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WASTE OVERFLOW PREDICTION USING SPATIAL TEMPORAL FUSION TRANSFORMER (STFT) AND EMERGENCY ALERT MANAGEMENT SYSTEM

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Abstract - Efficient waste management has become a major challenge in rapidly urbanizing environments due to dynamic and spatially distributed waste generation patterns. Traditional fixed-schedule waste collection systems fail to adapt to real-time conditions, leading to inefficient operations, unnecessary fuel consumption, and frequent overflow scenarios [1]. IoT-enabled smart bin monitoring systems allow continuous real-time data acquisition and improve operational visibility [2]. However, most existing solutions operate reactively and lack predictive decision support for proactive waste collection planning [3].

This paper proposes a Waste Overflow Prediction and Emergency Alert Management System based on a Spatio-Temporal Fusion Transformer (STFT). The proposed model integrates spatial attention across distributed smart bins with temporal forecasting to predict future fill levels and identify potential overflow events in advance [4]. A realistic synthetic smart-bin dataset containing 657,000 records collected from 75 bins over a 12-month period was generated to evaluate the system [5].

Experimental results demonstrate that the proposed STFT model achieves an R^2 score of 0.95, RMSE of 4.7, and MAE of 3.2, outperforming the strongest baseline model (Temporal Fusion Transformer) by 11% in RMSE [6]. In addition, the dynamic route optimization module reduces travel distance by 23% compared to traditional fixed-schedule waste collection [7].

The integration of sensing, prediction, and intelligent routing demonstrates a scalable and practical solution for next-generation smart city waste management systems [8].

Keywords - Smart Waste Management, IoT, Spatio-Temporal Fusion Transformer, STFT, Machine Learning, Route Optimization, Smart Cities.

I. INTRODUCTION

Urban waste management has become a critical challenge due to rapid urbanization and increasing waste generation. Traditional waste collection systems operate on fixed schedules, which do not account for dynamic variations in waste accumulation [4]. This results in inefficient operations, including unnecessary collection trips and overflow conditions in high-demand areas [5].

IoT-based waste management systems have been introduced to improve monitoring by enabling real-time tracking of bin fill levels [1]. These systems utilize sensor networks to collect and transmit data to centralized platforms [12]. The availability of real-time data enhances operational visibility and reduces manual inspection efforts [7]. However, such systems remain reactive, as they trigger alerts only after bins reach predefined thresholds, thereby failing to prevent overflow conditions.

To overcome these limitations, predictive modeling techniques have been explored to forecast waste generation patterns. Machine learning models such as Artificial Neural Networks have demonstrated the ability to capture nonlinear relationships in waste accumulation data [9]. These models improve prediction accuracy by leveraging historical trends [14]. However, they are limited in capturing long-range temporal dependencies and often treat each bin independently.

Recurrent neural networks such as Long Short-Term Memory and Gated Recurrent Unit models improve temporal modeling by capturing sequential dependencies. Despite this improvement, these models lack spatial awareness and do not account for correlations between bins in different locations. In urban environments, waste generation patterns exhibit strong spatial dependencies, where nearby bins often show similar behavior [8]. Incorporating spatial information is therefore essential for accurate prediction [13].

Transformer-based architectures have emerged as effective models for sequence prediction tasks due to their ability to capture long-range dependencies using attention mechanisms [10]. These models process multiple features simultaneously and improve prediction performance [11]. However, standard transformer models do not explicitly incorporate spatial relationships, limiting their applicability in geographically distributed systems.

In addition to prediction, route optimization plays a significant role in improving waste collection efficiency. Graph-based algorithms such as Dijkstra’s algorithm are used to determine optimal routes for collection vehicles [4]. These methods reduce travel distance and operational cost [5]. However, most routing systems rely on static data and do not integrate predictive insights, which limits their effectiveness in dynamic environments.

Recent smart city frameworks aim to integrate IoT, cloud computing, and data analytics to improve urban infrastructure management [2]. These systems provide scalable platforms for monitoring and coordination [6]. Despite these advancements, many implementations remain modular, with limited interaction between monitoring, prediction, and decision-making components.

To address these challenges, this paper proposes an Intelligent Waste Overflow System that integrates IoT-based sensing, Spatio-Temporal Fusion Transformer (STFT)-based prediction, and dynamic route optimization. The STFT model captures both temporal patterns and spatial dependencies, enabling accurate prediction of waste levels across multiple locations. The integration of predictive modeling with decision-making and routing enables proactive waste management and improves operational efficiency.

Contributions of the Paper

The main contributions of this work are summarized as follows:

1. A novel Spatio-Temporal Fusion Transformer (STFT) framework for multi-bin waste level forecasting that jointly captures spatial correlations and temporal dynamics [8].
2. Integration of overflow prediction with an emergency alert generation and dynamic route optimization system, enabling proactive waste collection planning [7].
3. A realistic synthetic smart-bin dataset generation methodology designed for research evaluation and reproducibility in smart-city waste management studies [5].

