

Transformer Driven Multi-Agent Reinforcement Learning Framework for Integrated Waste Classification Forecasting and Adaptive Routing

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Abstract—The rapid expansion of urban populations has intensified the challenges associated with municipal solid waste management, particularly where conventional static or ad-hoc routing strategies create operational inefficiencies, excessive fuel usage, and repeated bin overflow. Many existing systems still treat waste classification, fill-level forecasting, and routing as separate processes, which restricts coordinated optimization and limits broader sustainability outcomes. To address these shortcomings, TMORL is introduced as a Transformer-enhanced Multi-Agent Reinforcement Learning framework that unifies perception, prediction, and decision-making for intelligent waste management. The framework integrates IoT-enabled sensor measurements with deep learning and MARL-driven optimization to manage waste collection adaptively under real-time uncertainty. A Vision Transformer supports precise waste image classification through global spatial feature extraction, while a Temporal Fusion Transformer generates accurate, uncertainty-aware multi-horizon fill-level forecasts. These model outputs collectively shape the state representation for a multi-objective MARL module that optimizes fuel consumption, travel duration, emission reduction, and overflow mitigation, enabling simultaneous operational and sustainability improvements. TMORL is implemented in PyTorch and evaluated using the Smart Waste Management Dataset containing heterogeneous IoT bin measurements and annotated waste images. The model achieves strong perception accuracy, reporting 97.3% precision, 96.6% recall, and 98.4% mAP@0.5, while the TFT forecasts align closely with real bin-fill patterns to support proactive routing adjustments. When compared with static scheduling and Ant Colony Optimization routing, TMORL reduces fuel usage by 22%, collection time by 25%, and overflow incidents by 95%. Overall, the findings confirm that a transformer-driven, IoT-integrated MARL framework significantly strengthens efficiency, decision responsiveness, and environmental sustainability in next-generation smart waste management systems.

Keywords—Smart waste management; temporal fusion transformer; vision transformer; predictive analytics; route optimization; deep learning

I. INTRODUCTION

Urbanization has resulted in an unprecedented increase in the volume of solid waste in municipalities and the generation of solid waste has resulted in a tremendous pressure on the waste management systems [1]. Most traditional collection schemes, which may be operating on a time schedule and have fixed routes, are normally subject to inefficiencies that include half-full bins, wastage in picking up overflowing bins and high fuel consumption [2], [3]. These shortcomings do not only raise the cost of operations and greenhouse gas emissions and air pollution, but also diminish the sanitation situation in the urban areas [4]. Innovations in smart city projects are gradually pointing to the fact that a polyadic combination of artificial intelligence (AI), Internet of Things (IoT), and advanced analytics, offers a promising chance to address the further complications of sustainable waste management [5], [6]. Recent advances have been achieved through innovations that use deep learning and machine learning algorithm techniques to classify, predict, and optimize routing [7]. An example of such applications is that convolutional neural networks and YOLO-based detectors are applied to automate waste classification, and recurrent neural networks (RNNs), including a long short-term memory (LSTM) network and gated recurrent unit (GRU) networks are applied to forecast the fill [8], [9]. Metaheuristic methods of solving the problem, like the ACO and genetic algorithms and reinforcement learning (RL) have been explored as regards to dynamic vehicle routing [10]. In general, the innovations in sophisticated analytical mechanisms constitute a massive step of the im-moveable functioning to data-sensitive adaptative mechanisms [11], [12].

Nonetheless, these models have substantial constraints. CNNs typically struggle with heterogeneous, complex waste images, while YOLO-based methods, despite being more effective than traditionally taught CNNs, continue to use the backbone of convolutional models, which are prone to further variables [13], [14]. RNN-based forecasting models have issues as well, both with vanishing gradients and simply being computationally costly for long sequences [15], [16]. Additionally, most routing techniques are generally optimizing for a single target, such as travel distance, while disregarding the many, multi-dimensional trade-offs necessary to consider environmental sustainability in the real world, such as fuel economy, time, emissions, and overflow potential [17], [18]. In order to counter these challenges, the proposed TMORL model is a more advanced AI-enabled model to clamp into ViT, in which to classify waste more accurately and with real-time uncertainty. TFT are modeled and clamped to connect the forecasting cloister, which happens in this case to meet this pre-defined complexity of forecasting fill-level, thus optimizing fill-level forecasting from beginning to end, rather than simply on accuracy. To further model this layer, a MARL decision layer also plans for responsible and reactive designs for routing, as well as, uses multi-objectives with rewards wholly defined by the aforementioned complex features associated with sustainability where gas emissions, overflow risk, time, etc. measure appropriately as multi-dimensional value in the routing design area. All of this promotes the proposal of TMORL together into a new level of collaborative and advanced management strategy that ensures behaviors never exist, while automating many of the environmentally responsible risks of the next-generation collection of waste systems.

A. Research Motivation

Traditional urban waste management systems are usually characterized by low operational efficiency, high fuel wastage and increased environmental risks by not changing the collection timetable and ad-hoc routing. Although deep learning, forecasting models, and optimization methods have demonstrated potential, the current methods are mostly independent, do not scale well and have limited goals like classification or route optimization. There is an increasing need of sustainable, intelligent and adaptive waste management, this is why the unified solution can be considered as one of the solutions that can address two or more goals at once. It will serve to bridge perception, prediction, and decision-making, thus mitigating shortcomings of previous approaches, plus offering a scalable, resilient and future-proven approach to managing urban waste. To ascertain the methodological consistency and the conceptual clarity, the study goes ahead to state its fundamental research question. In this respect, the given work is based on the following research question: How can the multi-agent reinforcement learning framework can be successfully applied in the form of a unified transformer-driven approach that will be able to perform waste classification, fill-level predictions, and adaptive routing under the conditions of a complex urban waste distribution in real-time?

