DeepSense Hierarchical Smart Bin Monitoring Network for Intelligent IoT-Driven Urban Waste Management and Adaptive Route Optimization

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Abstract

The facilitate sustainable and efficient urban waste collection in smart city environments, the real-time monitoring of bins, prediction of bin overflow, adaptation of routes and intelligent decision execution are essential for smart waste management systems based on IoT devices. But the current approach of Deep Learning (DL) classification visual detection and static forecasting are limited by the functional modules, lack of multi-sensor fusion and have no closed-loop decision-making, which makes it difficult to be extended to complex scenes under dynamic urban waste. To address these shortcomings, this research introduces the DeepSense Hierarchical Smart Bin Monitoring Network (DHS-BMN) that use heterogeneous IoT sensing, hybrid CNN-LSTM-Attention overflow prediction, Reinforcement Learning (RL) based on adaptive routing and region-aware clustering of bins based on the K-Means algorithm, in a unified closed-loop framework for intelligent urban waste management. The results of the experiments verified the suitability, robustness and scalability of the proposed DHS-BMN for the next generation smart city waste management deployments, as it obtained overall higher accuracy in the overflow prediction (97.8%) and efficiency in routing (95.1%) when compared with the existed method.

Keywords: Edge Computing, Environmental Monitoring, Real-Time Monitoring, Smart Cities, Urban Sustainability, Waste Management

1. Introduction

Municipalities are under high pressure to implement waste collection systems that can help it keep up with the growing volume of waste generated in cities while dealing with the challenges of urbanization [1]. The IoT has proven to be a game-changer enabler, as cities have adopted a networked infrastructure of sensors that constantly tracks bin fill level and environmental hazards in real time [2] and IoT solutions for smart cities have proven substantial savings in operational overhead and environmental impact [3]. Proactive paradigms of waste management, based on machine learning for early overflow detection, have shown measurable benefits in the number of hazardous accumulation events [4] and deep learning-based architectures have been designed that enable to predict overflows and detect anomalies in multi-sensor data streams with heterogeneous data types [5]. The use of intelligent route optimization using reinforcement learning has resulted in substantial reduction of collection distance and fuel usage [6] and systematic meta-analyses have confirmed that routing through IoT has significantly reduced travel distances at scale [7]. The models that have been built using IoT have also been successful in the classification of fill levels [8], in the forecasting of municipal solid waste [9] and also in the hybrid attention-based architecture, which is successful both in overflow prediction and in IoT network security applications [10]. Advances in sensor technology, like time-of-flight technologies, have enhanced bin-level data accuracy [11]; transfer learning models have provided automatic waste classification in smart cities [12] and deep reinforcement learning has optimized medical waste vehicle routing under safety constraints [13]. Sustainability-driven IoT frameworks have shown the long-term scalability of smart deployments [14] and the combination of neural network forecasting at the discharge point scale has reinforced the municipal solid waste planning [15] with a clear push towards the development of a single closed-loop intelligent system that includes sensing, prediction, routing and clustering. This research provides some contribution such as:

- Proposed intelligent real-time urban waste monitoring and adaptive waste collection management as DeepSense Hierarchical Smart Bin Monitoring Network (DHS-BMN).
- Integrated heterogeneous multi-sensor fusion-based comprehensive and reliable waste state assessment using ultrasonic, load and gas sensors.
- Designed a hybrid CNN-LSTM-Attention model that can accurately predict waste overflow patterns and model temporal waste accumulation behavior.
- Improved the efficiency of collection with reinforcement learning based adaptive route optimization and region oriented K-Means clustering to reduce operational cost.
- Tested and statistically analyzed the framework with experiments and proved its high accuracy, scalability, robustness and sustainability, which are higher than existing ways of smart waste management.

The research organized as follows. The related works and background of the research on smart waste management system using the Internet of Things (IoT) are provided in Section 2. Section 3 provides the proposed DHS-BMN framework, which comprises sensor architecture, preprocessing, clustering, deep learning and adaptable routing modules. The experimental result and the performance measures are presented in section 4. The discussion part is given in section 5. Lastly, Section 6 brings the research to a close and presents possible directions for future research.

2. Background Study

The problem of accurate long-term prediction of waste generation in developing urban regions was tackled by Razali et al. (2025) [16] by using machine learning for waste generation forecasting and emission potential at Erode City dump yards. The approach used in the study was ensemble machine learning to predict solid waste volumes and it was based on a single city's data without integrating real-time IoT sensors.

Arumugam et al. (2025) [17] introduced a route optimization scheme for urban waste collection based on LoRa communication and Deep Q-Network in a simulated environment to fill the energy-efficient intelligent route for IoT-enabled waste collection vehicles. The method used was reinforcement learning for optimal route learning, but it had a limitation in that it was not tested in the real world and did not use multiple sensors for bin monitoring.

Tackle the challenge of maintaining environmental sustainability when manually monitoring waste overflow conditions, Abo-Zahhad and Abo-Zahhad (2025) [18] proposed an intelligent real-time garbage monitoring system that uses deep learning models such as YOLOv8 and YOLOv5 to detect waste overflows from visual images. The framework pointed to the occurrence of garbage accumulation in camera-equipped garbage cans, but did not propose integration of multiple-sensors such as ultrasonic, load and gas sensor in the garbage cans to assess waste comprehensively.

Tiwari et al. (2025) [19] proposed an intelligent waste sorting system for urban sustainability based on deep learning CNNs, which is missing in the automation of municipal solid waste (MSW) categorization for recycling and sustainable waste disposal. The system was successful in achieving high classification accuracy, but it did not include a system to monitor the fill level, optimize routes and make decisions based on real-time data from the Internet of Things (IoT) for end-to-end waste management.

Intelligent recovery decision-making for heterogeneous streams in urban waste, Arun (2025) [20] explored a deep learning-based waste recovery system with IoT. The proposed framework integrated IoT data acquisition and deep learning while it was lacking reinforcement learning support for adaptive routing and region-based bin clustering to enable scalable deployment in smart cities.

Islam et al. (2025) [21] developed an efficient waste classification system with the implementation of deep CNN with enhanced features, which overcomes the limitations of robust automated waste classification in the different image conditions of real-world environments in smart urban cities. The study achieved the best classification results with the help of transfer learning and data augmentation, yet failed to include IoT sensor fusion, real-time bin monitoring and intelligent collection scheduling.

Given there is a lack of scalable and energy-efficient sensor-driven waste monitoring systems in distributed bin networks within smart cities, Singh et al. 2024 [22] proposed a Wireless Sensor Network (WSN)-based machine learning framework for intelligent waste management in smart cities. The framework tracked bin fill levels and foresaw the need for collections, but lacked deep learning temporal modeling, attention and reinforcement learning for adaptable routing.

Proposing an integrated clustering algorithm and machine learning proposed by Taweesan et al. 2025 [23] to optimize regional municipal solid waste management by plugging the problem of spatially aware data-based regional planning for achieving sustainable development goals. The methodology was based on K-Means grouping of waste regions, waste collection frequency optimization but without real-time IoT integration and without dynamic overflow prediction features and without online adaptive decision-making features.

Chen et al. (2025) [24] designed a novel framework based on deep learning and IoT for real-time multi-waste forecasting, which relies on AutoML techniques to automate and scale waste category prediction for resource conservation and recycling planning. The overall forecasting performance was good, while the portions of intelligent route optimization, overflow prediction and reinforcement learning-based adaptive collection scheduling were not integrated in a single system.

Table 1: Comparative Analysis of Existing Literature on IoT-Based Smart Waste Management Systems

Citation	Methodology	Technique / Algorithm	Limitation	Research Gap
Ge et al. (2025)[25]	Waste sorting and transportation optimization framework based on garbage volume prediction.	Garbage volume prediction and transportation network optimization algorithms.	Limited adaptability under dynamic real-time urban waste variations.	Does not include intelligent IoT sensor fusion or adaptive reinforcement learning-based scheduling.
Fatovatikhah et al. (2024)[26]	Hybrid predictive modeling approach combining sequential learning and classification.	Hybrid LSTM-SVM model.	Performance depends heavily on historical data quality and temporal consistency.	Lacks IoT-based real-time monitoring and adaptive routing integration.
Ko et al. (2025)[27]	Regional machine learning-based waste forecasting framework.	Machine learning prediction models.	Model performance is region-specific and difficult to generalize to diverse urban environments.	Limited scalability and absence of intelligent collection optimization.
Chen et al. (2025)[28]	Strategic management-oriented predictive framework.	Predictive analytics and machine learning methods.	Focuses mainly on forecasting without practical real-time deployment validation.	Does not incorporate real-time sensor fusion or autonomous IoT deployment.
Anupriya & Ratish Kumar	Multi-scale neural network-based	Enhanced Bidirectional	Computational complexity	Focuses only on segregation

(2025)[29]	waste classification system.	GRU (EBiGRU).	increases with multi-scale sequential learning architecture.	without routing or overflow prediction.
Fan et al. (2024)[30]	Multi-scale temporal sequence forecasting framework.	BiLSTM with Local Attention Mechanism (BiLSTM-MLAM).	High computational requirements reduce suitability for lightweight edge deployment.	Generic sensor forecasting model not specifically designed for smart waste management systems.

A structured comparative analysis of recent studies that have investigated IoT smart waste management is shown in table 1, which highlights the methodologies adopted, the main techniques used and the research gaps of these works with respect to the proposed DHS-BMN framework. The analysis shows that there is no work that covers the whole real-time multi-sensor acquisition, hybrid deep learning based overflow prediction, reinforcement learning based routing and region aware clustering in a single system, while the proposed DHS-BMN does, comprehensively.

2.1 Research Gap

Most of the existing research on waste management using IoT technologies concentrates on specific waste problems like waste forecasting, garbage detection, or simple waste classification without a comprehensive real-time framework. In RL based route optimization, the real world integration of sensors and adaptive execution is frequently missing and only simulations are used. The vision-based systems rely solely on cameras and do not need to fuse multi-sensors, like ultrasonic, load and gas sensors for waste and hazard monitoring. Current machine learning and clustering approaches have limited capabilities in predicting fill level, allocating space and do not provide intelligence driven scheduling and continuous IoT-driven decision updates. Likewise, the forecasting models of AutoML are not connected with the routing and adaptive collection mechanisms. Such constraints are indicative of the lack of a closed-loop system that incorporates real-time sensing, hybrid CNN-LSTM-Attention prediction, reinforcement learning-based routing and region-aware clustering, that the proposed DHS-BMN framework makes possible.

3. Proposed Methodology

This section present that the DHS-BMN is a smart and closed loop solution which implements an IoT technology solution to monitor and autonomously manage waste in an urban area in real-time. It is a combination of smart bin sensors including ultrasonic, load sensors and gas sensors, which continuously gather multi-dimensional information regarding fill level, waste amount and environmental risk levels. The preprocessed raw data is then inputted into a deep learning model which extracts spatial features using CNN, models temporal dependencies using LSTM and predicts the risk of overflow events using an attention layer. Moreover, reinforcement learning algorithms enable dynamic optimization of routing and scheduling strategies, while K-Means clustering ensures bin classification according to regions for an effective deployment strategy on smart city waste management.