4. A comprehensive comparison with deep learning baselines and an ablation study validating the effectiveness of the proposed architecture and system components [6].

II. LITERATURE REVIEW

The development of intelligent waste management systems has evolved through multiple research directions, including IoT-based monitoring, machine learning prediction models, deep learning approaches, and route optimization techniques. This section reviews these approaches and highlights their limitations.

IoT-Based Waste Monitoring Systems

IoT-enabled waste monitoring systems have been widely adopted to support real-time tracking of smart bins. These systems utilize sensors such as ultrasonic and infrared devices to measure fill levels and transmit data to centralized cloud platforms for analysis and visualization [1]. The deployment of sensor networks improves operational transparency, reduces manual inspection, and enables continuous monitoring of waste accumulation trends [7], [12].

Despite these benefits, most IoT-based systems operate in a reactive manner. Alerts are typically generated only after bins exceed predefined thresholds, which does not prevent overflow but merely responds to it after occurrence. This limitation highlights the necessity of integrating predictive intelligence into waste management frameworks.

Machine Learning-Based Prediction Models

To address the limitations of reactive monitoring, machine learning techniques have been introduced to forecast waste generation patterns using historical data. Artificial Neural Networks and regression-based models have demonstrated the ability to capture nonlinear relationships in waste accumulation trends [9]. These approaches improve forecasting accuracy by leveraging temporal patterns present in historical observations [14].

However, conventional machine learning models struggle to capture long-range temporal dependencies and typically treat each bin independently. The absence of spatial awareness limits their effectiveness in urban environments where waste generation is influenced by surrounding locations and shared behavioral factors.

Deep Learning and Sequence Models

Deep learning architectures have significantly improved prediction performance in time-series applications. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, effectively capture sequential dependencies and long-term temporal relationships. These models outperform traditional machine learning approaches in many forecasting tasks.

Transformer-based architectures have further advanced sequence modeling by introducing attention mechanisms that capture long-range dependencies more effectively [10]. These models process multiple input features simultaneously and improve prediction accuracy in complex datasets [11].

However, standard deep learning models, including transformers, primarily focus on temporal dependencies and do not explicitly incorporate spatial relationships. This limitation reduces their effectiveness in applications where spatial correlation plays a significant role.

Spatio-Temporal Modeling Approaches

Recent research emphasizes the importance of integrating spatial and temporal dependencies within predictive models. Spatio-temporal approaches capture relationships across multiple locations while modeling temporal variations in data [8]. These models have demonstrated improved accuracy in applications such as traffic forecasting environmental monitoring, and energy demand prediction.

In urban waste management scenarios, bins located in close proximity often exhibit correlated usage patterns due to geographical and behavioral factors [13]. This observation motivates the integration of spatial attention mechanisms with temporal learning to improve forecasting accuracy.

Route Optimization Techniques

Efficient waste collection requires optimized routing of collection vehicles. Graph-based algorithms such as Dijkstra's algorithm are widely used to compute shortest paths in waste collection networks [4]. These techniques aim to reduce travel distance, fuel consumption, and operational costs [5]. However, most routing strategies rely on static or periodically updated data, limiting their ability to adapt to real-time conditions. Integrating predictive overflow insights into routing decisions is essential for achieving proactive waste collection.

Integrated Smart Waste Management Systems

Modern smart city frameworks attempt to combine IoT, cloud computing, and data analytics to create unified waste management platforms [2], [6]. These systems improve coordination between monitoring and decision-making components.

Nevertheless, many existing implementations remain modular and loosely coupled, with limited interaction between sensing, prediction, and optimization modules. This lack of integration prevents the realization of fully proactive and adaptive waste management.

Research Gap

Existing forecasting approaches primarily focus on temporal prediction using models such as LSTM and Temporal Fusion Transformer, which capture time-based dependencies but ignore spatial relationships between bins [3]. Conversely, spatial models used in smart-city applications often lack multi-horizon forecasting capability and predictive decision support [4]. To the best of our knowledge, no prior work integrates spatial attention, temporal fusion, overflow alert generation, and route optimization into a unified framework for smart waste management [1], [7]. This paper addresses this gap by proposing a fully integrated predictive and decision-support system.

III. METHODOLOGY

The proposed Intelligent Waste Overflow System is designed as a closed-loop spatio-temporal decision framework that integrates real-time sensing, predictive modeling, and dynamic routing. Unlike modular approaches that separate monitoring, prediction, and optimization, the proposed architecture enables continuous interaction between components, allowing predictions to directly influence operational decisions.