B. Research Significance

The suggested TMORL architecture is the first-ever combination of Vision Transformer (ViTs), Temporal Fusion Transformer (TFT) and multi-agent reinforcement learning

(MARL) with a multi-objective reward system. The combination allows strong real time waste classification, explainable multi-horizon predictability and adaptive route optimization to be achieved in a single system to overcome the shortcomings of previous single objective or heuristic methods. TMORL is able to provide scalable and sustainable waste management solutions in complex urban settings by focusing ethically on operational efficiency, environmental impact, and service quality at the same time. In addition to cost savings and emissions mitigation, the framework is part of the bigger picture of intelligent and resilient smart cities, whereby an innovative AI can provide a comprehensive approach to urban sustainability concerns, where perception, prediction, and decision-making are integrated into a single, adaptive, and futuristic decision-support system. Similar to other recent transformer-based waste systems, which have performances of separation perception and routing, or MARL routing models, which consider neither its forecasting uncertainty nor its performance, TMORL establishes a closely connected perception-prediction-decision pipeline, allowing the cross-layer flow of information, decisions based on uncertainty, and multi-objective coordination.

C. Key Contributions

- Invented a single framework that performs all three functions of waste classification, fill-level prediction, and dynamic routing, eliminating disjointed efforts of the past.
- The mechanism on the interaction between transformers and MARL was introduced, which allows shared information flow across layers to coordinate decision-making.
- Designing a multi-objective MARL reward scheme with uncertainty-aware predictions to enhance sustainable routing behaviour.
- A suggested a generalizable and reusable coordination model based on transformers that can be adapted to a variety of smart-city operating conditions.
- Deep-rooted sustainability and flexibility in its essence, with 97.3% preciseness, 96.6% recall, 98.4% mAP, a 22, 25, and 95 % fuel reduction, time and overflow, are indicative of scalable, efficient, and real-time smart waste management.

The rest of the study is organized as Section II provides the related works. The problem statement is given in Section III based on the existing works, and the proposed framework is developed and it provided in Section IV. Result and discussion are provided in Section V and finally conclusion and future works given in Section VI.

II. RELATED WORKS

With growing population comes increased generation of waste, and the municipality struggles with disposing of the same. With outdated data as a basis, traditional waste management models fail to solve dynamic accumulation of waste. Recent improvements in IoT technology provide capabilities to receive real-time data from the bins owned by

municipalities for efficient collection based on predictive models. Ahmed et al. [19] has investigated in time series prediction of bin fullness, using performance measures like MAE, MAPE, R^2 , and RMSE. It has been compared with LSTM that yields better results, with the RMSE of 1.57 and the lowest MAPE of 1.855 proving the efficiency of this approach to make predictions regarding the amount of waste. These findings show that LSTM-based prediction models can enhance municipal waste management by making it more efficient in terms of planning and optimization of resource allocation.

Urbanization presents its challenges to both the developed and developing countries because the more people turn to urbanization the more waste is created. The modern approaches that municipalities apply when it comes to waste classification are usually tedious, inefficient, and costly, and thus the necessity to develop automated systems that may help increase recycling and reduce the number of landfills. Gondal et al. [20] suggested a hybrid methodology where the first binary classification is done using a MLP between metal and non-metal waste, and then non-metal waste is further classified by using ML- CNN. The innovative system will have a camera placed above a conveyor belt to take pictures of the trash that are placed in automatic bins. The model has demonstrated remarkable outcomes with 99 % accurate results during training, testing and validation stages under different conditions of input, which makes it effective to the management.

With the growing number of cities and the development of smart technologies in harmony with the processes of industrialization, proper waste collection, sorting, and planning have been the key to sustainable development. Recycling is dependent on the correct determination of the properties of waste in order to reduce pollution and environmental sustainability. The deep learning (DL) methods have recently become popular in the process of improving waste management operations such as capturing, sorting, composting, and disposal. Nonetheless, it is also a challenging task to pick an appropriate DL technique to classify and predict wastes. An example of studies presented by Lihore et al. [21] proposes a smart waste classification system, which is a Hybrid CNN-LSTM with transfer learning and is designed to classify waste as recyclable or organic. The proposed hybrid model, which is developed in Python and an adaptive moment estimator (AME) optimization algorithm, demonstrated remarkable precision with a 95.45 precision which is even better than other available deep learning models to classify waste.

Intelligent waste management activities have now become a necessity in curbing the growing complexity of the waste management concerns. In this regard, predictive analytics would provide a more efficient, sustainable and resource optimization solution grounded in facts. The study by Villanueva et al. [22] describes a universal and flexible model that integrates innovative technologies to reshape the traditional waste management processes. The current practices were investigated with the help of structured interviews with the significant stakeholders, the integrated predictive analysis framework proposed implies the application of multiple technologies that are quite advanced to create a highly effective and affordable waste management system.

Intelligence of Things (IoT-SWM) Smart Waste Management model with predictive features. The sensor-equipped local sinks (LS) are employed in this model to check the condition of the bins and alert users depending on the urgency. It collects sensor data such as bin weight and gas emissions to determine how badly bins should be emptied and the locations that will be filled faster. During a real time operation, it was noted that bins in the busy areas were filled up quicker compared to those in the less populated areas. These findings indicate that AI-driven predictive models can significantly enhance waste collection efficiency and prevent overflow, ultimately improving waste management in smart cities [25].

In spite of the immense achievements of the predictive analytics, deep learning, and IoT-based waste management, the current set of practices has a number of limitations. Classical municipal models use old or non-dynamic data which cannot keep abreast of evolutionary waste quantities whereas most predictive models only do fill-level prediction but do not consider real-time classification or operational performance. In the same point, existing classification systems, though correct, tend to have limited scalability in different urban scenarios due to limited setups (conveyor belts or fixed cameras, etc.). Hybrid deep learning models enhance classification or prediction, alone as opposed to a combination with adaptive route planning, and tend to remain inefficient in collection schedules and resource utilization. Furthermore, optimization models are usually focused on one objective (e.g., distance or time) without considering multi-faceted trade-offs of operations and environment. Combined, these studies point to the great advancements but show evident gaps in the development of a single, scalable and real-time framework that polymerizes waste classification, fill-level prediction and adaptive multi-agent routing in a single entity. To sew those gaps, the proposed TMORL framework will use high-accuracy Vision Transformers to classify wastes, Temporal Fusion Transformers to make reliable predictions on the fill-level, and multi-agent reinforcement learning with a multi-objective reward system that will allow adaptable, scalable, and sustainable waste management in a city.