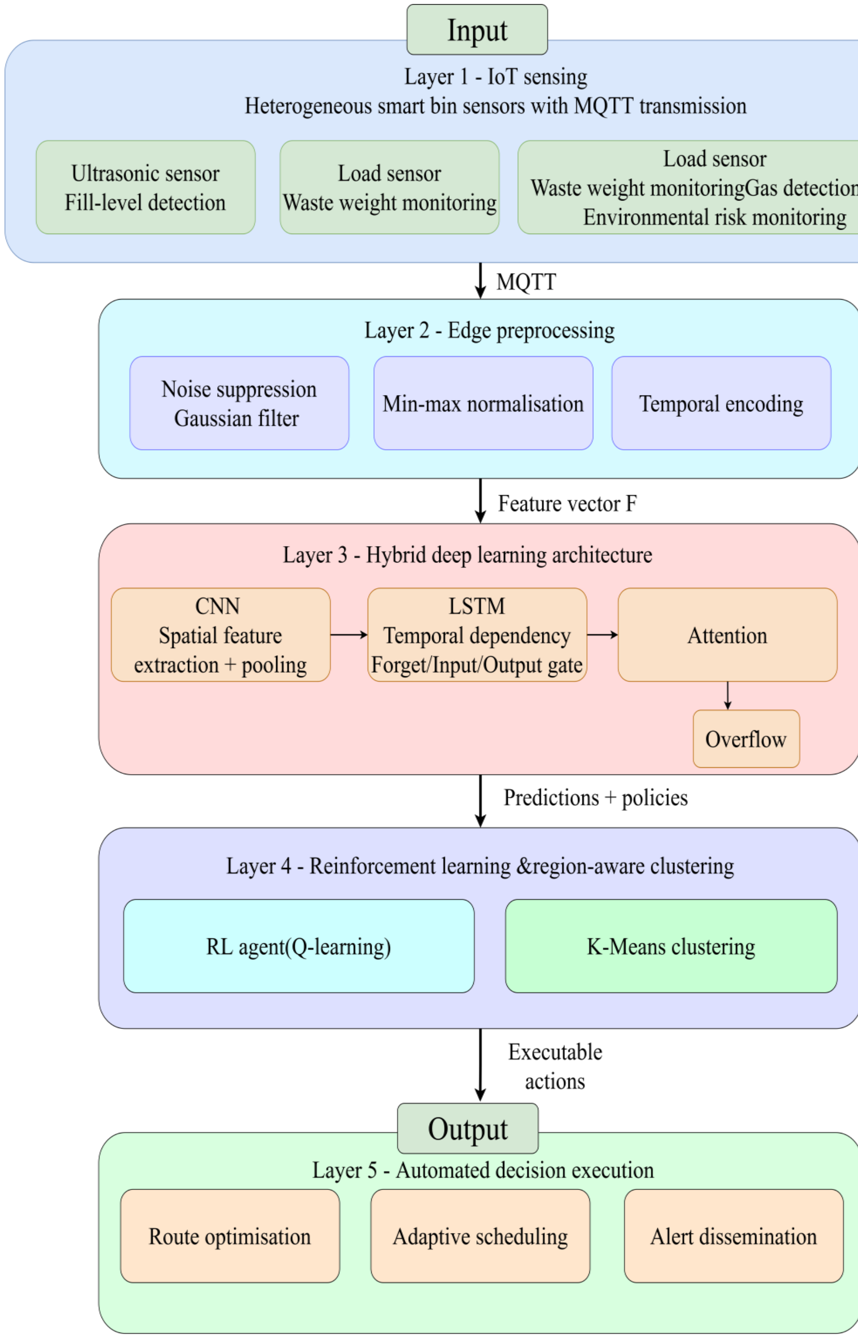


Figure 1: DHS-BMN Five-Layer Architecture

The smart waste management architecture with 5 layers is displayed in this figure 1. The collection of data with IoT sensors is done using MQTT in Layer 1. The edge preprocesses it it Layer 2. CNN-LSTM with attention for predictions is performed in the third layer. Optimization is done using reinforcement learning and clustering in Layer 4. The automation will be used to route, schedule and alert at Layer 5.

3.1 Dataset Description

To prove the proposed DHS-BMN framework, a proof-of-concept system with an IoT-based smart bin was developed in various scenarios around the city and deployed in a smart waste bin equipped with several fill level, load and gas sensors within the smart waste bin. Each data instance comes with time stamped measurements from each sensor and the location coordinates of the bin and the ground truth label, enabling a thorough evaluation of supervised learning and anomaly detection. The data set includes data from Residential, Commercial and Public Space environments and includes about 50,000 observation records of sensors over the course of day and over multiple seasons. The dataset has been divided into three sections: 70% for training, 15% for validation and 15% for testing to ensure unbiased model evaluation and the reliable evaluation of the generalizability of the proposed framework.

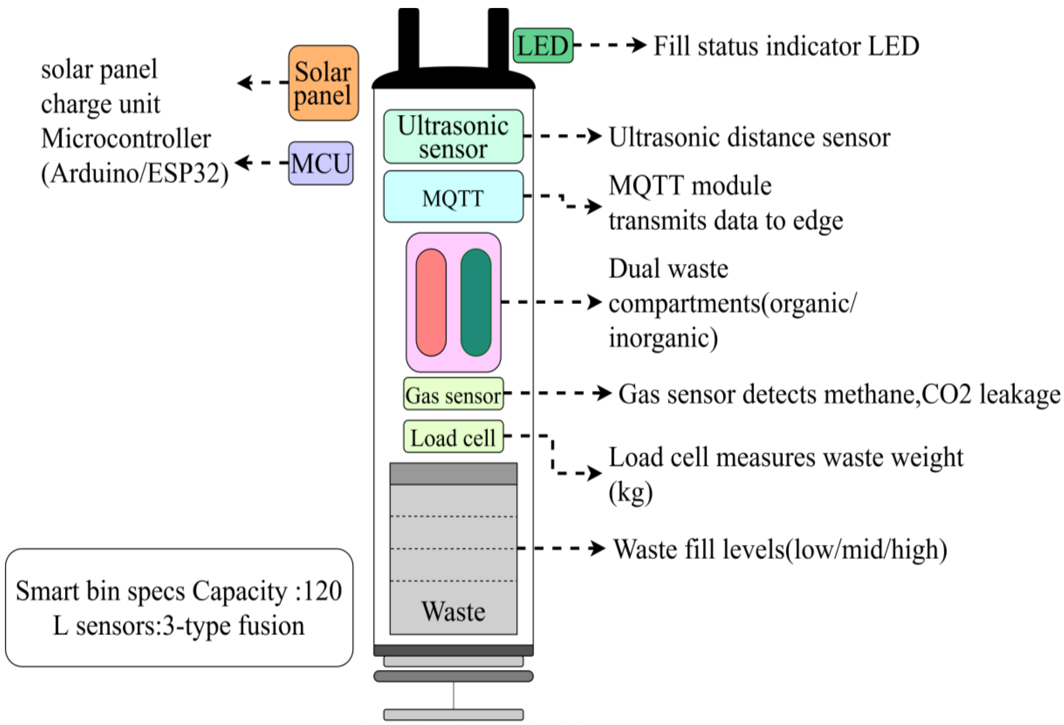


Figure 2: Smart Bin Hardware Architecture of the DHS-BMN Framework

This figure 2 shows the hardware architecture of this smart bin of 120L capacity, which uses three types of sensor ultrasonic fill-level sensor, gas (methane/CO2) sensor and load cell – for monitoring the fill level, methane/CO2 or weight respectively. Communication with data is done using MQTT from the Arduino/ESP32 MCU and there is a solar panel to provide self-power. Cost reduction in waste management by using two compartments (organic/organic) and by using motorised compaction base.

3.2 DeepSense Hierarchical Smart Bin Monitoring Network (DHS-BMN)

The proposed DHS-BMN is designed as an intelligent continuous closed-loop system, which is composed of three parts, namely real-time sensing of urban waste, adaptive decision modeling of urban waste and automatic execution of operation, so as to effectively solve the problem of urban waste. A range of IoT sensors is fitted inside the smart bins such as ultrasonic, load and gas detection sensors, which gather multi-dimensional data on the fill level, waste accumulation dynamics and the environment hazards on an ongoing basis. The data streams are sent using lightweight communication protocols like Message Queuing Telemetry Transport (MQTT) and undergo some processing, such as noise filtering, data normalization and temporal feature encoding, at the edge to maintain consistency and robustness in the data. These abstracted feature representations are fed into a hybrid deep learning system consisting of Convolutional Neural Networks (CNN) to learn spatial features, Long Short-Term Memory (LSTM) networks to learn temporal feature relationships and an attention mechanism to select important features of the input that are relevant to overflowing or abnormal conditions[29-31]. To take another step towards decision intelligence, a reinforcement learning framework is used to dynamically optimize the operational policies in each of the different states the system can be in and clustering techniques such as K-Means are applied to cluster bins in space to optimize the operational policies region-aware. Transformed systematically into executable actions, such as adaptive scheduling, alert distribution in real-time to the municipal control systems and dynamic route optimization to collect waste [32-34]. The framework is web based; predictions and decision policies are continuously updated according to the newly collected data, thus allowing for pro-active intervention and elimination of operational inefficiencies. A fixed model parameterization, standardized pipelines and data processing and containerized deployment models between the edge and cloud ensure the reproducibility and scalability of the system. As such, DHS-BMN is a strong, autonomous and expandable platform that will be able to monitor, analyze and respond to complex urban waste dynamics in real-time continuously.

$$S_t = \{u_t, w_t, g_t\} \tag{1}$$

The equation (1) represents real time sensor readings that can be retrieved from the smart bin at time t andu_t, w_t and g_t are the ultrasonic sensor, waste weight measurement and concentration of gas in the bin at time$t$, respectively. The information from the different sensors is merged to gain complete information about the waste accumulation and waste environment of the waste receptacle.

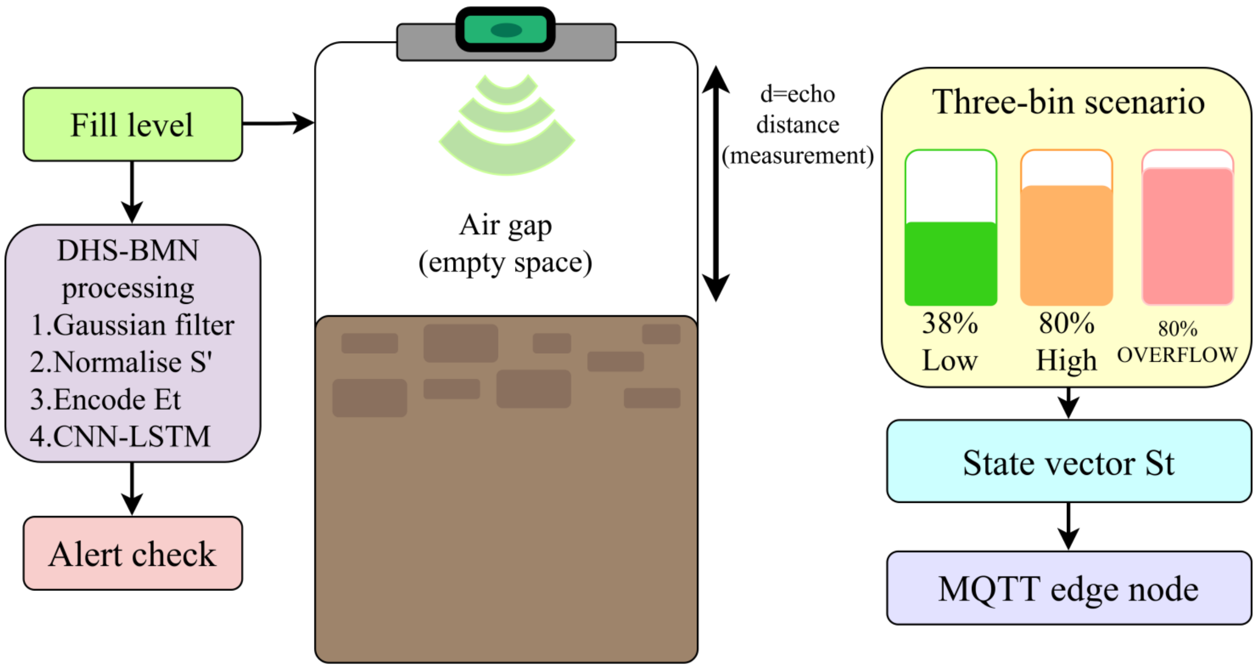


Figure 3: Ultrasonic Fill-Level Detection and DHS-BMN Process

The air gap echo distance is measured by the ultrasonic sensor as shown in figure 3 to detect the fill level of the three bins with 38% of time in the low fill level state, 80% in the high fill level state and 80% in the overflow state. The data collected on fill level is passed through a Gaussian filter, normalized, temporally encoded and then processed to have CNN-LSTM based inference and then passes to edge node to state vector via an MQTT connection to the state vector for transmission.