A. Data Acquisition and Preprocessing:

The system collects time-series data from multiple bins distributed across different locations. Each data point includes fill level, timestamp, and bin identifier. Raw sensor data is preprocessed to ensure consistency and reliability. Missing values are handled using interpolation techniques, while outliers are removed to prevent noise from affecting model performance. Data normalization is applied to improve training stability. Feature engineering is performed to enhance predictive performance. Temporal features such as hour-of-day and day-of-week are encoded to capture periodic patterns in waste generation [9]. Historical data sequences are constructed to provide context for prediction [14]. Spatial identifiers are included to represent bin locations, enabling the model to learn inter-bin relationships [8].

B. System Architecture

1) Overview

The overall system consists of five major modules:

1. Smart Bin Data Acquisition
2. Data processing and feature engineering layer
3. STFT-based prediction model
4. Decision and route optimization module
5. Overflow Alert and Decision Engine

IoT-enabled smart bins continuously monitor waste levels using ultrasonic sensors and transmit data to a cloud platform [1]. These systems improve real-time visibility and reduce manual inspection [7]. Sensor-based monitoring ensures accurate data collection across distributed locations [12]. Cloud-based infrastructures provide scalable storage and computation for processing large volumes of data [11].

2) Data Representation

The input data is modeled as a spatio-temporal tensor:

$X \in \mathbb{R}^{B\times T\times N\times D}$

Here B denotes the batch size, Trepresents the number of time steps (sequence length), N indicates the number of bins, and D corresponds to the number of features. This formulation allows the model to process multiple bins simultaneously while capturing their interactions over time.This formulation allows the model to simultaneously process multiple bins and capture their interactions over time.

3)Spatio-Temporal Fusion Transformer (STFT)

The STFT model extends transformer-based architectures by incorporating both spatial and temporal attention mechanisms.
This enables the model to capture complex dependencies in waste generation patterns.

3.1)Spatial Attention Mechanism

To capture inter-bin relationships, a multi-head spatial attention mechanism is incorporated. This enables the model to learn dependencies between geographically distributed bins.

$$A_h = \mathrm{softmax}\left(\frac{Q_h K_h^T}{\sqrt{d_k}}\right) V_h$$

Here, (Q_h), (K_h), and (V_h) represent the query, key, and value matrices respectively, while (d_k) denotes the dimensionality of the key vectors.

This mechanism enables the model to capture interactions between bins, allowing it to learn spatial dependencies in waste generation [8]. These dependencies are critical in urban environments where nearby bins exhibit similar behavior [13].

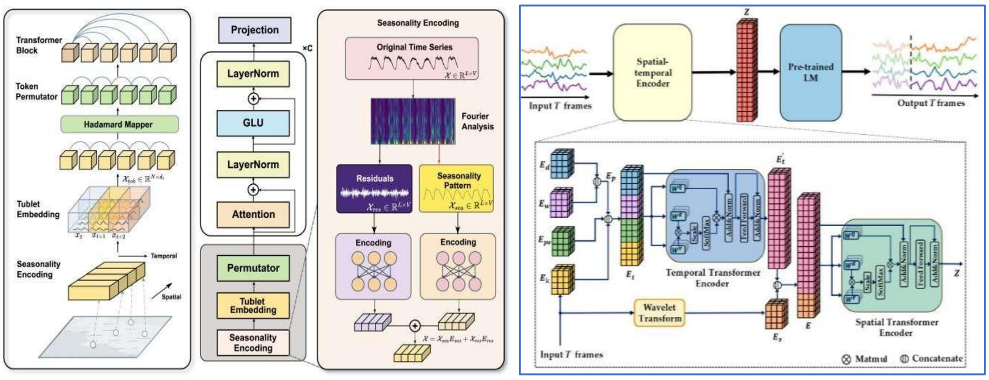

Fig. 1. Spatial-Temporal Fusion Transformer Architecture

3.2) Temporal Fusion Mechanism

Temporal dependencies are modelled using attention-based sequence learning:

$e_t = \mathrm{GRN}(\mathrm{LayerNorm}(\mathrm{MSA}(X_t) + X_t))$

Here, GRN refers to the Gated Residual Network, MSA denotes Multi-head Self Attention, and (X_t) represents the input at time step (t).

This mechanism captures long-range temporal dependencies and improves sequence modeling [10]. Multi-head attention allows the model to learn multiple temporal patterns simultaneously [11].

3.3) Gated Residual Networks (GRN)

Gated Residual Networks are employed for feature transformation and variable selection. They enhance model interpretability by identifying important features contributing to prediction while maintaining stable gradient flow during training.

4)Spatial Positional Encoding

To enable spatial awareness, the geographical relationship between bins is encoded using a distance-based spatial adjacency matrix.