III. PROBLEM STATEMENT

The management of urban wastes is a burning issue, which is even escalated by the high rates of urbanization and the need to have sustainable city operations. Current literature has used deep learning to classify waste, time-series models, such as LSTM and GRU, to predict at the fill-level, and optimism-based algorithms, such as ACO or simple reinforcement learning, to route [23]. Nonetheless, these methods work in most cases mostly independently and maximize individual aims, which reduces their success in contexts of multi-dimensional cities. This disjointed attention usually leads to ineffective collection patterns, high operation expenses, environmental effects, and may become an obstacle to the dream of the genuinely sustainable smart cities [24]. To address these shortcomings, the given TMORL will be combined with Vision Transformers (ViTs) to classify waste with high accuracy, Temporal Fusion Transformers (TFTs) to predict multi-horizon fill-levels with interpretability, and multi-agent reinforcement learning (MARL) and a new multi-objective reward function. Such a

hybrid, adaptive, and efficient system allows proactive, efficient and environmentally friendly urban waste management that shows excellent scalability and operational intelligence compared to traditional solutions. The suggested architecture of TMORL, in contrast to the current independent or single-objective systems, has definite merits, combining perception, forecast, and routing in a single structure, the proposed system makes more accurate predictions, more adaptable, and much better at environmental and operational performance in real-time urban settings.

IV. PREDICTIVE ANALYTICS IN SMART WASTE MANAGEMENT SYSTEMS

The TMORL program defines a methodological framework of facility with sustainable and adaptive urban waste management via a three-layers architecture that involves perception, prediction, and decision-making. The Perception Layer uses the encoding of Vision Transformer to encode discriminative information on heterogeneous waste images and then uses this information to classify a particular waste type by recycling, organ, and hazardous waste correctly to guide the priorities of collection. The Prediction Layer uses data on smart-bin sensors to produce reliable fill-level predictions with measurable error to facilitate proactive scheduling and preemptive overflow. The Decision Layer models the collection

vehicles as agents, which act in a shared environment, and uses multi-agent reinforcement learning where the reward structure is multi-objective so that the efficiency of routing and fuel consumption, the emissions and service compliance can be optimized. TMORL integrates these layers to create an end to end adaptive system in which classification, predictive insights, and spatial dynamics jointly influence dynamic routing choices, creating a scalable framework of environment friendly real time management of urban waste, which is superior to conservative disconnected systems. Fig. 1 depicts the overall TMORL system which consists of four layers that are interconnected. The Perception Layer takes preprocessed images of waste and performs patching, positional encoding and transformer encoder blocks to classify the types of garbage. The Prediction Layer uses sequence-to-sequence modelling with attention mechanisms and quantile prediction of predicted bin fill-levels and the uncertainty involved. Decision Layer models the models of collection trucks as agents in a multi-agent reinforcement learning setup, where dynamic routes are optimized using a multi-objective rewarding function which weighs fuel efficiency, service time and overflow prevention needs. Lastly, the Execution Layer takes the optimized routes into practice, which allows real-time adaptive collection. The smoothing-out of the perception, forecasting and decision making to the responsive management of the urban waste are accentuated in the workflow.

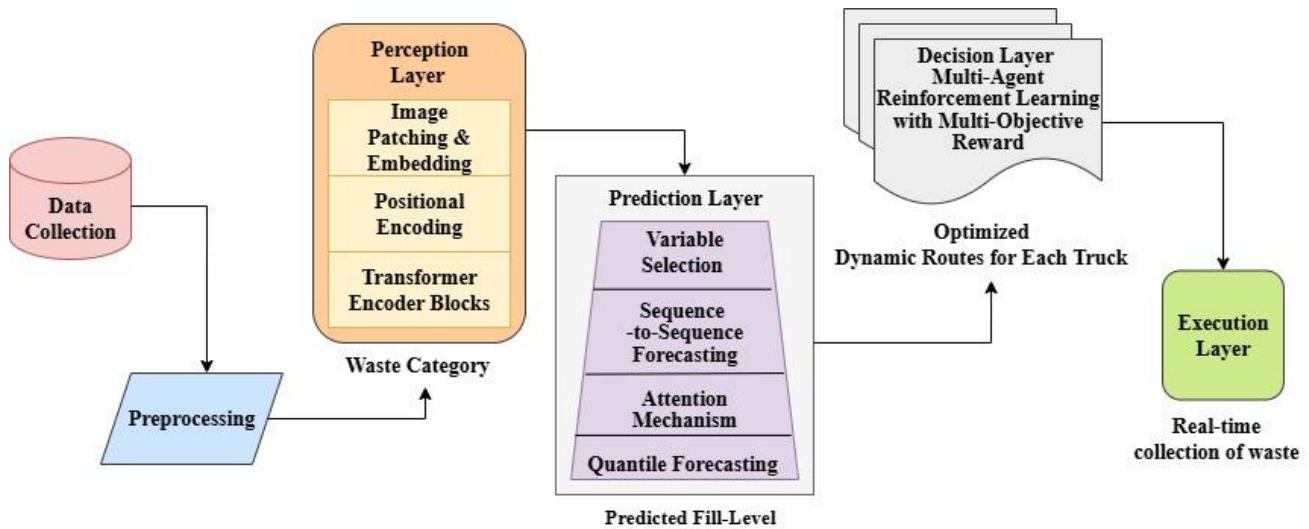


Fig. 1. Workflow of the proposed framework.