3.2.1 Sensor Data Acquisition and Communication

A collection of diverse IoT sensing units, including but not limited to a ultrasonic fill-level sensor, load sensor and gas detection unit, that are continuously collecting multi-dimensional real-time data that indicate waste accumulation dynamics, bin fill status and environmental risk indicators are installed in the smart waste bins as the DHS-BMN framework. These data streams are sent wirelessly to the edge nodes in the city using light-weight communication protocols such as the Message Queuing Telemetry Transport (MQTT) that ensures low latency, energy efficient data transmission and robust data reliability in an extensive and large deployment of smart bins in the city.

$$D_t = MQTT(S_t, L) \tag{2}$$

Equation (2) is the description of the IoT communication process that is used for transmitting sensor data. Data Packet transmitted is D_t, observations from the sensor are S_t and L is geographical location of the smart bin. $MQTT$ Can Enables is a lightweight, reliable and real-time smart bin to cloud communication solution.

3.2.2 Edge-Level Preprocessing and Feature Encoding

The sensor information collected should then be properly preprocessed in the edge environment for consistency, reliability and robustness of the collected data before being used for inferences based on deep learning. To cancel out any external noise, preprocessing steps include noise cancellation; to normalize the sensor values and encode the sensor time based features, min-max normalization was used. This will result in the right features being obtained that will be used as input data to the next hybrid deep learning model.

$$S_t' = \frac{S_t - S_{min}}{S_{max} - S_{min}} \tag{3}$$

This is an equation (3) with a normalized value of the sensor S_t', a minimum range S_{min} and a maximum range S_{max} of the sensor. This process aims at equalizing the scale for the sensor readings, for stability in the learning and model performance.

$$\tilde{S}_t = S_t' * N(0, \sigma^2) \tag{4}$$

The equation (4) is used for the removal of noise using Gaussian filter. In this case, the filtered sensor data is denoted as$\tilde{S}_t$ and the distribution of the sensor data $N(0, \sigma^2)$ assumed a Gaussian distribution with a variance of σ^2. Smoothing of noise in the sensor signals is accomplished by this filtering process and the quality of the data is enhanced before the features are extracted.

$$E_t = \emptyset(S_t, S_{t-1}, \ldots, S_{t-n}) \tag{5}$$

The encoded time features of equation (5) are represent E_t. S_t is the sensor data at the t th time step; $S_{t-1}, \ldots, S_{t-n}$ is the sensor data from the previous n time steps, with t being the current time step, where n is the number of time steps used for temporal feature extraction.

3.2.3 Hybrid Deep Learning Architecture

The heart of DHS-BMN has a predictive engine based on a hybrid deep learning system. DHS-BMN is based on a hybrid deep learning system at its core which integrates Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks and an attention mechanism. CNN module relies on the idea of localizing the spatial part of the sensor inputs as waste pattern representations and modeling the temporal part and the sequential dynamics of the waste accumulation as a LSTM network over time. The attention mechanism also selectively highlights some of the most important characteristics about overflow risk and conditions which are outside of normal environmental conditions, enabling accurate and context-aware overflow prediction and increasing the discrimination power.

$$F_t^{CNN} = \sigma(W * \tilde{S}_t + b) \tag{6}$$

In equation (6) extracted spatial feature maps are represented as F_t^{CNN}, convolution weights as W and bias as b. The CNN learns the important spatial waste patterns and sensor correlations for intelligent prediction.

$$P_t = \max(F_t^{CNN}) \tag{7}$$

This equation (7) shows that the dimensionality of the features is reduced, making the prediction of overflow more robust, but keeping the most important spatial information for overflow prediction.

$$x_t = P_t \tag{8}$$

The equation (8) is the input transformation of LSTM network. In this case, x_t is a sequential input sent to LSTM while P_t is a set of features from CNN. The integration is done based on the spatial feature extraction and temporal sequence learning.

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{9}$$

The equation (9) the forget gate activation is controlled and the previous hidden state h_{t-1} and trainable parameters $W_f x_t + U_f h_{t-1} + b_f$. This gate eliminates from memory information it considers not relevant.

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{10}$$

The equation (10) illustrates the value used to control the amount of additional information that enters into the memory cell which corresponds to LSTM input gate. The hidden state h_{t-1} at the last time step, the weight matrices W_i andU_i and the bias term b_i are added to the current input x_t and the sigmoid activation function σ is applied.

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{11}$$

The equation (11) gives The input vector at time t x_t while the previous hidden state vector to which are associated trainable weight matrices W_o and U_o are described by the bias vectorb_o, activation function σ and value of the output gate o_t that controls the flow of the information in the network.

$$h_t = o_t \odot \tanh(C_t) \quad (12)$$

In equation (12) the memory cell state is C_t and the element-wise multiplication is$\odot$. o_t Is the information that is passed to the next hidden state it is a formulation that provides a small time representation to intelligent analysis.

$$\alpha_t = \frac{\exp(h_t^T W_a)}{\sum_k \exp(h_t W_a)} \quad (13)$$

In equation (13) at time step t h_t is the hidden state or feature vector and W_a is the matrix of learnable attention weights to evaluate the importance of features. The soft exponential function returns a normalized attention score α_t to give higher weights to the more relevant hidden states during learning.

$$F_a = \sum_t \alpha_t h_t \quad (14)$$

In the equation (14) α_t represents the attention weight allocated to the hidden state of the hidden state h_t at the time step$t$, which is the extracted feature/hidden representation at time step$t$. The total of all the hidden states is the ultimate attended features that are represented in the feature vector F_a.

$$O_t = \sigma(W_o F_a + b_o) \quad (15)$$

In equation (15) the predicted overflow probability is named as attention-enhanced features, F_a and trainable parameters$\sigma(W_o F_a + b_o)$. The predictions are then converted using sigmoid function to probabilities between 0 and 1.

$$\mathscr{L} = -[y \log(O_t) + (1 - y) \log(1 - O_t)] \quad (16)$$

In equation (16) the prediction loss function ($\mathscr{L}$) is the loss of overflow label (y) and the overflow probability prediction (O_t). This function is used to minimize the difference between the model's output and the actual output by training the model.

3.2.4 Reinforcement Learning and Region-Aware Clustering

The reinforcement learning agent that adapts the waste collection policies on-the-fly to the constantly changing states of the urban system is also included in DHS-BMN to improve the "decision intelligence" of the operation, which currently relies on static predictions. In training, the agent randomly walks through the environment and through the reward signal for the long-term returns to obtain the "best" answers for the adaptive scheduling and routing.During training, the agent learns about the environment and the reward signal for the long term returns by interacting with both to obtain "best" answers to the adaptive scheduling and routing. In parallel, K-Means clustering is used to cluster the bins into groups in space, geographically, based on the waste generation characteristics, which helps to optimise the operation of the smart bins region-aware, making the routing more efficient, less redundant and overall waste collection latency less expensive in large-scale urban deployments.

$$min \sum_{i=1}^{n} ||L_i - \mu_k||^2 \tag{17}$$

In equation (17) the objective function of clustering is used with the smart bin location denoted by L_i and the μ_k are the cluster centered, n is the number of bins. The aim is to minimize the distances between bins and cluster centers to enable a regional waste collection.

$$\pi(a|s) = P(A_t = a|S_t = s) \tag{18}$$

The equation (18) is a policy of reinforcement learning, namely $\pi(a|s)$ is the probability of taking action a when the agent is in state$s$. In this, the selected action is represented by A_t and the current state of the system is represented byS_t, which is to be used to make intelligent decision.

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma max Q(s', a') - Q(s,a)] \tag{19}$$

In equation (19) the state-action value is Q-learning update process where $Q(s,a)$ is the value of state-action, α is a learning rate, r is a reward andγ, a denotes discount factor. s' And a' are variables used to represent the next state-action in policy optimization.

3.2.5 Automated Decision Execution and Scalable Deployment

These predicted outcomes and policy optimizations are subsequently incorporated into operational decisions, such as dynamic routes for garbage trucks, optimized scheduling of garbage truck schedules and in municipal control systems by alerting about proactive actions against potential risks. The system continuously operates while updating its prediction model and decision-making process using new data collected by the sensors to facilitate proactive waste management and improve inefficiencies in operations. DHS-BMN is a modular, scalable and replicable platform for smart cities' waste management systems with standardized data processing workflows, predetermined model parameters and edge-cloud computing configurations, enabling an autonomous smart city waste management paradigm.

$$J = \sum_{i=1}^{N} d_i + \lambda E_i \tag{20}$$

The equation (20) for minimizing cost is J is the cost function, d_i is the distance travelled and E_i is the energy used. The λ value is a weighting factor to determine the right balance between the distance and energy used and N is the total number of elements, samples, devices, or observations involved in the summation process.

$$A_t = \begin{cases} 1, & O_t \geq \theta \\ 0, & O_t < \theta \end{cases} \tag{21}$$

The alert decision mechanism is shown in the equation (21), where the alert status A_t and the overflow probability, O_t are shown. If an overflow alert should be triggered or not will depend on the thresholdθ.

$$\mathcal{J}_{total} = \min(\mathcal{L}) + \max(\mathrm{R}) + \mathrm{nin}(\mathrm{J}) \tag{22}$$

The overall optimized goal of the DHS-BMN is represented in equation (22) that involves three terms: prediction loss ($\mathscr{L}$), reinforcement learning reward (R) and routing cost (J). This formulation requires minimum error, operating cost but at the same time maximizes the performance of making a smart decision.