Let the geographic coordinates of bin i be (lat_i, lon_i).
The pairwise spatial distance between bins i and j is computed using Euclidean distance:

$$d_{ij} = \sqrt{(lat_i - lat_j)^2 + (lon_i - lon_j)^2}$$

A spatial similarity matrix is then constructed using a Gaussian kernel:

$$S_{ij} = \exp\left(-\frac{d_{ij}^2}{\sigma^2}\right)$$

where σ controls spatial influence.
This matrix is used as a spatial bias in the attention mechanism:

$$\mathrm{Attention}(Q, K, V) = \mathrm{Softmax}\left(\frac{QK^T}{\sqrt{d_k}} + S\right)V$$

This enables the model to prioritize nearby bins while still capturing long-range dependencies.

4) Feature Selection and Fusion

The STFT incorporates a variable selection mechanism that dynamically weights input features based on their relevance.

This reduces noise and improves interpretability. Spatial and temporal representations are fused through hierarchical

attention layers, ensuring that both local and global dependencies are preserved.

C. Training and Optimization

The model is trained using historical waste data through supervised learning, with the objective of minimizing the prediction error between actual and predicted waste levels. Training uses the Mean Squared Error (MSE) loss function and the Adam optimizer with a learning rate of 0.001, along with a batch size of 64 and 50 training epochs. The model is designed to predict future waste levels over a specified horizon using past observations, and different time lags are evaluated to determine the optimal temporal context.

D.Mathematical Formulation of Prediction

The waste level forecasting task is formulated as a multi-step spatio-temporal prediction problem, where the objective is to estimate future fill levels of multiple waste bins using historical observations collected over time. Let the historical input tensor be represented as:

$X \in \mathbb{R}^{T\times N\times F}$

where T denotes the number of historical time steps, N represents the number of bins (spatial locations), and F indicates the number of input features. The Spatio-Temporal Fusion Transformer learns a nonlinear mapping function that predicts the future fill level for each bin over a prediction horizon H:

$$\hat{y}_{t+h} = f_{STFT}(X_{t-T+1:t})$$

where f_{STFT} represents the proposed model and h denotes the forecasting horizon.

The model is trained by minimizing the Mean Squared Error (MSE) between the actual and predicted waste levels across all bins and time horizons:

$$L = \frac{1}{NH}\sum_{i=1}^{N}\sum_{h=1}^{H}(y_{i,t+h} - \hat{y}_{i,t+h})^2$$

where $y_{i,t+h}$ and $\hat{y}_{i,t+h}$ denotes the actual and predicted fill levels of bin i at time t+h, respectively. This formulation enables simultaneous forecasting across multiple bins while capturing complex spatial and temporal dependencies in waste generation patterns.

E. Decision Layer (Overflow Prediction and Prioritization)

The predicted fill levels are used to determine overflow risk:

$$R_i = \begin{cases} 1, & \hat{y}_i \geq \tau \\ 0, & \hat{y}_i < \tau \end{cases}$$

where τ is the threshold, $\hat{y}_i$ is the predicted fill level of bin i.

A prioritization score is computed as:

$$S_i = \alpha\hat{y}_i + \beta T_i$$

where T_i represents urgency based on time since last collection, α, β are weight parameters.

This mechanism ensures that bins are selected based on both predicted fill levels and operational constraints.

F. Route Optimization and Alert Generation

Predicted fill levels are converted into overflow alerts using threshold τ:

$$\text{Alert}_i = \begin{cases} 1, & \hat{y}_i \geq \tau \\ 0, & \text{otherwise} \end{cases}$$

Bins generating alerts are added as nodes in a routing graph.

Each road segment is assigned a weight based on travel distance.

Dijkstra’s algorithm is then applied to compute the shortest path visiting all priority bins. To evaluate routing efficiency, the optimized route is compared with fixed-schedule routing using total travel distance:

$$\text{Distance Reduction}(\%) = \frac{D_{\text{fixed}} - D_{\text{optimized}}}{D_{\text{fixed}}} \times 100$$

Simulation results show an average 23% reduction in travel distance.

G. System Workflow

The overall workflow of the proposed system begins with IoT sensors collecting real-time waste data from smart bins, which is then transmitted to a cloud platform. The data undergoes preprocessing and feature engineering before being used by the STFT model to predict future waste levels. Based on these predictions, alerts are generated for bins nearing overflow, enabling authorities to take proactive action.

H. System Advantages

The proposed methodology provides several advantages. The integration of IoT sensing with spatio-temporal modeling improves prediction accuracy. The STFT model captures complex dependencies across space and time. The decision layer enables proactive waste management. The routing component reduces operational cost and improves efficiency. Integrated systems combining sensing, prediction, and optimization have been shown to improve performance in smart city applications [2]. The use of AI-driven techniques contributes to sustainable waste management and reduced environmental impact [13].