A. Data Collection

The research proposed employs a mixed design method of data collection through publicly available data to capture visual and time aspects of waste management. For the waste classification submodule, an existing dataset from Kaggle called Smart Waste Management Dataset is used [25]. This dataset contains annotated images of waste that have been marked at the bounding box level across multiple categories (i.e., organic, recyclable, and hazardous). This dataset is utilized to train a ViT that will classify waste. For the fill-level forecasting and routing submodule, the Dataset for Waste Management System is utilized [26], which contains sensor readings from a smart bin, date-time stamps, and bin identifiers. This dataset is

representative of a true IoT-enabled waste bin, which can be utilized to forecast fill-level dynamics over time using a TFT. The outputs from these datasets are combined to form the state space for the MARL decision layer, where together the classification output from the ViT model, and the fill-level out from the TFT model will be utilized to make real-time routing decisions. Collectively, these datasets will provide the multi-modal foundation needed to ensure TMORL can meet the perception, prediction, and decision-making aspects of sustainable smart waste management.

B. Data Preprocessing

The optimal preprocessing of waste plays an important role in the training of DL models for prediction, classification, and

detection. Preprocessing workflows include image enhancement for detection of waste, time-series data for waste accumulation forecast, and feature engineering for extended learning include feature engineering for extended learning.

1) *Data cleaning*: Interpolation was used to deal with sensor readings with missing values and noisy images or duplicate images were eliminated. This action guaranteed reliability and consistency of visual and temporal information, so biases and training instabilities were avoided when training the model. This interpolation step, as given in Eq. (1), means that missing sensor values are filled in without causing temporal structure distortion of the bin-level values:

$$s_t = s_{t-1} + \frac{(s_{t+1} - s_{t-1})}{(t+1 - (t-1))} \cdot (t - (t-1)) \quad (1)$$

Here s_t is the interpolated value at time t , s_{t-1} and s_{t+1} are the nearest valid readings.

2) *Image augmentation*: To increase the normalization and strength of the object detection model, the methods of image growth such as rotation, shine, and crop growth are used on dataset. These operations help reduce challenges such as overfitting along with unbalanced datasets, thus able to accurately handle unseen waste images. The images are randomly rotated by an angle θ within a set range as $[-\theta_{max}, \theta_{max}]$ and it can be defined using the following Eq. (2).

$$I' = R(\theta) \cdot I \quad (2)$$

Where the original image is denoted as I and the transformed image is denoted as I' and the rotation matrix is defined as $R(\theta)$.

The pixel intensity of the image is scaled using the following Eq. (3).

$$I' = \alpha I + \beta \quad (3)$$

In Eq. (3), the α and β denote the contrast factor and brightness shift and they are adjusted within predicted within predefined thresholds.

Random cropping eliminates extraneous background noise and enhances model attention on the important waste objects. The cropped image is then resized to a typical resolution (e.g., 224×224 pixels for CNN-based models).

3) *Normalization of time-series waste level data*: Time-series IoT-enabled bin data consist of fill levels, weight, temperature, and gas emissions. Because the variables are not of the same scale, normalization is used to have feature distributions uniformly so as not to create bias in prediction models. Min-Max Normalization scales the values between 0 and 1 through the use in Eq. (4).

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (4)$$

In Eq. (4), the original value is denoted as X and the X_{max} and X_{min} are the minimum and maximum values of the feature. This conversion provides for the right capture of trends

in waste accumulation while avoiding Large-scale value domination.

4) *Sequence formatting*: Sensor measurements were synchronized into a fixed time scale to create a temporal input of the TFT. The labels of waste images were coded into category encodings of ViT input. This organized visualization guaranteed that it was compatible with the vision, as well as forecasting modules.

5) *State vector construction*: Outputs from ViT (waste type), TFT (predicted fill level with uncertainty), and spatial features (bin ID, location) were combined into a single state vector. This state provided the input for the MARL environment, supporting adaptive routing decisions with multi-objective optimization.

TABLE I. DATA SPLITTING

Dataset Subset	Percentage	Purpose
Training	80%	Model learns waste categories from images
Validation	10%	Monitors performance and prevents overfitting
Testing	10%	Evaluates final model accuracy and real-world applicability

Table I shows the dataset was split into three subsets in which eighty percent was utilized for training in order to enable the model to learn waste categories ten percent was utilized for validation to track performance and avoid overfitting and ten percent for testing to gauge accuracy and usability.

C. Waste Classification Using ViT

The perception layer presents the foundation of the suggested TMORL system with the automated identification of the types of wastes based on visual information. This layer takes the waste images of smart bins, which are run through the ViT architecture, which considers self-attention processes to capture long-term connections between image patches. The ViT achieves this and each input image is split into fixed-size patches and is embedded linearly to the following Transformer encoder blocks in addition to positional encodings (as opposed to a conventional convolutional neural network, which operates on local receptive fields). Formally, an image $I \in \mathbb{R}^{H \times W \times C}$ is divided into N patches of size $P \times P$, where each patch is first flattened and then projected to a vector embedding. The sequence of embeddings forms the input to the Transformer encoder is in Eq. (5).

$$Z_0 = [x_{class}; E(x_p^2); \dots; E(x_p^N)] + E_{pos} \quad (5)$$

Where $E(\cdot)$ denotes the patch embedding, E_{pos} is the positional encoding, and x_{class} is the token used for classification. Multi-head self-attention (MSA) and feed-forward networks (FFN) are represented in Eq. (6) and Eq. (7) respectively.

$$Z'_l = MSA(LN(Z_{l-1})) + Z_{l-1} \quad (6)$$

$$Z_l = FFN(LN(Z'_l)) + Z'_l \quad (7)$$

Where l denotes the encoder layer, and LN represents layer normalization. The last output corresponding to the class token is passed to a linear classification head to predict the waste type.