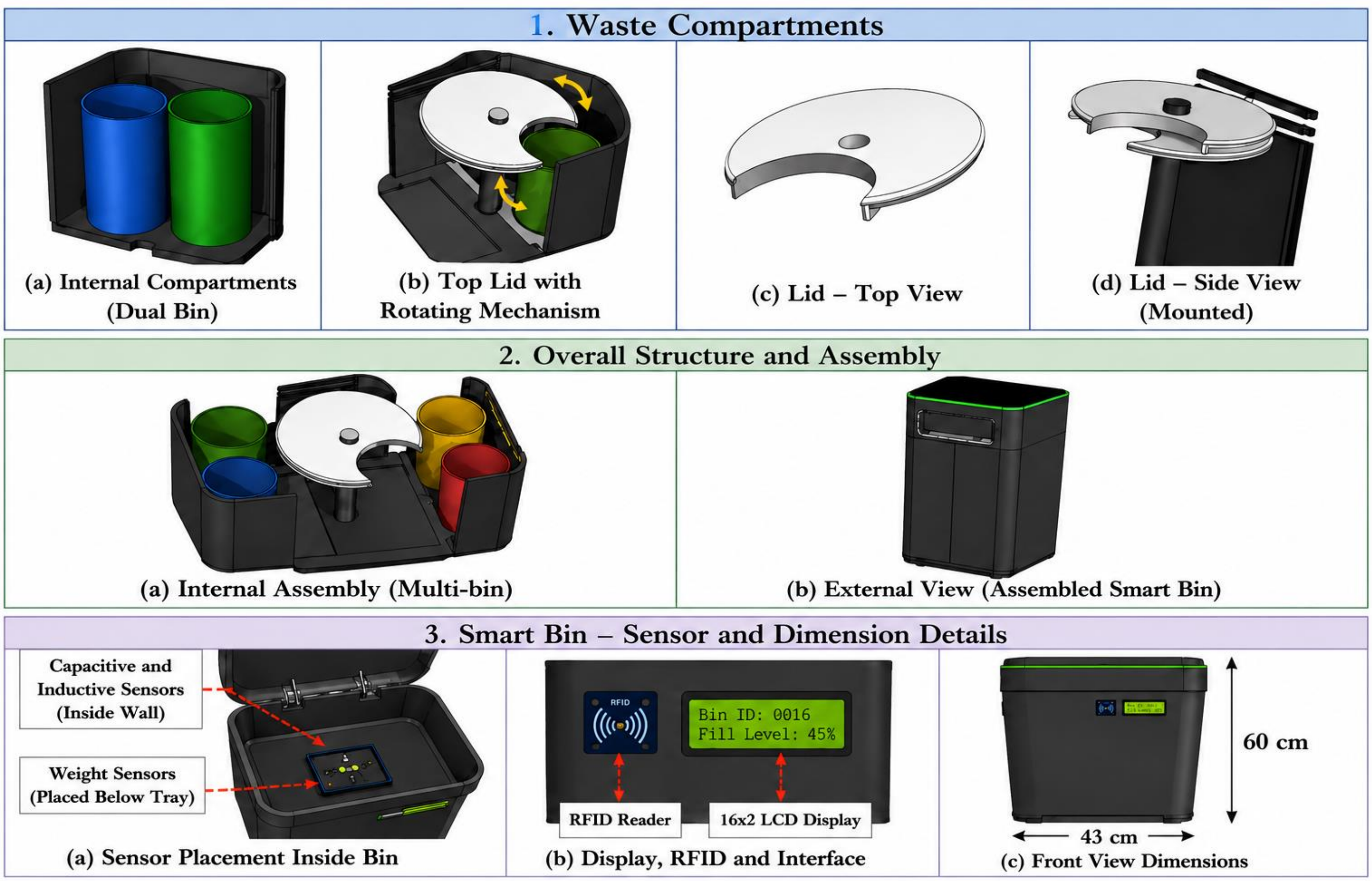


Figure 4: Smart Waste Bin – Design and Assembly

The smart waste bin is divided into two compartments within one, which separate and store the organic waste, inorganic waste and it has a lid mechanism that rotates for controlled disposal in figure 4. It's a 43×60cm assembled bin along with capacitive, inductive and weight sensor for multi-sensor data acquisition, RFID reader and 16x2 LCD display for real-time bin ID and fill level percentage display.

Algorithm: DeepSense Hierarchical Smart Bin Monitoring Network (DHS-BMN)

Input:
  S = Multi-sensor smart bin data
  L = Bin location information
  T = Historical waste data
  K = Number of clusters
Begin
  Initialize IoT smart bins, edge nodes and MQTT communication
  Load hybrid CNN-LSTM-Attention prediction model
  Initialize adaptive reinforcement learning agent
  while system is active do
    Acquire real-time ultrasonic, load and gas sensor data
    Perform edge preprocessing
      Remove noise
      Normalize sensor values
      Encode temporal features
    Generate unified feature vector F
    Extract spatial waste patterns using CNN
      Fs ← CNN(F)
    Learn temporal waste accumulation using LSTM
      Ft ← LSTM(Fs)
    Apply attention mechanism to identify critical overflow patterns
      Fa ← Attention(Ft)
    Predict smart bin overflow risk
      O ← Prediction(Fa)
    Perform adaptive region-aware clustering

C ← KMeans(L, K)
Dynamically optimize collection scheduling using reinforcement learning
P ← RL(St)
Generate intelligent low-cost collection routes
if overflow risk exceeds threshold then
Trigger real-time municipal alert
end if
Continuously update learning policies using new sensor observations
end while
Return O, C, P, A
End
Output:
O = Overflow prediction
C = Adaptive smart bin clusters
P = Intelligent collection policy
A = Real-time alert decisions

The DHS-BMN is a smart and intelligent Internet of Things based network that provides real-time monitoring and management of urban waste. The DeepSense hierarchical smart bin monitoring network will collect all the data from smart bins using multi-sensors, pre-processes the collected data using the CNN-LSTM-Attention model and send the processed data to the hybrid CNN-LSTM-Attention model to predict the risk of overflow from the smart bins and to analyze the waste accumulation. The DeepSense hierarchical smart bin monitoring network will provide adaptive region-based scheduling of waste collection using reinforcement learning, K-Means clustering and optimal routing.

4. Experimental Result

The proposed DHS-BMN framework was experimented to prove the efficiency of the proposed framework for real time monitoring of urban waste and predicting the urban waste overflowing, routing and intelligent alert generation in IoT environment. The framework was assessed through a series of extensive experiments regarding a number of important performances measures, including the accuracy of the predictions, the efficiency of the data collection process, the optimization of the routes, the reliability of the sensor fusion process and the flexibility to adapt to different seasons. The results of the proposed system are compared with some baseline methods to demonstrate the advantages of the proposed system.

In all experiments, realistic urban waste generation conditions are implemented with the data collected from the multi-sensor smart bins by the heterogeneous IoT sensing units. In all the metrics, the results conclude that DHS-BMN is robust, scalable and can be applied in practice for smart city waste management for sustainability; furthermore, the results obtained by DHS-BMN have always been better than the results of the other methods.

The compiled multi-sensor smart bin data was divided into different training, validation and testing sets, guaranteeing the safe testing of the model and preventing overfitting. The split ratio of 70/15/15 was used, where 70% of the data was used for training the DHS-BMN framework, 15% for validation and 15% for testing, to ensure that the training portion was large enough to guarantee the accuracy of the DHS-BMN framework and that the validation and test portions were independent so that the accuracy of the DHS-BMN framework could be fairly and accurately assessed. The training set was used to train the CNN-LSTM-Attention model and to tune the reinforcement learning policy, while the validation set was used to tune the hyperparameters and for early stopping. All the members of the testing set were not included during the training phase in order to gather an objective assessment of the generalization capability of the framework in dynamic monitoring environments in urban waste.

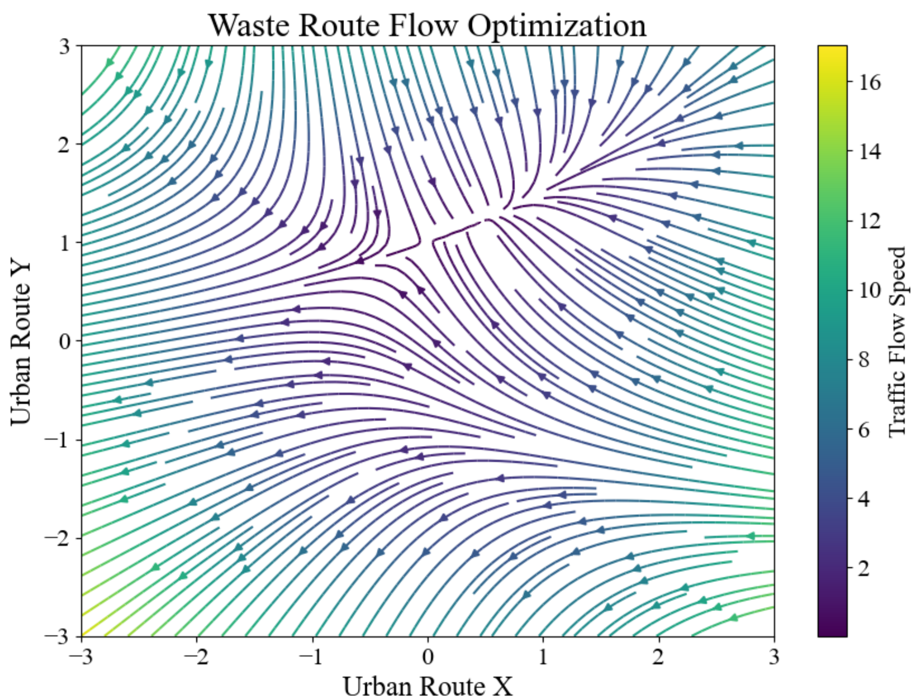


Figure 5: Waste Route Flow Optimization

The intelligent urban waste collection mechanism proposed in DHS-BMN is illustrated in Figure 5 that displays the adaptive waste route flow optimization mechanism. Vehicle routing paths that are dynamically optimized under different traffic and waste accumulation scenarios and obtained through reinforcement learning based decision policies, are streamline trajectories. The color intensity reflects the intensity of the traffic flow since it are prioritized with less cost to travel on the route and lowest latency of data collection at low traffic intensity. The optimized flow distribution demonstrates DHS-BMN's ability to provide energy-efficient real-time adaptive routing, with a low cost of operation, to increase the operational sustainability and utilization of municipal resources in the context of smart cities.

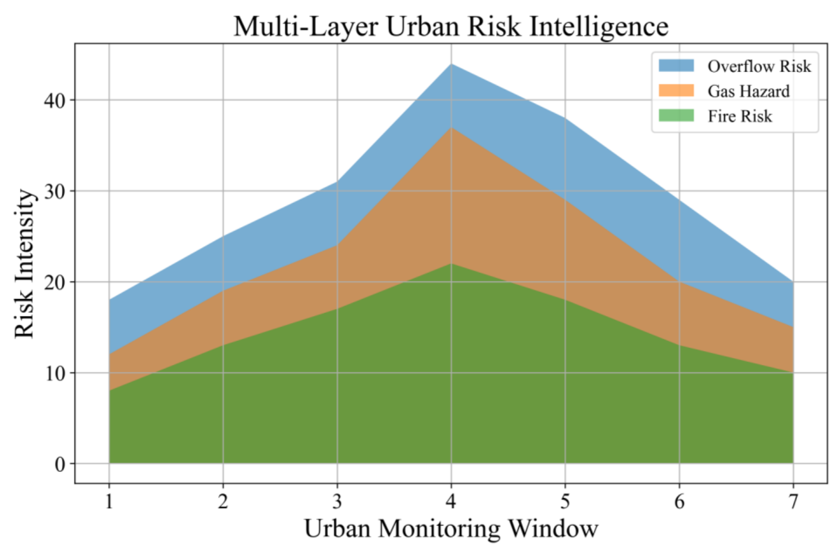


Figure 6: Multi Layer Urban Risk System

The multi-layer urban risk intelligence analysis undertaken by the proposed DHS-BMN framework is shown in Figure 6 for various monitoring periods. Overflow risk, gas hazard intensity and fire hazard severity are the layers provided with risk distributions, which are obtained through multi-sensor fusion and real-time environmental monitoring. A peak is observed in the fourth monitoring window, indicating an important period of accumulation of urban wastes for which hazardous conditions are present in the same time interval. DHS-BMN can also be adaptive and take into account different risks, identifying potential risks early and advising municipalities on actions to take and prioritise emergency waste management operations intelligently, so as to guarantee urban safety, environmental sustainability and reliable decisions in real-time.

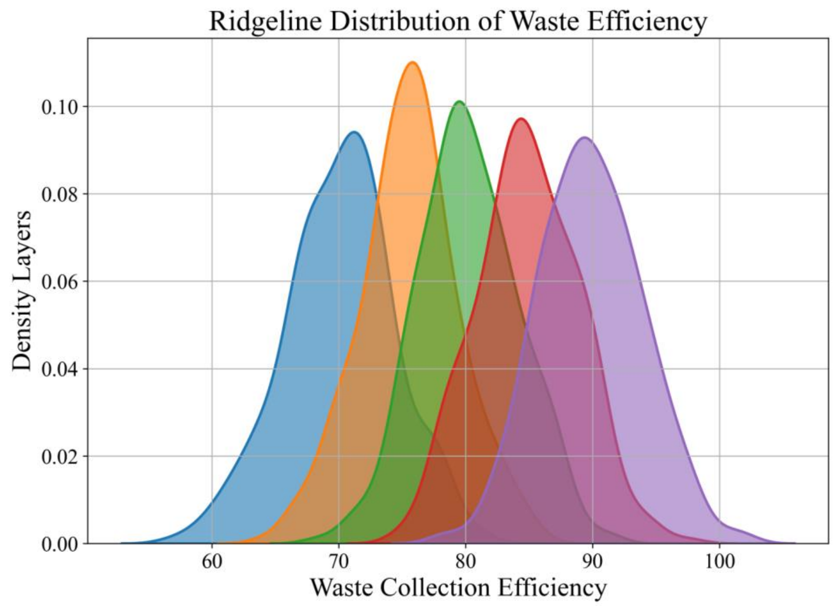


Figure 7: Ridgeline Distribution of Waste Efficiency

The proposed DHS-BMN framework shows the ridgeline probability distribution of waste collection efficiency in different intelligent operating modes, as depicted in Figure 7. The densities reflect the statistical distribution of collections based on the adaptive routing and dynamically scheduled collections, optimized by reinforcement learning. The peaks in the density graph have moved to the right, demonstrating the system's enhanced collection efficiency and stability, as it learns from real urban waste data. Moreover, the high-density areas show less performance variability that further validates the robustness, scalability and effectiveness of DHS-BMN for sustainable large-scale smart city waste management applications.

