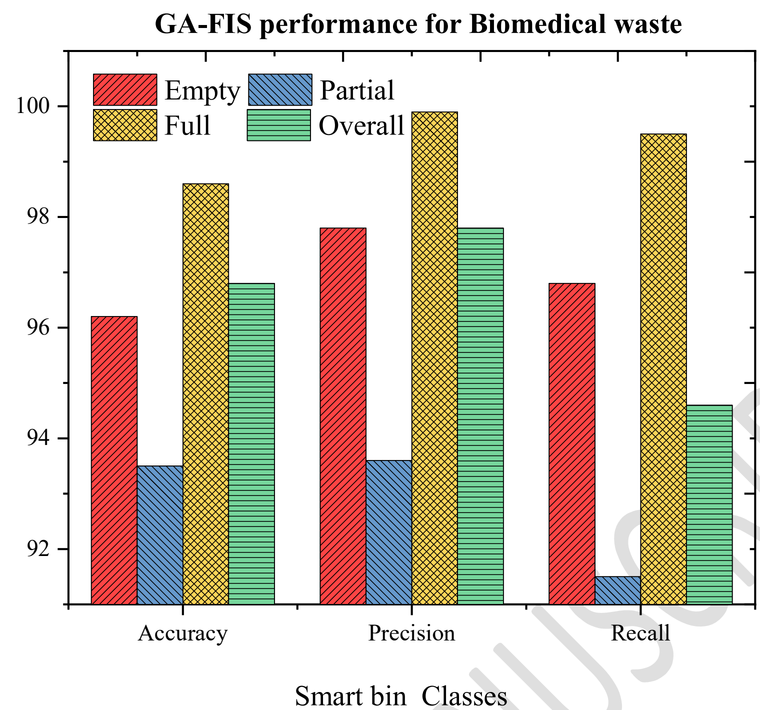

Figure 5 Performance metrics analysis

Figure 6 displays the confusion matrix detailing the waste element segregation performance using the proposed model. The matrix categorizes waste into five classes: PCR tubes, Bandage spool, Syringes, Inhalers, and Medicine Bottles. The below figure represents the number of instances classified for a specific waste type against actual observations. For instance, PCR tubes were classified accurately in 102 out of 168 cases, resulting in a correct percentage of 102%. Similarly, Bandage spool and Syringes were classified with 102% and 99% accuracy respectively. Inhalers and Medicine Bottles, while accurately classified in 90% and 88% of cases respectively, show slightly lower correct percentages. Overall, the model demonstrates effective waste segregation capabilities, with an average correct percentage of 95% across all waste categories, indicating robust performance in identifying and segregating different types of waste elements.

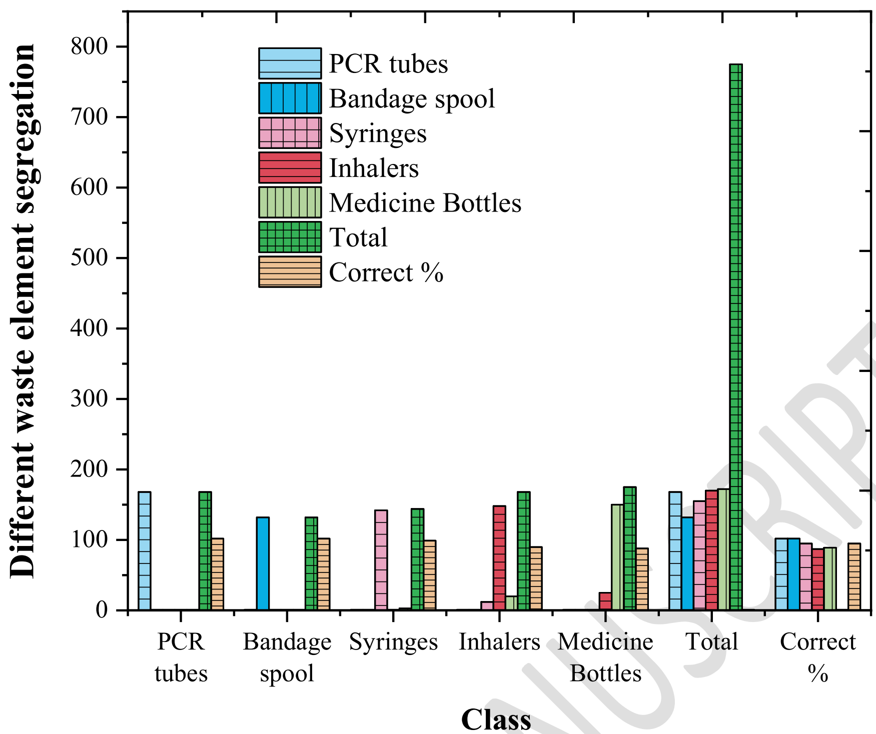

Figure 6 Confusion matrix for various waste element divisions using the suggested methodology.

3.2. Comparative analysis of existing and proposed model

Figure 7 provides a comparative analysis between the proposed GA-FIS model and existing smart garbage systems using various techniques. The figure below evaluates these systems based on Accuracy, Precision, and Recall metrics. CNN achieves an Accuracy of 88.2%, with Precision and Recall values of 89.5% and 97.2% respectively. CNN combined with MLP improves Accuracy to 92.5%, with Precision at 98.2% and Recall at 92.8%. KNN achieves an Accuracy of 89.2%, with Precision and Recall values both at 89.5% and 89.4% respectively. MLP and Naïve Bayes demonstrate similar performance, with MLP achieving 86.8% Accuracy, 88.6% Precision, and 87.7% Recall, and Naïve Bayes at 86.9% Accuracy, 88.9% Precision, and 88.6% Recall. In contrast, the proposed GA-FIS model outperforms all other techniques with an impressive Accuracy of 96.4%, Precision of 96.8%, and Recall of 94.8%.