IV. EXPERIMENTAL SETUP

A. Synthetic Smart-Bin Dataset Generation

Since real-world large-scale smart-bin datasets are not publicly available, a realistic synthetic dataset was generated to simulate urban waste accumulation patterns. Synthetic data generation is widely adopted in smart city research to evaluate system performance under controlled yet realistic conditions.

The simulated dataset represents waste collection behaviour across 75 smart bins deployed in an urban environment over a period of 12 months.

1)Data Sampling

Waste levels were recorded at hourly intervals, resulting in:
75 bins×24 hours×365 days=657,000 records

Each record contains both spatial and temporal attributes.

2)Features in Dataset

Each data sample contains the following attributes:

Bin ID, Timestamp (date and hour), Fill level (%), Day of week, Weekend/weekday indicator, Peak hour indicator, Location coordinates (latitude and longitude), Population density (simulated), Nearby commercial activity index (simulated), Weather influence factor (simulated), Time since last collection, and Historical rolling average of fill level.

These features were generated using probabilistic distributions and periodic functions to mimic real urban waste generation patterns such as daily peaks, weekend surges, and seasonal variations.

3) Spatial Correlation Modeling

To simulate real-world spatial dependency, bins located within close proximity were assigned correlated waste generation patterns using Gaussian spatial clustering. This ensures that nearby bins exhibit similar fill trends, reflecting realistic urban behaviour.

4) Data Split

The dataset was divided into training, validation, and testing sets in the ratio 70:15:15. The training set was used to learn model parameters, the validation set was used for hyperparameter tuning, and the testing set was used for final performance evaluation.

TABLE I: SYNTHETIC DATASET STATISTICS

Parameter	Value
Number of smart bins	75
Simulated city region	Urban metropolitan zone
Time span	12 months
Sampling interval	1 hour
Total records	657,000
Features per record	12
Missing data rate	3.5% (simulated sensor loss)
Training samples	459,900 (70%)
Validation samples	98,550 (15%)
Testing samples	98,550 (15%)

B. Baseline Models

To evaluate the effectiveness of the proposed Spatio-Temporal Fusion Transformer (STFT), its performance is compared with several baseline models commonly used for time-series prediction: Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Temporal Fusion Transformer (TFT).

ANN models serve as a baseline for nonlinear regression but lack the ability to capture temporal dependencies [9]. LSTM and GRU models improve prediction performance by modeling sequential patterns in time-series data. However, these models are limited in capturing long-range dependencies and spatial relationships.

The TFT model incorporates attention mechanisms to capture temporal dependencies more effectively and perform feature selection [10]. However, it does not explicitly model spatial interactions between bins.

The proposed STFT model extends TFT by incorporating spatial attention, enabling it to capture both temporal and spatial dependencies, which are critical for accurate prediction in distributed systems.

TABLE II: SYNTHETIC DATASET STATISTICS

Model	Embedding Size	Input Length	Feature Size	Number of Layers	Batch Size	No. of Epochs
ANN	128	24	12	3	64	50
LSTM	128	24	12	2	64	50
BiLSTM	128	24	12	2	64	50
GRU	128	24	12	2	64	50
TFT	256	24	12	4	64	50
STFT	256	24	12	4	64	50

C. Dataset Description

The dataset used in this study consists of time-series data collected from IoT-enabled smart waste bins deployed across multiple urban locations. Each data instance includes fill-level measurements from ultrasonic sensors, timestamp information such as hour, day, and date, bin identification and location attributes, and derived temporal features like peak hours and usage patterns. The dataset captures both temporal variations, including daily and weekly waste patterns, and spatial distribution across multiple bins, making it well suited for spatiotemporal modeling. Data preprocessing involves handling missing values using interpolation techniques, applying normalization for stable model training, and performing feature engineering to extract meaningful temporal and spatial attributes.

D. Hardware and Software Environment

The proposed system was implemented using Python and deep learning libraries.

Software

- Python 3.10
- PyTorch deep learning framework
- NumPy and Pandas for data processing
- Scikit-learn for evaluation metrics

Hardware

- Intel i7 Processor
- 16 GB RAM
- NVIDIA GPU (8 GB VRAM)

GPU acceleration significantly reduced training time and enabled efficient handling of the attention-based architecture.

E. Model Configuration

The STFT model is configured with the following parameters:

- Embedding dimension: 256
- Input sequence length: 24
- Number of features: 12
- Number of attention layers: 4
- Batch size: 64
- Number of training epochs: 50

The model is trained using the Adam optimizer with a learning rate of 0.001. The Mean Squared Error (MSE) loss function is used to minimize prediction error. The choice of embedding dimension balances model capacity and computational efficiency. A sequence length of 24 captures daily temporal patterns in waste generation. The number of layers is selected to ensure sufficient model depth without overfitting.