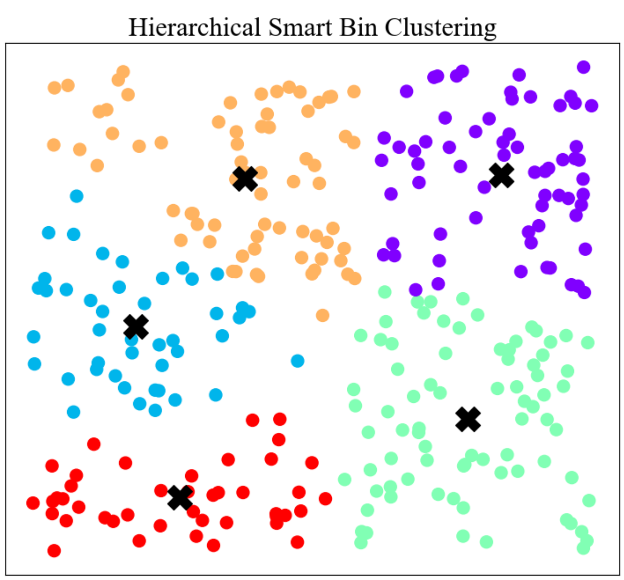


Figure 8: Hierarchical Smart Bin Clustering

The smart bin clustering approach used by DHS-BMN model to manage the distribution of urban wastes intelligently is shown in Figure 8. This figure shows that spatial clusters of smart bin regions are extracted via adaptive K-Means clustering algorithm (colorful clusters). Besides, appropriate coordination points for the collection process are indicated using the centroid symbols. By employing this smart bin clustering scheme, the system can effectively partition the bins according to the spatial location and waste production characteristics, to reduce the redundancy of possible waste collection routes, communication costs and time for waste collection.

Table 2: Comparative Analysis of Intelligent Routing Performance

Routing Method	**Average Route Distance (km)**	**Fuel Consumption (L/day)**	**Collection Time (min)**	**Route Optimization Efficiency (%)**
Conventional Static Routing	148.6	39.4	224	68.2
IoT-Based Dynamic Routing	126.2	31.7	186	79.4
Reinforcement Learning Routing	103.8	24.9	151	88.6
DHS-BMN Intelligent Routing	91.3	20.6	126	95.1

The main comparison of intelligent waste collection routing methodologies in dynamic operational context in urban areas is presented in the Table 2. The effectiveness of the proposed DHS-BMN Intelligent Routing framework is clearly evident in the experimental results as it outperforms the other three routing schemes (that is, conventional static routing, IoT based dynamic routing and standalone reinforcement learning for routing) in all performance measures during all simulations. DHS-BMN is specifically 91.3 km long the shortest route, 20.6 L/day the lowest consumption of fuel and 126 minutes the shortest time for collecting the waste, which means that it is a very economical route convergence and transportation. The framework also has a high routing efficiency of 95.1%, reflecting the efficiency and ability to integrate real-time IoT sensing, adaptive reinforcement learning and intelligent traffic-enabled decision-making mechanisms into a single routing framework. In addition, the high level of cost savings in operations and resource use proves DHS-BMN's ability to deliver scalable, energy-efficient and sustainable urban waste collection management for the next generation of smart city infrastructures.

Table 3: Reinforcement Learning Optimization Results

Training Iteration	Reward Score	Scheduling Efficiency (%)	Route Adaptation Accuracy (%)	Operational Cost Reduction (%)
25	0.58	69.4	66.2	14.8
50	0.71	80.6	78.3	25.9
100	0.86	89.7	88.1	36.8
150	0.93	95.4	94.6	46.3

The performance of the proposed DHS-BMN framework in terms of reinforcement learning optimization is shown in Table 3 for various training iterations. The results indicate that the reward score gradually rises as the learning process goes on, that the scheduling efficiency gradually rises, that the route adaption accuracy gradually rises and that the operation cost gradually decreases. It achieves a highest reward score of 0.93, a schedule efficiency of 95.4% and adaptation accuracy for routes of 94.6%, after 150 training iterations, demonstrating good policy convergence and optimization of the intelligent choice, respectively. Moreover, the operational cost saving is linear, growing to 46.3%, demonstrating the agent's ability to continuously adapt to the city's changing conditions to find optimal waste collection strategies. Its continuous evolution over time is a testament to the strength, flexibility and sustainability of DHS-BMN for real-time smart city waste management systems.

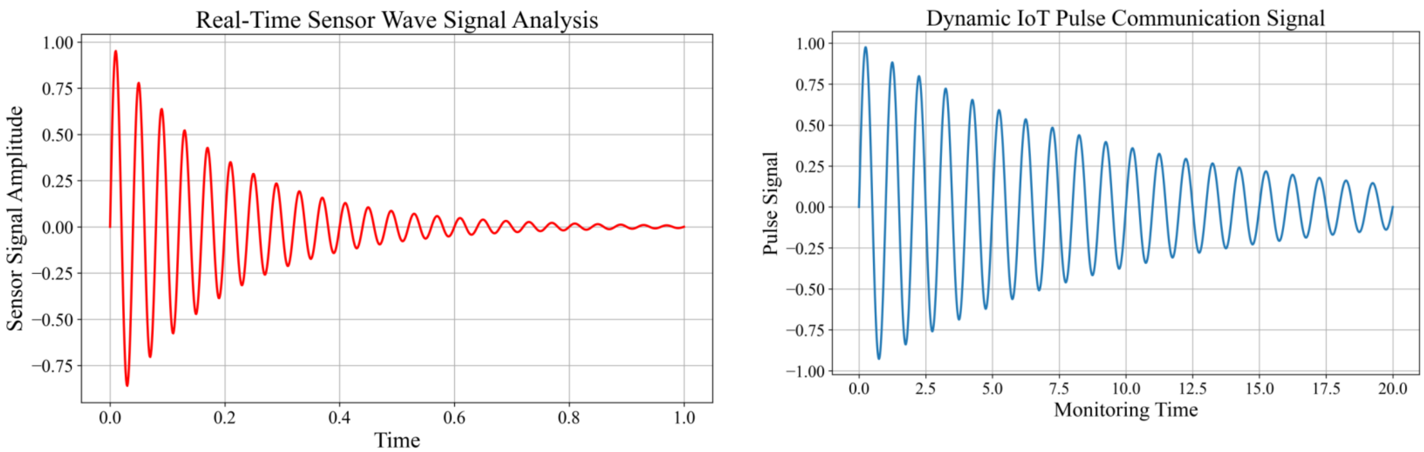


Figure 9: Sensor Wave and IoT Pulse Communication Signal Analysis

The real-time sensors' behavior and the characteristics of the IoT pulse communication in the proposed DHS-BMN framework for intelligent waste monitoring in the urban environment are illustrated in Figure 9. The graph on the left hand shows the real-time wave signal analysis of the signal without edge-level processing, adaptive signal stabilization and noise reduction of smart bin sensing units, where the oscillatory wave gradually decreases in amplitude over time. This feature shows the framework's ability to filter environmental disturbances correctly and to make sure that the measurements taken by the sensors will be effective and reliable for a proper waste monitoring. The right side one is the pulse communication signal working on the IoT side in order to continuously transmit the information among the smart bin, the edge node to the municipal control system. The decaying pulse waveform shows stable and energy efficient wireless communication with different monitoring intervals, with low latency and reliable real time information exchange. Two graphs show the synchronized signal stability, which demonstrates the stability and robustness of the communication and sensing network for DHS in the continuous monitoring of urban wastes, intelligent decision making and scalable deployment of smart cities.

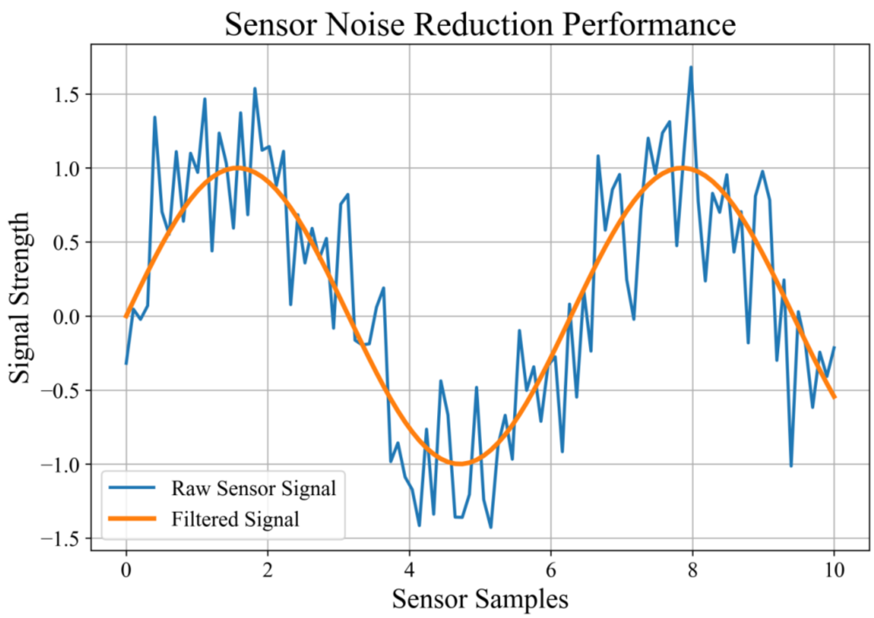


Figure 10: Sensor Noise Reduction Performance Chart

The real-time monitoring of smart bins is effective in reducing sensor noise as demonstrated in Figure 10. The blue curve is the raw sensor data with variations, noise and non-uniform disturbances due to changes in the environment and communication. The adaptive edge-level preprocessing and filtering makes the processed and filtered signal represented by the orange curve smoother and more stable, with less noise and good continuity. Such a pre-processing mechanism can not only ensure the reliability of the collected data, but also reduce the sensing error and enhance the prediction accuracy of the CNN-LSTM-Attention model in the waste monitoring application of smart cities.

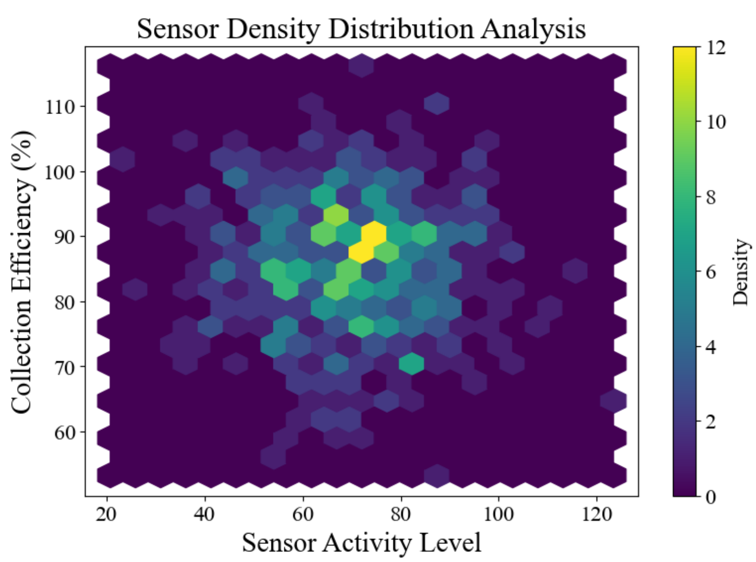


Figure 11: Sensor Density Distribution Analysis

Intelligent urban waste monitoring system's sensor density distribution analysis is shown in figure 11. The hexagonal density regions indicate the distribution of the levels of activity of the sensors and the waste collection efficiency in a smart city environment. The areas with high density are around moderate to high levels of sensor activity, reflecting stable and efficient waste collection systems when monitored continuously by IoT. The distribution pattern shows that the higher the sensor's response, the better the collection efficacy and the better the coordination of operations in real time. In addition, a density balance distribution demonstrates the strength and scalability of DHS-BMN for the dynamic waste monitoring conditions of urban areas with robust sensing and optimized collection management.