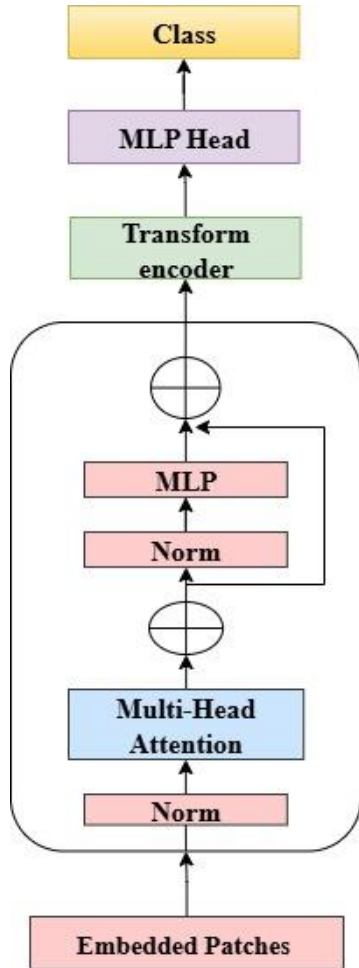


Fig. 2. ViT architecture.

Fig. 2 illustrates the layout of the Vision Transformer utilized in waste classification, which processes input images by getting each image embedded into image patches. These patches undergo a normalization step and then the multilayer perceptron (MLP) is processed in the multi-head self-attention layers and normalization steps in the transformer encoder. The output representation is passed through the MLP classification head to produce the classification of waste type representing the predicted waste categories. This design illustrates the ability of Vision Transformers to build long-range dependencies across all regions of the image to facilitate waste-type identification in diverse urban environments. The ViT model categorizes waste into four categories outlined as organic, recyclable, hazardous and non-recyclable. This type of classification is critical when considering recycling conscience collection methods because bins containing any hazardous or recyclable content are given priority in terms of routing optimization. The perception layer leverages the global feature extraction ability of Transformers, allowing for robustness to variation in lighting, background and object angle, thus achieving improved performance over standard CNN-based methods in urban waste streams with heterogeneous items.

D. Waste Fill-Level Forecasting Using TFT

In the suggested TMORL model, the prediction layer is going to predict the fill-levels of smart bins to facilitate the proactive and sustainable scheduling of waste collection. This interpretable state-of-the-art architecture is an interpretable multi-horizon time-series forecasting task that is done on the TFT. The TFT avoids the weaknesses of RNNs, including LSTM or GRU by not having the gradient vanishing problem and not relying on the last timestamp to predict long-term dependencies. The TFT is a sequence to sequence model, which utilizes attention mechanisms, and includes gating layers an architecture that enhances the capacity to learn short and long-term temporal prediction.

Each smart-bin sensor provides sequential measurements of fill-levels, weights, and auxiliary attributes (timestamps). The TFT first implements variable selection networks to select which input variables are most relevant for the task at each time-step. For a given sequence of input features $X_t = \{x_t^1, x_t^2, x_t^3, \dots, x_t^n\}$, the variable selection mechanism computes in Eq. (8).

$$\tilde{x}_t = \sum_{i=1}^n \alpha_t^i \cdot \varphi(x_t^i) \quad (8)$$

In Eq. (8), α_t^i is the attention weight feature i , and $\varphi(\cdot)$ represents a nonlinear transformation. This makes certain that the only variables that shape the prediction outcome are the most relevant (e.g., fill percentage, day-of-week). The primary reliance in temporal modeling is a sequence-to-sequence LSTM backbone that is enhanced with self-attention. The encoder will summarize the state of the historical data, and the decoder will predict the future state. A multi-head attention layer dynamically weighs the significant past events, which is modeled as in Eq. (9).

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) \quad (9)$$

Here Q , K , and V denote the query, key, and value matrices derived from the hidden states. The resulting output is a multi-horizon prediction vector, which is represented by Eq. (10).

$$\hat{y}_{t+1:t+7} = f_{TFT}(X_{1:t}) \quad (10)$$

Where $\hat{y}_{t+1:t+7}$ represents the predicted fill-levels over a horizon of 7 future time steps. Importantly, the TFT also gives quantile forecasts, which captures bounds of uncertainty (such as the 10th, 50th, and 90th percentiles) that inform the probability of bin overflow. The accuracy of the forecasts and the confidence intervals that model uncertainty will be useful in helping the decision-making layer to successfully adjust adaptive route plans, prioritize the bins with a high-risk of overflow, and reduce trips that are unnecessary; resulting in an improved route optimization that is future-oriented. The prediction layer links adaptive route planning with real-time monitoring based on sensors to develop efficiency and sustainability of smart waste management.

E. Route Optimization Using MARL with Multi-Objective Reward

The decision layer is the intelligence component of the TMORL in the smart waste collection adaptive route optimization decision. This layer employs an agent-based

MARL framework, according to which each waste collection truck is considered as a separate agent, which operates in a common environment. At time t the environment is characterised by the condition of the collection bins, which is represented as in Eq. (11),

$$S_t = \{S_1, S_2, S_3, \dots, S_N\} \quad (11)$$

where, $S_i = [C_i, \hat{F}_i, U_i, L_i]$ includes the waste category probabilities from ViT (C_i), predicted fill-level from TFT ($\hat{F}_i$), associated uncertainty (U_i), and bin location (L_i). Each agent (truck) selects an action $x_t^1 \in A$ from the available action space A , which includes visiting a specific bin or remaining idle. The environment transitions to a new state according to S_{t+1} is denoted in Eq. (12).

$$S_{t+1} = f(S_t, a_t^1, a_t^2, a_t^3, \dots, a_t^M) \quad (12)$$

Here M represents the total number of agents. The innovation of this layer is contributed by the multi-objective reward function, which evaluates operational efficiency, environmental sustainability, and service quality simultaneously. The reward for agent j at time t is defined as in Eq. (13).