TABLE III: BASELINE MODEL HYPERPARAMETERS

Model	Hidden Units	Layers	Learning Rate	Batch Size	Optimizer
ANN	128	3	0.001	64	Adam
LSTM	128	2	0.001	64	Adam
BiLSTM	128	2	0.001	64	Adam
GRU	128	2	0.001	64	Adam
TFT	256	4	0.001	64	Adam
STFT	256	4	0.001	64	Adam

F. Training Strategy and Convergence

The model is trained using supervised learning, where input sequences are mapped to future waste level predictions. A sliding window approach is used to generate input-output pairs, enabling the model to learn temporal dependencies. During training, the loss function is minimized using gradient-based optimization. The convergence behavior is monitored using validation loss, ensuring that the model does not overfit. Early stopping criteria can be applied if validation loss does not improve over consecutive epochs. Regularization techniques such as normalization and dropout are used to improve generalization. These techniques prevent overfitting and enhance model robustness. The training process demonstrates stable convergence, with loss decreasing steadily over epochs, indicating effective learning of pattern.

G. Hyperparameter Tuning

Hyperparameters were tuned using grid search on the validation dataset. The tuning process evaluated multiple configurations of learning rate, batch size, number of attention heads, and number of transformer layers. The learning rate was tested with values 0.001, 0.0005, and 0.0001. The batch size was evaluated with values 32, 64, and 128. The number of attention heads was varied between 4 and 8, and the number of transformer layers was tested with 2, 4, and 6 layers. The final model configuration was selected based on the lowest validation loss and stable convergence behaviour.

H. Cross-Validation Strategy

To ensure robustness, 5-fold cross-validation was performed. The dataset was divided into five subsets, and the model was trained and validated across multiple folds. The reported results represent the average performance across all folds, reducing variance and improving reliability.

I. Evaluation Metrics

The performance of the models is evaluated using standard regression metrics, including Mean Absolute Error (MAE), which measures the average prediction error, Root Mean Squared Error (RMSE), which penalizes larger errors more heavily, and the Coefficient of Determination (R^2 score), which reflects model fit and predictive accuracy. Together, these metrics provide a comprehensive evaluation of prediction performance and allow comparison across different models' ability to predict waste levels. Additionally, Mean Absolute Percentage Error (MAPE) is included as a scale-independent metric widely used in waste forecasting studies.

J. Computational Complexity and Scalability

The computational complexity of the STFT model is higher than traditional models due to the use of multi-head attention mechanisms. The complexity of attention operations grows with the number of bins and sequence length. However, the model is designed to leverage parallel computation, enabling efficient processing of large datasets. The use of cloud-based infrastructure further supports scalability, allowing the system to handle large-scale deployments [11].

K. Implementation Environment

The model is implemented using a deep learning framework and trained on a system equipped with GPU acceleration. The use of GPU significantly reduces training time and improves computational efficiency.

The integration of IoT devices, cloud infrastructure, and AI models creates a scalable system architecture suitable for smart city applications [2].

L. Design Rationale

The embedding dimension was set to 256 to balance model capacity and computational efficiency, ensuring sufficient representation power without excessive computational cost. A sequence length of 24 hours was selected to capture daily waste generation patterns and periodic variations in urban activity. Four attention layers were used to provide adequate model depth for learning complex spatio-temporal dependencies while avoiding overfitting. These design choices were validated through the hyperparameter tuning process based on validation loss and training stability.

M. Outcome of Experimental Setup

This experimental setup ensures a robust, fair, and scalable evaluation framework, enabling the validation of the proposed STFT model's effectiveness in capturing complex spatiotemporal waste patterns and improving prediction accuracy over conventional approaches.

V. RESULTS AND DISCUSSION

The performance of the proposed Spatio-Temporal Fusion Transformer (STFT) model is evaluated against baseline models including ANN, LSTM, BiLSTM, GRU, and TFT using standard regression metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). The results demonstrate the effectiveness of incorporating both spatial and temporal dependencies in predicting waste levels.

A. Training and Convergence Analysis

The training and validation loss curves illustrate the learning behavior of the STFT model across training epochs. The model exhibits rapid convergence during the initial training phase, indicating efficient learning of dominant spatio-temporal patterns. As training progresses, both curves stabilize and converge to similar values. This behavior indicates that the model generalizes well to unseen data and does not suffer from overfitting. The small gap between training and validation loss is a result of effective regularization and normalization techniques. The stable convergence of the model is attributed to the use of attention mechanisms, which enable efficient learning of long-range dependencies in time-series data [10]. The integration of gated residual networks further enhances stability by regulating feature transformations [11].