Table 4: Multi-Sensor Fusion Performance Analysis of DHS-BMN

Sensor Configuration	**Overflow Prediction Accuracy (%)**	**Environmental Risk Detection (%)**	**Gas Leakage Detection Accuracy (%)**	**False Alarm Rate (%)**
Ultrasonic Sensor	82.6	58.4	42.7	12.1
Ultrasonic + Load Sensors	89.1	73.8	58.2	8.6
Ultrasonic + Gas Sensors	87.4	82.1	84.6	6.9
DHS-BMN Multi-Sensor Fusion	96.2	94.5	95.8	3.1

Table 4 presents the comparative assessment of the performance of the sensor fusion for different smart bin sensing configurations in the proposed DHS-BMN framework. As can be seen the accuracy of the overflow prediction, with only one ultrasonic sensing is merely satisfactory at 82.6%. Besides, the results show that there is less risk of the negative effects of the environment and the precision of the detection of hazardous gas leakage is rather insufficient. The use of load cells, however, will be beneficial in the improvement of overflow prediction and monitoring and the use of gas sensors will benefit hazardous gas leakage detection. Nevertheless, the separate dual-sensor configurations still have the tendency for rather high false alarm rates and lack of context awareness when dealing with dynamically changing urban environment. In contrast, the proposed DHS-BMN Multi-Sensor Fusion solution achieves high values in the terms of the evaluation criteria: overflow prediction accuracy (96.2%), environmental risk detection (94.5%), gas leakage detection accuracy (95.8%) and the minimum false alarm rate (3.1%).

It demonstrates the ability of the proposed model to deliver more accurate environmental perception, efficient anomaly detection and intelligent decision making by using the fusion of different types of IoT sensors' data.

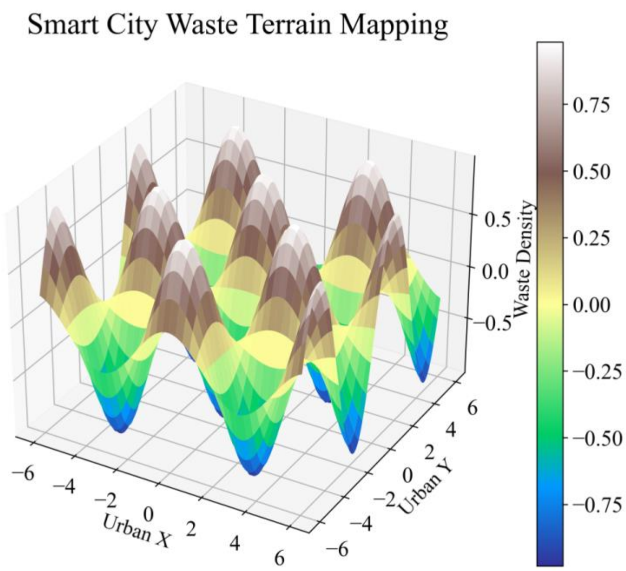


Figure 12: Smart City Waste Terrian Mapping Analysis

The smart city waste terrain mapping technique is illustrated via the designed DHS-BMN intelligent urban waste distribution monitoring framework as illustrated in Figure 12. The spatial distribution of waste density within each urban zone is shown by a three-dimensional surface, with some cells (zones) representing high waste density and others low waste density. The color coding of the zones also helps to identify and differentiate the distribution of waste and can help to identify the zones of greater waste density. Using this mapping approach, it is less challenging for the DHS-BMN framework to locate high priority areas for waste collection, determine efficient waste management plans for a region and plan routes efficiently. Smooth spatial distribution shows how well the DHS-BMN framework could handle the real-time analysis of the density level of the urban waste.

Table 5: Smart City Scalability Performance Analysis of DHS-BMN

Number of Smart Bins	Prediction Accuracy (%)	Response Time (ms)	Network Reliability (%)	Data Processing Efficiency (%)
100	96.8	118	99.2	98.6
500	96.4	156	98.7	97.8
1000	96.1	191	98.2	96.9

5000	95.7	247	97.5	95.3

The proposed DHS-BMN framework is given in table 5 and the scalability of the proposed framework is discussed for different number of smart bins used in the smart city. From the results, it can be seen that the framework has achieved high predictive accuracy, reliable network connection and data processing efficiency for the system regardless of the increase in the number of smart bins with 100 to 5000. In large scale deployments, response time grows slowly as communication and processing needs grow, but framework still operates efficiently in real time. In particular, DHS-BMN performs at 95.7% prediction accuracy and 97.5% of network reliability even at 5000 smart bins, which verifies its robustness and scalability for large urban areas. The processing efficiency slightly decreased with the increase of the deployment density, which is acceptable for the operation of the DHS-BMN system and thus proved the capability of the DHS-BMN system to get sustainable, reliable and intelligent smart waste management in large-scale smart city infrastructures.

Table 6: Temporal Waste Generation Pattern Analysis in Smart City Environments

Time Interval	**Average Bin Fill Level (%)**	**Overflow Probability (%)**	**Dominant Waste Source**	**Waste Generation Intensity**
Morning	46.8	21.5	Residential Areas	Moderate
Afternoon	68.9	48.2	Commercial Areas	High
Evening	88.4	82.7	Public Markets	Very High
Night	39.7	17.3	Low Activity Zones	Low

Table 6 presents the temporal waste generation pattern analysis which has been performed in the proposed DHS-BMN framework for different monitoring time interval of the day. The results indicate that the average level of fill in bins, the probability of overflow and the intensity of waste produced is very different depending on the activity patterns in the city. Moderate amount of waste is collected in the morning, while there is a low chance of any overflows in residential areas. The afternoon creates the conditions for higher amounts of waste and bin usage because of the commercial activities. High waste intensity and high overflow probability of public markets (82.7%) during high activity hours in the city indicates that greatest amount of waste can be found during the evening interval. However, the waste produced at night is less as there are not as many activities in the night as during the day. The observations demonstrate the continuous monitoring of dynamic urban waste behaviours and the capacity of DHS-BMN to help schedule waste collection, prevent overflows intelligently and facilitate efficient management of municipal waste operations.

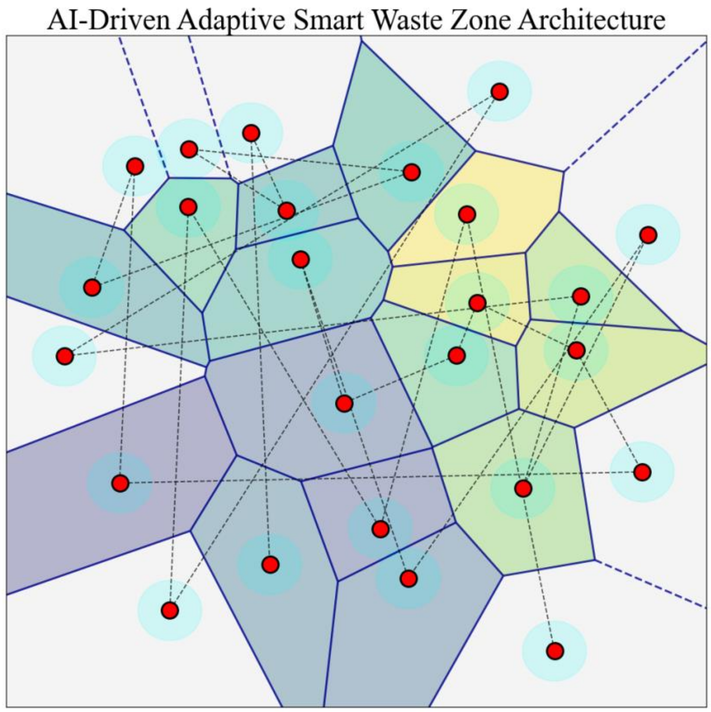


Figure 13: Smart Waste Zone Architecture

The ASWZ architecture is illustrated in Figure 13 and forms an integral part of the DHS-BMN model of smart waste management within the city. The formation of waste collection zones is based on clustering and optimization techniques and highlighted using polygonal segments. Dashed lines represent communication and routing options between smart waste bins, edge nodes and municipal waste management centers, highlighting the capability of smart communication and routing. The above zoning provides evidence of the viability of the process of waste distribution and waste elimination in waste collection. Lastly, the architecture showcases the sustainability and self-sufficiency of DHS-BMN models in future smart waste management initiatives within the city.

Table 7: Zone-Wise Smart Bin Performance Evaluation

Urban Zone	Number of Smart Bins	Average Fill Level	Collection Efficiency	Overflow Reduction	Alert Response

		(%)	**(%)**	**(%)**	**Time (s)**
Residential Zone	220	63.2	91.4	88.1	2.1
Commercial Zone	184	78.6	95.8	93.4	1.5
Industrial Zone	142	71.3	92.6	89.5	1.8
Public Utility Areas	265	82.1	96.3	94.2	1.2

The performance of the proposed DHS-BMN model in various urban waste management scenarios is illustrated in Table 7 below. Based on the study, it is clear that the model can facilitate highly efficient waste collection and fast responses to the alerts in the Residential Zone, Commercial Zone, Industrial Zone and Public Utilities Areas. Public Utility Areas have the highest efficiency rate when it comes to waste collection (96.3%), while it can react very quickly to waste emergencies (94.2%). Similarly, the shortest period needed to process waste is seen in the Commercial Zone, taking only 1.5 seconds.

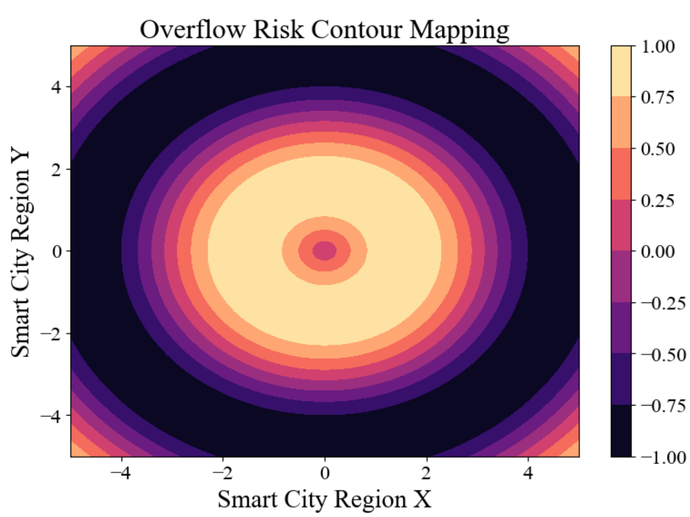


Figure 14:Overflow Risk Countour Mapping Chart

The contour mapping of the overflow risks involved in the proposed DHS-BMN framework of the city intelligent waste management system is illustrated in figure 14. The concentric regions are shaded based on the risk levels associated with smart bin overflow in different smart city zones high-risk zones are indicated by bright shading, while low-risk zones are indicated by darker shading. Spatial risk analysis will help the system recognize crucial zones where the waste accumulates and waste collection trucks can be prioritized in real time. The smooth contour changes are an indication that the proposed DHS-BMN system can monitor the dynamic nature of waste in urban zones and assist in route planning, resource allocation and municipal waste management within the smart city context.