This comparison underscores the superior performance of the proposed GA-FIS model in smart garbage systems, highlighting its effectiveness in waste classification and management.

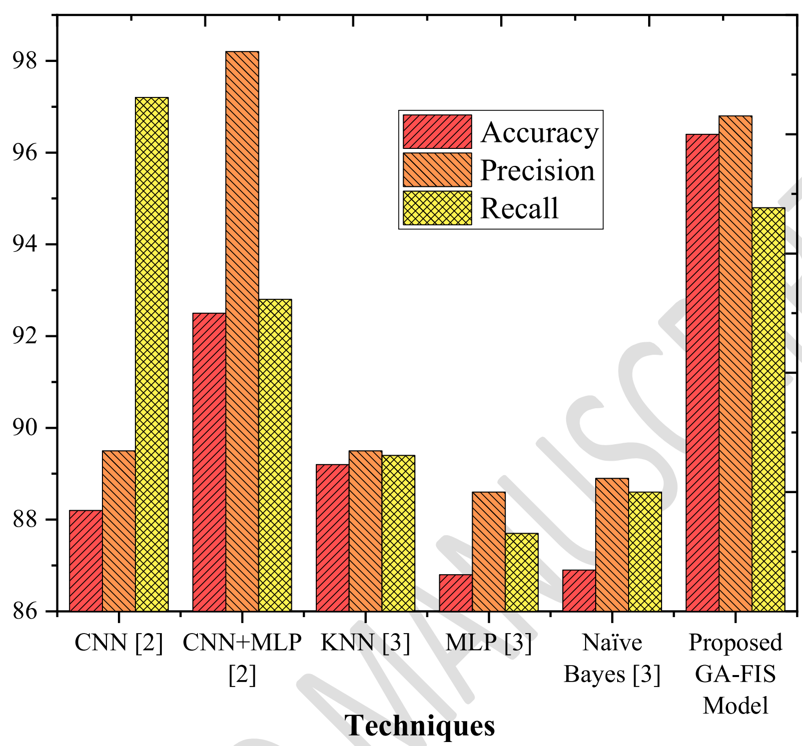

Figure 7 Comparative analysis

4. Conclusion

This study presents an innovative hybrid approach combining a Genetic Algorithm (GA) with a Fuzzy Inference System (FIS) to advance waste management within smart city infrastructures, with a focus on healthcare waste segregation. The dynamic fuzzy inference engine integrated into the system boosts both the precision and efficiency of waste collection processes, reducing potential errors. GA optimization enhances the FIS, ensuring more accurate classification and segregation of biomedical waste, based on comprehensive data collected over six months from Apollo Hospitals and Fortis Malar Hospital in Chennai. The resulting GA-FIS model is capable of categorizing five distinct types of biomedical waste.

Additionally, the system includes AUTOM, an automated disposal tool that leverages fuzzy logic to guide decision-making in waste sorting, thus improving operational efficiency in healthcare settings. This approach represents a step forward in environmentally sustainable biomedical waste management within the framework of smart city initiatives.

1. The performance metrics of the proposed model demonstrate its effectiveness across different smart bin states—Empty, Partial, and Full—yielding highest accuracy for the Full state at 98.6%, followed by 96.2% for Empty and 93.5% for Partial. Precision values similarly highlight superior performance in the Full state at 99.9%, with 97.8% for Empty and 93.6% for Partial.
2. Recall rates confirm robust performance across all states, with the Full state achieving 99.5%, followed by 96.8% for Empty and 91.5% for Partial. Overall, these metrics underscore the model's reliability in accurately classifying smart bin operational states and effectively managing waste diversity.
3. Furthermore, the confusion matrix illustrates the model's proficiency in segregating waste elements, achieving an average correct percentage of 95% across categories such as PCR tubes, Bandage spool, Syringes, Inhalers, and Medicine Bottles. This confirms the model's capability in identifying and managing various types of waste elements with high accuracy.
4. Comparative analysis against existing smart garbage systems using techniques like CNN, CNN+MLP, KNN, MLP, and Naïve Bayes further establishes the superiority of the proposed GA-FIS model. With an outstanding accuracy of 96.4%, precision of 96.8%, and recall of 94.8%, the GA-FIS model outperforms all other techniques, highlighting its efficacy in waste classification and management within smart city infrastructures.

To sum up, the proposed GA-FIS model not only enhances waste management efficiency and accuracy but also contributes significantly to environmental sustainability and public health through improved waste segregation and recycling practices. Future research in Biomedical Waste Management can focus on developing AI and IoT-based systems for real-time waste monitoring and segregation, exploring advanced sustainable treatment technologies like plasma gasification, and utilizing blockchain for secure tracking and transparency in waste disposal processes.

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.

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Abbreviation

GA-FIS - genetic algorithm (GA)–fuzzy inference system

BWM - Biomedical Waste Management

DEMATAL - Decision-Making Trial and Evaluation Laboratory

TISM - total interpretive structural modeling

ANFIS - Adaptive Neuro-Fuzzy Inference System

AUTOM - Automatic Waste Disposal Master Tool

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