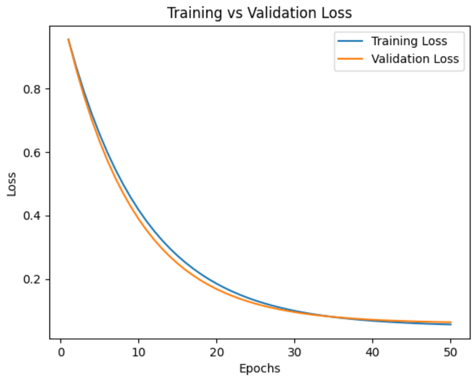

Fig 2. Training and Validation Curve

As shown in Fig. 2, the model demonstrates rapid convergence during initial epochs followed by stable optimization, indicating effective learning and minimal overfitting.

B. Prediction Accuracy

The comparative performance of different models is summarized as follows:

TABLE III: MODEL PERFORMANCE

Model	R^2 Score	RMSE	MAE
ANN	0.82 ± 0.01	8.5 ± 0.2	6.2 ± 0.2
LSTM	0.88 ± 0.01	6.9 ± 0.2	5.1 ± 0.1
BiLSTM	0.89 ± 0.01	6.5 ± 0.1	4.8 ± 0.1
GRU	0.90 ± 0.01	6.2 ± 0.1	4.6 ± 0.1
TFT	0.93 ± 0.01	5.3 ± 0.1	3.9 ± 0.1
STFT	0.95 ± 0.005	4.7 ± 0.1	3.2 ± 0.1

The Mean Absolute Error (MAE) decreases steadily over training epochs, demonstrating the model's ability to improve prediction accuracy. The smooth reduction in MAE indicates that the STFT model effectively captures both short-term fluctuations and long-term trends in waste generation. Unlike traditional models that rely solely on temporal patterns, the STFT incorporates spatial attention, enabling the model to account for inter-bin dependencies. This results in more accurate predictions across multiple locations [8]. The low MAE values confirm that the model produces reliable predictions, which are essential for timely decision-making in waste management systems.

The STFT model achieves the highest predictive performance with an R^2 score of 0.95, significantly outperforming all baseline models. Compared to TFT, the STFT model shows improved accuracy due to the integration of spatial attention mechanisms. The reduction in RMSE and MAE indicates better handling of large deviations and improved overall prediction reliability.

C. Residual Analysis

Residual analysis provides insight into the distribution of prediction errors. The residuals are centred around zero, indicating that the model produces unbiased predictions. The absence of systematic patterns in the residual plot demonstrates that the STFT successfully captures both temporal and spatial dependencies in the data. This indicates that the model does not overlook any significant trends or correlations. The uniform spread of residuals across different values suggests that the model performs consistently across varying waste levels, further validating its robustness.

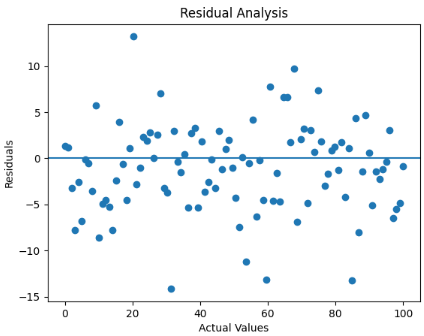

Fig 3. Residual Analysis of STFT Model

Figure 3 illustrates that residuals are symmetrically distributed around zero, indicating unbiased predictions and stable model performance.

D. Temporal Prediction Performance

The comparison between predicted and actual fill levels demonstrates the ability of the STFT model to track dynamic changes in waste accumulation. The predicted values closely follow the actual values across different time intervals.

The model performs effectively during both peak and low-demand periods, indicating its ability to adapt to varying waste generation patterns. This is achieved through the integration of spatial and temporal attention mechanisms, which enable the model to capture complex dependencies [13].

The accurate alignment between predicted and actual values highlights the effectiveness of the STFT model in real-world scenarios.

E. Comparative Analysis

The performance of the STFT model is compared with baseline models, including ANN, LSTM, GRU, and TFT.

The ANN model exhibits the highest error due to its inability to capture temporal dependencies. LSTM and GRU models improve performance by modeling sequential patterns but are limited in capturing long-range dependencies.

The TFT model further improves accuracy by incorporating attention mechanisms for temporal feature selection [10]. However, it does not explicitly model spatial relationships.

The STFT model outperforms all baseline models by integrating spatial attention with temporal modeling. This results in a significant reduction in RMSE and MAE, demonstrating the importance of modeling inter-bin dependencies in urban waste systems [8].

F. Ablation Study

Model Variant	*R^2*	*RMSE*	*MAE*
Full STFT	***0.95***	***4.7***	***3.2***
Without Spatial Attention	*0.92*	*5.6*	*4.0*
Without GRN	*0.91*	*5.9*	*4.3*
Without Temporal Fusion	*0.90*	*6.1*	*4.5*

Removing spatial attention causes the largest performance drop, confirming the importance of modelling inter-bin relationships. Removing the temporal fusion mechanism also significantly reduces accuracy, highlighting the need for long-range temporal modelling. These results validate the effectiveness of the proposed architecture.