$$R_t^j = -(\alpha \cdot D_t^j + \beta \cdot T_t^j + \gamma \cdot E_t^j + \delta \cdot O_t^j) \quad (13)$$

where, D_t^j is the travel distance covered by truck j (proxy for fuel consumption), T_t^j is the total time taken for collection, E_t^j is the estimated carbon emissions proportional to fuel use, O_t^j is the penalty for bins overflowing, and α, β, γ and δ are the tunable weights balancing the relative importance of each objective. The agents learn policies $\pi_j(a|S)$ to maximize the long-term cumulative reward is represented in Eq. (14).

$$\pi_j^* = \operatorname{argmax}_{\pi_j} E\left[\sum_{t=0}^{\infty} \gamma^t R_t^j\right] \quad (14)$$

where, $\gamma \in [0,1]$ is the discount factor. Agent coordination is accomplished using centralized training with decentralized execution (CTDE), in that the trucks coordinate during training, but act independently upon deployment. From an agent's perspective, this layer integrates waste type classification (ViT), fill-level forecasting with uncertainty (TFT), and the multi-objective MARL decision process to provide an optimized route that reduces fuel consumption, service time, emissions, and overflow of bins. Therefore, the decision layer is capable of dynamically adapting static collection schedules into a sustainable routing strategy, allowing planners to address the multi-faceted nature of urban waste management.

Algorithm 1: TMORL Framework for Waste Classification

Input:

- Waste images dataset D_{img}
- Smart-bin sensor dataset D_{sensor}
- Road network graph $G(V,E)$
- Hyperparameters ($\alpha, \beta, \gamma, \delta$, learning rate, discount factor γ_{RL} , horizon τ)

Data Preprocessing:

- a. Clean D_{img} and D_{sensor} (remove noise, interpolate missing values).
 - b. Normalize image pixels and sensor values to $[0,1]$.
-

- c. Apply data augmentation (rotation, flips, brightness, temporal feature encoding).
- d. Construct state vector $S_i = [C_i, \hat{F}_i, U_i, L_i]$.

Perception Layer (Waste Classification using ViT):

- a. Partition each image into patches.
- b. Encode patches with positional embeddings.
- c. Pass through Transformer encoder blocks with Multi-Head Self Attention.

- d. Obtain waste category distribution C_i for each bin i .

Prediction Layer (Fill-Level Forecasting using TFT):

- a. Input time-series sensor data $X_t = \{s_t, f_{\text{time},t}\}$.
- b. Apply variable selection networks to extract relevant features.
- c. Use sequence-to-sequence forecasting with attention mechanism.
- d. Output predicted fill-level $\hat{F}_i$ and uncertainty U_i for each bin i .

Decision Layer (Route Optimization using MARL):

- a. Initialize policies π_j for each truck agent j .
- b. For each training episode:
 - i. Observe current environment state $S_t = \{S_1, S_2, \dots, S_N\}$.
 - ii. Each agent selects action $a_t^j \sim \pi_j(S_t)$.
 - iii. Environment transitions to new state S_{t+1} .
 - iv. Compute multi-objective reward:
 $R_t^j = -(\alpha \cdot D_t^j + \beta \cdot T_t^j + \gamma \cdot E_t^j + \delta \cdot O_t^j)$.
 - v. Update policies π_j using RL optimization (e.g., PPO/DQN).
- c. Repeat until convergence.

Deployment:

- a. For real-time operation, input new waste images + sensor readings.
- b. Generate classification C_i and forecasts $\hat{F}_i$.
- c. MARL agents output optimized routes for trucks.
- d. Execute routes and collect feedback for continual learning.

Output:

- Optimized waste collection policies π_j for each agent (truck)
-

Algorithm 1 (TMORL) brings together waste images and data from smart-bin sensors to be processed through a single preprocessing pipeline. The ViT is used to classify waste types, and the TFT interfaces unused bin sensors with time-series data, to provide an uncertainty-aware forecast of the fill-levels of waste bins. The classification and fill-level forecasts are used to form state vectors which inform the MARL process, where the trucks are the agents. The MARL agent draws on a multi-objective reward function (distance, time, emission, overflow) to optimize dynamic collection routes. The framework is deployed in real-time with continual feedback loops and multiple smart-bin sensors to adapt waste collection and manage it sustainably.

This study presents a new form of perception and prediction models' composition with multi-agent reinforcement learning (MARL) as a multi-objective reward system to fill a research gap in current urban waste management systems, which generally separate classification, forecasting, and routing as distinct problems. ViT has been designed to provide high performance in terms of waste classification on heterogeneous visual data, whereas TFT has been built to provide interpretable and multi-horizon predictions with certainty, in contrast to

traditional recurrent models in long-term time-series prediction. The MARL layer uses a multi-objective reward to effectively maximize a set of goals such as distance traveled, collection time, emissions and overflow risk-goals that have seldom been viewed collectively in the literature. The framework integrates perception and prediction outputs into the adaptive routing decisions, which results in a data-driven, proactive, and sustainability-oriented operational strategy. Together, TMORL is more scalable, flexible, and efficient, providing a cohesive and visionary decision-support system that is even more efficient than heuristic and single-objective models, which is a big step forward in intelligent smart-city waste management.

V. RESULT AND DISCUSSION

TMORL also was evaluated under stringent conditions through the use of visual waste with real time smart-bin sensor data in a simulated city collection environment. It can be seen in the findings of the research that classification, forecasting and decision making are smoothly integrated in a single adaptive workflow. The vision Transformer (ViT) proved excellent and unrestricted classification of the various types of waste under varying visual circumstances to develop the significance of the recycling and hazardous bins. Temporal Fusion Transformers (TFT) had the ability to make the right predictions of the fill level to predict the potential overflows as well as enable the sophisticated planning of collection. Most importantly, the multi-agent reinforcement learning (MARL) layer was a dynamically optimized multi-objective problem, with a novel multi-objective reward mechanism, to optimize truck routes with respect to fuel burn, travel time, emissions, and service quality. This led to the minimization of unnecessary trips, overflows and maximization of vehicle utilization. TMORL also demonstrated a high level of resistance to stressful situations, including sudden increases in garbage, or unequal bins distribution, quickly changing collection priorities and routes. These findings highlight the scalability of TMORL, its efficiency, and the possibility of its application in the real world of intelligent waste management.