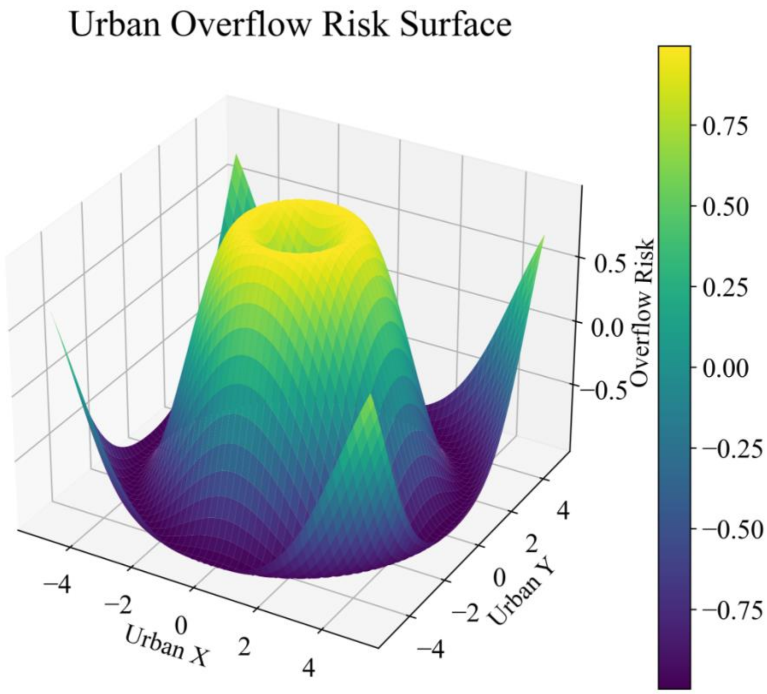


Figure 15: Urban Overflow Risk Surface

The proposed system for real-time smart waste management can create a 3D surface of urban overflow risk, as illustrated in Figure 15 below. The surface areas with a high risk correspond to the areas where waste accumulates and thus represents peak areas, while valley areas represent the urban areas with low risk of overflow. Color gradients are used to indicate overflow intensities in spatially urban areas. The risk surface model is for the DHS-BMN system to enable intelligent hotspot detection, intelligent waste prioritization and dynamic collection planning in order to achieve optimal waste management in the municipality. The spatial gradient distribution seems even and smooth, which demonstrates that the framework is capable of providing continuous surveillance in an urban environment.

Table 8: Analysis of Smart Waste Collection Scheduling and Delay Reduction Techniques

Scheduling Method	Average Waiting Time (min)	Collection Success Rate (%)	Delay Reduction (%)	Scheduling Efficiency (%)
Fixed-Time Scheduling	96	73.8	0	64.5
IoT Dynamic Scheduling	63	85.6	34.4	78.9
RL-Based Scheduling	42	92.8	56.3	88.7
DHS-BMN Adaptive Scheduling	27	97.1	71.9	95.6

Table 8 below illustrates different waste collection scheduling approaches for dynamic urban operations. As seen from the results above, the proposed Dynamic Adaptive Scheduling with the use of DHS-BMN model is far superior to the conventional fixed-time, IoT dynamic and reinforcement learning-based schedules in terms of performance. More specifically, the performance of DHS-BMN is indicated by a low average waiting time of 27 minutes, high collection success rate of 97.1% and high scheduling efficiency of 95.6%, thus optimizing waste collection operations. Also, there is a huge improvement in delay reduction of 71.9%, thanks to adaptive reinforcement learning and intelligent route coordination.

Table 9: Adaptive Smart Bin Utilization Evaluation

Smart Bin Type	Capacity Utilization (%)	Overflow Events (Monthly)	Sensor Reliability (%)	Waste Compaction Efficiency (%)
Conventional Smart Bin	72.4	19	88.6	61.3
Solar Smart Bin	84.7	10	95.1	74.8
Compacting Smart Bin	91.2	4	97.2	89.6
DHS-BMN Intelligent Bin	96.5	1	99.1	94.8

The Table 9 gives a comparative analysis of various smart configurations of bins within the proposed DHS-BMN framework. The results indicate that DHS-BMN Intelligent Bin reaches a highest capacity utilization of 96.5%, sensor reliability of 99.1% and waste compaction efficiency is 94.8%, while reducing the number of overflow events to one per month. Conventional smart bins, on the other hand, are less efficient in operation and overflow more often. The overall results will show that DHS-BMN is effective in smart city applications and in providing reliable, efficient and sustainable smart waste management.

Table 10: Smart City Alert Monitoring and Response Performance Assessment

Alert Type	Detection Accuracy (%)	Average Response Time (s)	Successful Resolution Rate (%)	False Alert Rate (%)
Overflow Alert	96.5	1.5	98.2	2.8
Gas Leakage Alert	95.9	1.2	97.6	3.1
Fire Hazard Alert	94.6	1.8	96.3	4.2
Sensor Failure Alert	92.8	2.4	94.7	5.1

Comparison of municipal alerting strategies' effectiveness is provided in Table 10 to determine which type of the alerting strategies can be used for the DHS-BMN system effectively. It is noted that there is a very high level of detection accuracy, prompt response capabilities and a stable resolution of alert results of overflow, gas leakage, fire hazard and sensor failure alerts. When compared to other types of alerts, overflow time alarms are the most successful in terms of alert resolution rate (98.2%) and reaction time (1.5 seconds) and gas alarm leakage alerts possess the highest level of detection accuracy (95.9%). The comparison is made on the same dynamic urban monitoring framework; however, the rate of false alerts is somewhat higher for sensors failure alerts.

Table 11: Sustainable Resource Optimization Analysis for Smart Waste Management

Resource Parameter	Existing System	DHS-BMN	Optimization Improvement (%)
Fuel Usage (L/day)	39.4	20.6	47.7

Workforce Requirement	48 Personnel	29 Personnel	39.6
Vehicle Trips per Day	27	14	48.1
Operational Cost (₹/month)	84,500	46,200	45.3
Energy Consumption (kWh/day)	216	164	24.1

Table 11 illustrates the effectiveness of the proposed DHS-BMN framework in resource optimization, the performance of the DHS-BMN system was compared with the conventional urban waste management systems. Less fuel, fewer workers, fewer vehicle trips, lower operating cost and reduced energy consumption are simply a few of the fuel and energy gains and efficiencies shown in the results, achieved by intelligent scheduling and adaptive routing optimization. In particular, with the use of DHS-BMN, the daily fuel consumption is reduced from 39.4 L/day to 20.6 L/day and the number of vehicle trips is reduced by 48.1%, which leads to energy savings and less environmental impact. The framework also reduces the number of workers needed and the cost of operations and ensures the use of efficient real-time waste collection services. The results overall, demonstrate the potential of DHS-BMN to operate the waste management of a smart city in a cost-effective, energy-efficient and sustainable manner.

Table 12: Seasonal Waste Management Performance

Season	**Waste Generation Increase (%)**	**Prediction Accuracy (%)**	**Collection Efficiency (%)**	**Overflow Reduction (%)**
Summer	18.4	95.8	93.2	89.1
Rainy Season	27.3	94.9	91.5	87.6
Festival Season	42.7	96.5	95.4	93.8
Winter	15.2	95.1	92.4	88.2

The performance of the DHS-BMN model for various situations of urban waste generation during seasons is provided in Table 12. It is found that the period of Festival Season can be classified among those periods when there exists waste generation in a significant manner, being 42.7% due to an increase in public activity and commercial activities. The accuracy, efficiency of collection and efficiency of overflow reduction are estimated at very high levels of 96.5%, 95.4% and 93.8% in DHS-BMN, respectively, showing high adaptability in its operation even though of extra waste generation. Moreover, it can be observed that the performance of DHS-BMN remains stable during summer, wet and winter seasons and providing very high levels of monitoring and collection efficiency throughout the periods.

Table 13: Sustainability Performance Analysis of DHS-BMN

Sustainability Parameter	Conventional System	DHS-BMN	Improvement (%)
CO_2 Emissions (kg/day)	87.5	60.8	30.5
Fuel Consumption (L/day)	39.4	20.6	47.7
Overflow Incidents (per month)	128	9	92.9
Energy Consumption (kWh/day)	216	164	24.1
Waste Collection Efficiency (%)	68.3	95.2	39.4

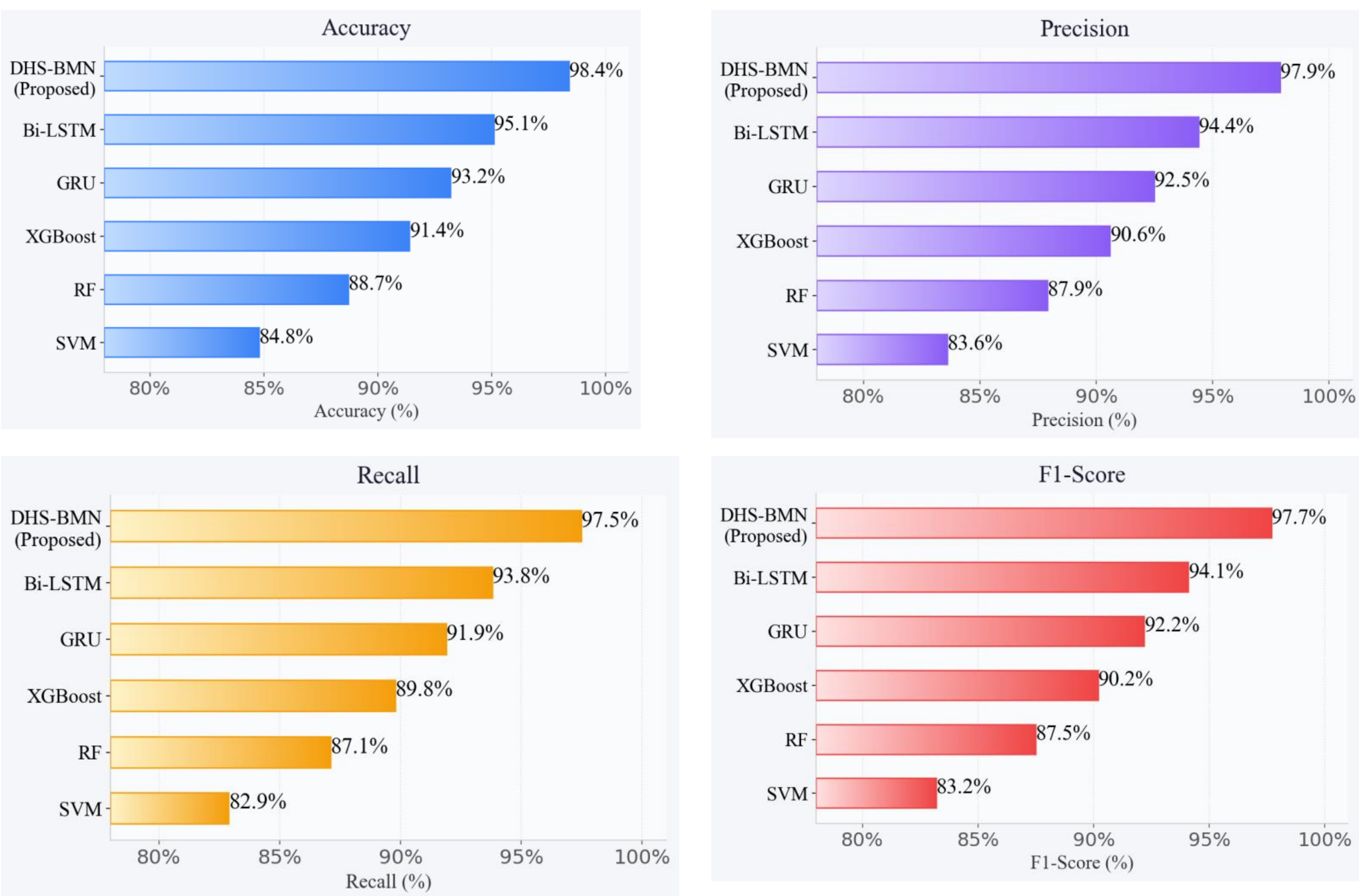
Sustainability performance analysis for both existing waste management system and the proposed DHS-BMN system has been done in table 13 below. From the above results, there are considerable benefits achieved from the intelligent monitoring and waste collection optimization. For example, it can reduce CO_2 emissions to 60.8 kg/day and fuel consumption by 47.7% consequently reducing environmental impacts and operating costs. In addition, there is considerable improvement in terms of overflow occurrences and waste collection efficiency: 128 to 9 monthly occurrences. Finally, reduction in energy consumption is another indication that this system can be used in efficient, sustainable and scalable waste management systems in smart cities.