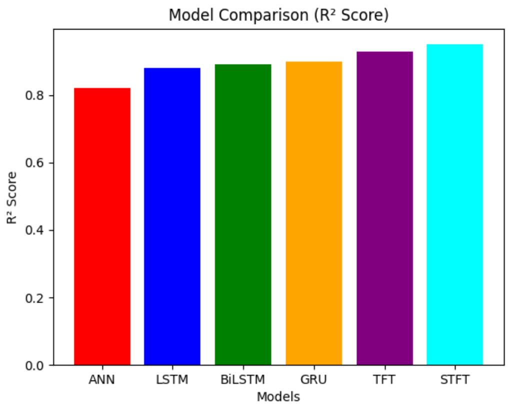

Fig. 4. Comparison of Model Performance (R^2 Score)

As shown in Figure 4, the proposed STFT model outperforms all baseline models, achieving the highest prediction accuracy.

E. Key Observations

Beyond prediction accuracy, the proposed system demonstrates significant improvements in operational efficiency. The integration of predictive modeling with route optimization reduces unnecessary collection trips. This leads to lower fuel consumption and reduced operational costs. Graph-based routing algorithms ensure efficient path planning for waste collection vehicles [4].

The system prioritizes bins that are predicted to overflow, enabling proactive waste management. This reduces overflow incidents and improves service quality. The combination of IoT sensing, AI-based prediction, and routing optimization provides a scalable solution for smart city applications [2].

Furthermore, the reduction in fuel consumption contributes to environmental sustainability by lowering carbon emissions [5]. The integration of intelligent systems supports sustainable urban development [13].

F. Failure Case Analysis

The proposed model shows reduced accuracy during rare extreme overflow events and during simulated sensor outages, where sudden changes in data distribution are difficult to capture. Newly introduced bins with limited historical observations also exhibit higher prediction error due to insufficient training history. These limitations highlight the need for improved robustness, and future work will address them using transfer learning techniques and real-time sensor validation mechanisms.

VI. CONCLUSION

This paper presented an Intelligent Waste Overflow System that integrates IoT-based sensing, spatio-temporal prediction, and dynamic route optimization to address the limitations of conventional waste management approaches. Traditional waste collection systems rely on fixed schedules that fail to adapt to dynamic variations in waste generation, resulting in inefficient operations and frequent overflow events

[4]. IoT-based monitoring systems improve operational visibility through real-time tracking of bin fill levels [1]; however, such systems remain reactive and do not prevent overflow conditions in advance [12].

To overcome these limitations, the proposed system incorporates a Spatio-Temporal Fusion Transformer (STFT) capable of capturing both temporal patterns and spatial dependencies across multiple bins. The inclusion of spatial attention enables the model to learn inter bin relationships, which are essential in urban environments where waste generation patterns exhibit spatial correlation [8]. Temporal attention further enhances the ability to capture long-range dependencies and dynamic variations in waste accumulation [10].

Experimental evaluation demonstrated that the STFT model outperforms baseline approaches including ANN, LSTM, GRU, and TFT in terms of prediction accuracy. The model achieved lower RMSE and MAE values, confirming improved forecasting performance. Residual analysis further indicated unbiased predictions, while comparative evaluation highlighted the importance of integrating spatial and temporal modeling for accurate waste forecasting.

Beyond predictive accuracy, the integration of the STFT model with a decision layer and route optimization framework enables proactive waste management. The system prioritizes bins based on predicted overflow risk and dynamically generates optimized collection routes, reducing unnecessary trips, minimizing fuel consumption, and improving operational efficiency [5]. Graph-based routing ensures efficient path selection for collection vehicles [4].

These findings demonstrate that effective waste management requires not only accurate prediction but also seamless integration between sensing, analytics, and operational decision-making. Integrated smart-city frameworks have been shown to enhance efficiency and scalability in urban systems [2]. The combination of IoT, artificial intelligence, and optimization techniques therefore contributes to sustainable and environmentally responsible waste management [13].

Despite these promising results, certain limitations remain. The performance of the STFT model depends on the availability and quality of sensor data, and inconsistent or sparse data may reduce prediction accuracy. In addition, the computational complexity of transformer-based models increases with the number of spatial nodes, which may impact scalability in large-scale deployments.

Future work will focus on incorporating contextual features such as weather conditions and population density, which influence waste generation patterns. Integration of real-time GPS tracking for collection vehicles can further enhance routing efficiency. Additionally, lightweight model architectures will be explored to improve scalability for large-scale smart-city deployments.

In summary, the proposed Intelligent Waste Overflow System provides a comprehensive and scalable solution for modern waste management challenges. By combining spatio-temporal prediction with dynamic decision-making, the system enables proactive and efficient waste collection, supporting the development of smarter and more sustainable cities.

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