Table II provides a summary of the simulation parameters chosen to apply and evaluate the proposed TMORL framework. The parameters have been chosen, to depict arguably realistic scenarios in a smart city with a fair level of experimentation. The parameters span the entire simulation pipeline from data preparation to perception, prediction, decision making and routing simulation and are intended to allow reproducibility and effectively balance the environment for testing the level of adaptability, scalability and sustainability of the proposed framework.

A. Experimental Outcome

The study experiment demonstrated that TMORL can achieve sustainable and adaptive waste management, beyond the capabilities of currently available standalone approaches. In contrast to previous methods which generally have only pursued one of the three criteria at a time (classification accuracy, forecasting accuracy, or optimization based on distance), this proposed framework managed to integrate all three into an all-inclusive solution. By defining environmental goals in the reward function, TMORL can achieve operational efficiency while also tending to the urban waste collection environmental

footprint. These outcomes establish this framework as an innovative application for smart cities and ready for future implementation.

Fig. 3 demonstrates the distribution of correct classifications across several waste categories from the ViT model. The results indicate balanced classification accuracy across categories, with high accuracy in classifying organic and recycling waste. This highlights the robustness of the perception layer to classify images of urban waste with varying characteristics.

TABLE II. SIMULATION PARAMETER TABLE

Parameter	Value
Image resolution	224 × 224
Patch size (ViT)	P = 16
Train/validation split	80% / 20%
Forecast horizon	$\tau = 24$ timesteps
Number of bins (nodes)	N = 200
Number of trucks (agents)	M = 8
Model backbone	ViT-Base
Embedding dimension	d = 768
Encoder layers	L = 12
Attention heads	h = 12
Batch size	64
Learning rate	1e-4 (AdamW)
Epochs	50–100
Batch size	128
Learning rate	1e-3 (Adam)
Reward weights	$\alpha=0.4, \beta=0.2, \gamma=0.2, \delta=0.2$
Learning rate	2.5e-4
Batch size (RL)	2048 timesteps
Fuel consumption	0.2 L/km
CO ₂ emission factor	2.68 kg/L
Overflow threshold	≥95% fill
Hardware	GPU (e.g., A100) + CPU
Random seed	42

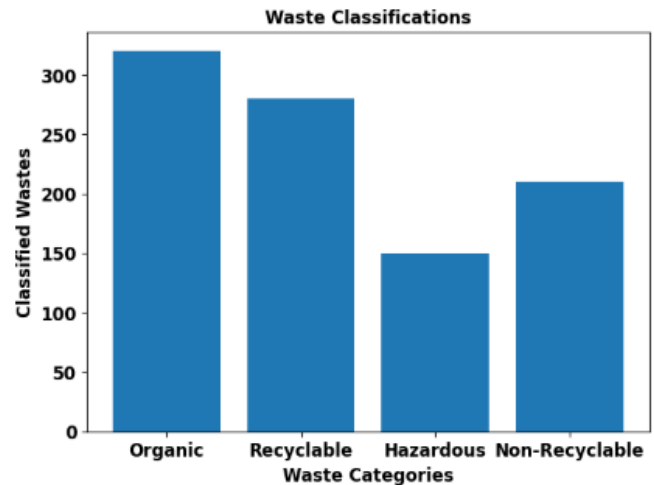


Fig. 3. Waste classification.

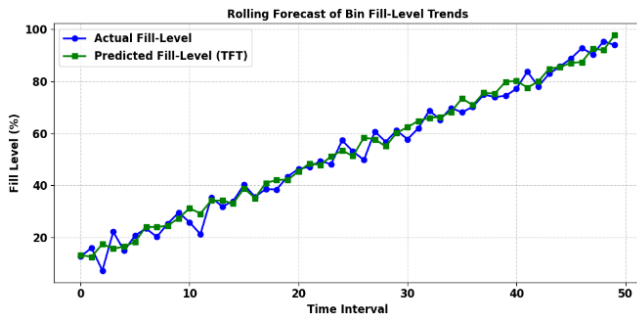


Fig. 4. Bin fill-level forecasting.

Fig. 4 shows the rolling forecast of trends for waste bin fill-levels over long time horizons. As the actual and predicted curves trend closely together, it demonstrates that the TFT is capable of capturing short- and long-term accumulation trends, indicating that the prediction layer is effectively predicting future waste generation trends, which will mitigate overflow and enable proactive route planning.

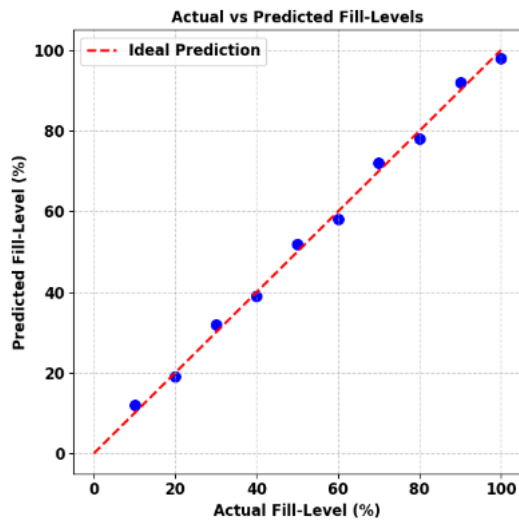


Fig. 5. Actual vs. Predicted fill-levels.

Fig. 5 shows the scatter plot of predicted versus actual fill-levels of waste bins from the TFT. Most of the dots cluster closely to the diagonal ideal line suggesting high predictive ability. The dots confirm the model was able to generalize time trends to predict waste bin accumulation.