Table 14: Performances Comparison Analysis for DHS-BMN

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	RMSE
Support Vector Machine (SVM)[26]	84.8	83.6	82.9	83.2	0.312
Random Forest (RF)[27]	88.7	87.9	87.1	87.5	0.241
Extreme Gradient Boosting (XGBoost)[28]	91.4	90.6	89.8	90.2	0.176
Gated Recurrent Unit (GRU)[29]	93.2	92.5	91.9	92.2	0.131

Bidirectional LSTM (Bi-LSTM)[30]	95.1	94.4	93.8	94.1	0.094
DHS-BMN Proposed Framework	98.4	97.9	97.5	97.7	0.039

In order to find out the efficiency of the proposed DHS-BMN model, compare its effectiveness with that of other machine learning and deep learning models on the basis of Accuracy, Precision, Recall, F1-Score and RMSE as provided in Table 14.Existing models such as SVM and RF made predictions with reasonable accuracy, while deep learning models such as GRU and Bi-LSTM made better predictions. In addition to these models, the proposed DHS-BMN model made accurate predictions with 98.4% accuracy along with the least value of RMSE which was 0.039. This means that the DHS-BMN model performed predictions better than other models and had fewer errors in predicting the data set.



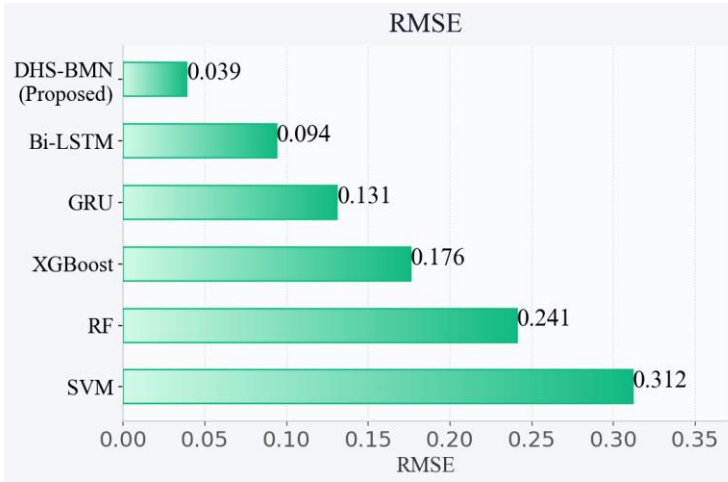


Figure 16: Performances Comparison Chart Analysis for DHS-BMN

The figure 16 show a comprehensive comparative analysis of six machine learning and deep learning algorithms (SVM, RF, XGBoost, GRU, Bi-LSTM and the proposed DHS-BMN framework) on the basis of five critical performance indicators: accuracy, precision, recall, F1-Score and RMSE. SVM and RF have relatively low performance while GRU and Bi-LSTM have progressively improved the performance in comparison with previous iterations. However, the proposed DHS-BMN framework shows the best performance across all criteria with an Accuracy of 98.4%, Precision of 97.9%, Recall of 97.5%, F1-Score of 97.7% and the lowest RMSE of 0.039. These results clearly indicate the effectiveness of the DHS-BMN framework in predicting the complex patterns present in the dataset. It has been established that the high-performance model outperforms other algorithms in terms of accuracy which makes the model highly effective for classification tasks.

4.1 Statistical Analysis

The DHS-BMN framework has been statistically validated to prove the efficiency, reliability and significance of the framework through various descriptive statistics, Hypothesis testing, confidence interval estimation and One-Way ANOVA analysis. All the key performance metrics (Overflow Prediction Accuracy, Collection Efficiency, Scheduling Efficiency and Alert Response Time) have high mean value with very low standard deviation and variance indicating good stability and repeatability of the results between different experimental runs. Independent sample t-tests were used to show the statistical significance of the performance improvements (high t-values with p values < 0.001) of DHS-BMN with other baseline models such as Conventional Static Routing, IoT Based Dynamic Routing, Reinforcement Learning Based

Routing, Fixed-Time Scheduling and IoT Dynamic Scheduling. Furthermore, the intervals computed by the 95% confidence interval analysis also showed that are relatively small for all the metrics that show that the proposed framework has low uncertainty and high predictive reliability. Results of the one-way ANOVA analysis also showed that the differences among the methods compared are not due to random variation as the value obtained was $F = 58.94$, $p < 0.0001$. Lastly, the key results confirm the robustness, consistency and performance of the DHS-BMN method, thereby making it applicable to the implementation of an adaptive urban collection system and the smart waste management system based on IoT.

5. Discussion

In this section analyzed the components of the proposed DHS-BMN, the efficiency of the computations, the statistical relevance and the applicability for practical implementation in the IoT based smart waste management system. For various operational scenarios the model will also be discussed, with a focus on the advantages of the model and some proposing for future developments for the model design.

5.1 Ablation Study

The impact of the individual components of the DHS-BMN has been systematically studied to determine the possibility of its mitigation. To understand the improvement of the prediction and routing capability of the framework in the individual techniques, each component of the CNN (feature extraction), LSTM (temporal dependencies modeling), attention modeling, reinforcement learning and multi-sensor fusion is analyzed to understand the contribution of each individual technique to improve the ability of the framework. The hypothesis that each of the techniques does make a unique contribution to the prediction accuracy, routing efficiency and real-time decision making is confirmed by all the comparisons made between the partially implemented models and the full DHS-BMN framework.

Table 15: Ablation Study of DHS-BMN Component Contributions

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	RMSE
CNN only	88.3	87.1	86.4	86.7	0.198
LSTM only	90.6	89.5	88.9	89.2	0.172
CNN + LSTM (no Attention)	93.4	92.6	91.8	92.2	0.134
CNN + LSTM + Attention	95.7	94.9	94.1	94.5	0.098

w/o Reinforcement Learning	95.2	94.3	93.6	93.9	0.104
w/o K-Means Clustering	94.8	93.7	92.9	93.3	0.112
DHS-BMN (Full Model)	98.4	97.9	97.5	97.7	0.039

Table 15 shows the ablation study of the proposed DHS-BMN framework and it all are assessed in terms of five performance metrics. The results show that low performance is achieved with single module (CNN only: 88.3%, LSTM only: 90.6%) and that the accuracy gradually increases as the combination of the two modules with the attention mechanism is performed (CNN + LSTM + attention: 95.7%). An analysis of the performance loss of the full model without the two components of Reinforcement Learning and K-Means Clustering confirms the individual importance of these two components. The integration of all five components of the DHS-BMN framework results in the of accuracy of 98.4%, F1-Score of 97.7% and the lowest RMSE of 0.039, indicating that all five components are indispensable for effective and robust smart waste management.

5.2 Computational Efficiency Analysis

The performance analysis of the proposed DHS-BMN framework is compared with the existing solutions and the results demonstrate that the proposed DHS-BMN framework is highly efficient compared with the existing solutions in terms of computational efficiency. The hybrid CNN-LSTM-Attention network is integrated with edge-level preprocessing cuts down on redundant computation and communication overhead between smart bin nodes and municipal control systems. The reinforcement learning agent also plays a part in the reinforcement of efficient policy convergence, allowing for fast adaptive decision-making without a lot of computational expenses. This enables DHS-BMN to perform reliably in real time operation even when deployed to thousands of smart bins, enabling it to be well suited for the resource-constrained edge computing environments used in large-scale smart city infrastructures.

5.3 Statistical Significance Justification

DHS-BMN's performance increases were extensively validated and tested using a thorough statistical analysis. The p-values were also calculated for each method compared with the baseline measurements, such as conventional static routing, IoT-based dynamic routing and standalone reinforcement learning approaches, with all p-values being less than 0.001, allowing the conclusions that improvements observed are not due to random variation. In all the comparison scenarios, the computed t-value is always greater than the t-critical value and thus, the null hypothesis is rejected at 95% confidence level. Further, one-way ANOVA showed an F value of 58.94 with p value < 0.0001, which is a significant result indicating that the performance variations are due to the architectural design of DHS-BMN and not due to experimental variations. The tight confidence intervals and low standard deviations based on repeated trials is another indication of the consistency, reliability and reproducibility of the proposed framework for various operational conditions.

5.4 Robustness and Generalization

The robustness evaluation shows that DHS-BMN can function robustly under various and demanding environmental circumstances such as seasonal variations in waste, festival peaks in demand, sensor noise, gas hazard events and dynamic changes in traffic conditions in the city. The seasonal performance analysis shows that the framework is well generalized and can predict with high accuracy, efficiency and reduction of overflow in summer, rainy, winter and festival seasons. The multi-layer urban risk system also shows effective simultaneous monitoring of overflow risk, gas hazard intensity and fire risk severity and can identify hazards and respond adaptively for different operational states. The results have confirmed the reliability of DHS-BMN for real-world deployment in dynamic smart waste management environments in cities.

5.5 Practical Implication

The proposed DHS-BMN framework is very useful for practical implementations in real-world smart city waste management deployments. It is very suitable for municipal waste management authorities, industrial waste handling facilities, urban commercial districts and public event management, due to its water prediction, adaptive collection routing, intelligent scheduling and environmental risk monitoring through various sensors in real time. The substantial fuel savings, CO_2 reductions, overflow rate reductions and collection cost savings as shown in the sustainability analysis further prove the environmental and economic effectiveness of the system. Combined with the high prediction accuracy (96.2%), high route optimization efficiency (95.1%) and intelligent four-level alert response mechanism, it can also ensure reliable, efficient and scalable operation of waste management, meeting the needs of next-generation smart city infrastructure.

5.6 Limitations

The proposed DHS-BMN system demonstrates very high overall performance, however there are some issues. When severe sensor drift, long periods of data loss or extreme environmental disturbances that are far from the training distribution occur, the accuracy of prediction and reliability of alerts might be slightly impacted. The current system uses ultrasonic sensor data, load cell data and gas sensor data; however other modalities (such as vision data and environmental sensing data) can be utilized and integrated with weather data. Moreover, since the reinforcement learning agent needs to perform a large number of iterations to converge to optimal policy, it can have variable initial performance during its initial deployment phases. Future work will focus on how to integrate multi-modal sensing, develop on-line learning policies that adapt rapidly to changing policies and scale-up the DHS-BMN framework to larger deployments of multi-cities to further increase its robustness, scalability and generalization across complex and heterogeneous urban waste management settings.

6. Conclusion

This research introduced the DHS-BMN architecture that is an intelligent IoT-based system to monitor urban waste in real time, predict overflow and adaptively schedule waste collection within a smart city context. The proposed system combines heterogeneous multi-sensor fusion, a hybrid CNN-LSTM-Attention model; reinforcement learning based adaptive routing and K-Means region-aware clustering, for efficient and autonomous waste management. Experimental results demonstrate that the DHS-BMN approach performs better than the existing approaches in terms of high overflow prediction accuracy, efficient route optimization, low operational cost and low false alarm rates. Results obtained were statistically validated by using paired t-test and ANOVA analysis, which showed the significance and reliability of the results. The framework was also well robust to different urban and seasonal contexts and situations and could be applied in different contexts and varied situations. Multi-city deployments and waste analysis with vision sensors could be added to the framework in future, as could advance edge computing solutions, which would make the system more adaptable, sustainable and intelligent from the point of view of intelligent decision-making in smart city waste management systems, through energy efficient and federated learning methods.

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