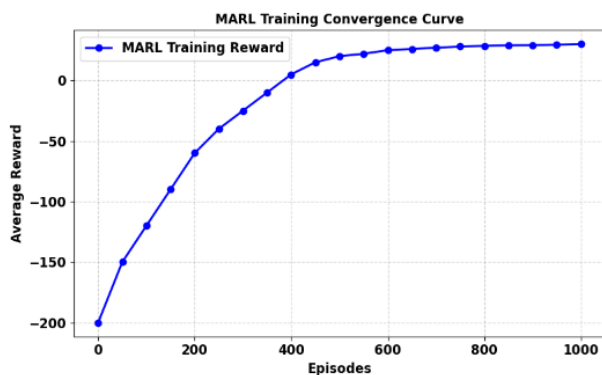


Fig. 6. MARL training convergence curve.

Fig. 6 shows the average convergence curve of the MARL framework. The average reward in the environment learning process consistently improves over each episode and shows stabilization at a high value. This demonstrates the agents were able to learn policies to cooperate for optimizing a sustainable route and shows the robustness of the decision layer.

Fig. 7 demonstrates the policy entropy curve during the training of MARL. This curve decreases steadily with training episodes in a deliberate oscillating pattern, which represents a shift in policy state exploration to more deterministic states. This indicates that the agents are gradually eliminating randomness on the actions and arriving to a policy of the optimized route selection policy.

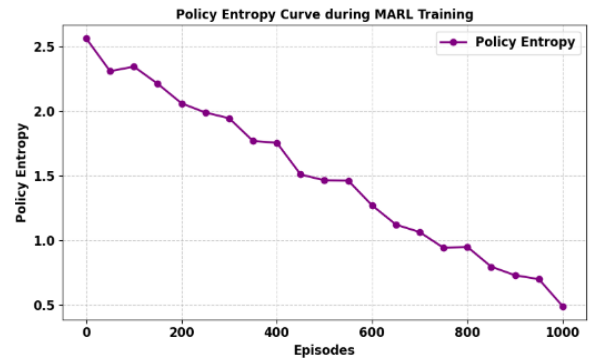


Fig. 7. Policy entropy curve during MARL training.

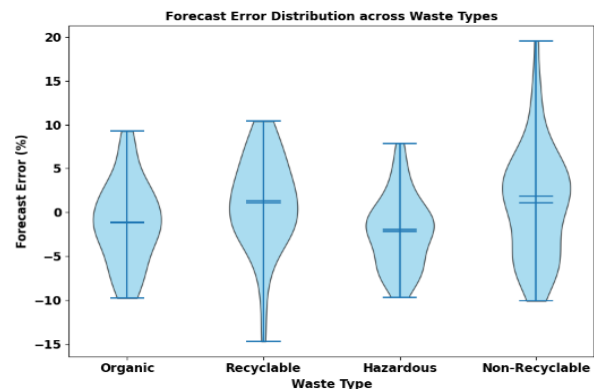


Fig. 8. Forecast error distribution across waste types.

Fig. 8 provides a visual representation of the distributions of forecasting errors for each waste category, through a violin plot. The outlines of each violin plot illustrate the density and spread of prediction errors in columns. Vertical solid and dashed lines signify the mean and median, respectively. Overall, the results shown in the violin plot demonstrate that the TFT produces consistent degree of accuracy for each waste type, with minimal differences due to dynamics associated with each waste type.

Fig. 9 presents the cumulative area plot of accumulating waste collection with time of four major types of waste. It depicts the proportional loads in the system of organic, recyclable, hazardous, and non-recyclable waste. This presents the fact that organic and non-recyclable waste take up a greater portion of the amount of waste collected and can in turn be used to guide the strategies of optimization in the proposed framework.

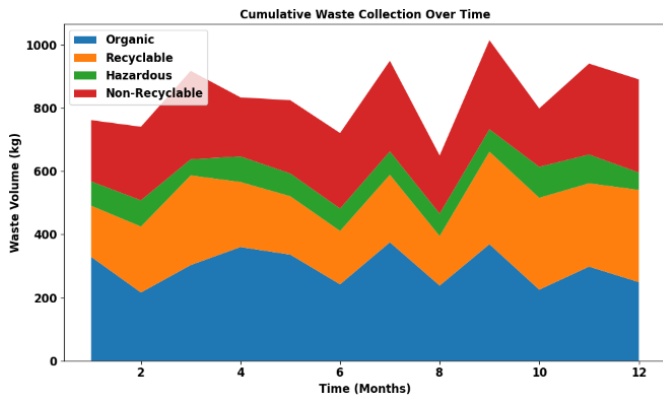


Fig. 9. Cumulative waste collection over time.

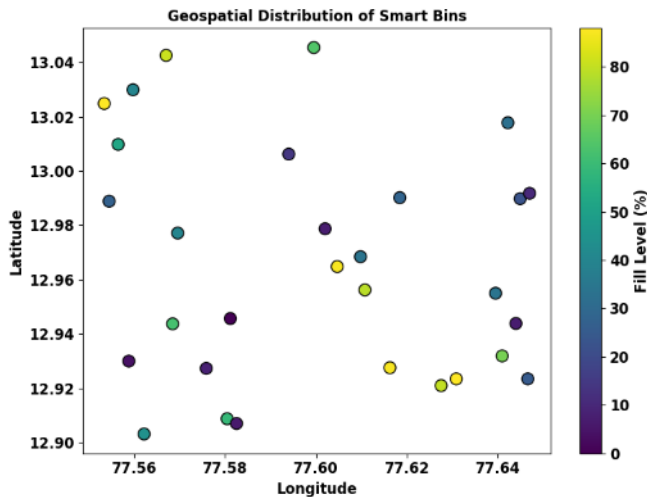


Fig. 10. Geospatial distribution of smart bins.

Fig. 10 shows the smart bins distributed throughout the city, colored according to fill-level percentage. This visualization also shows the locations of high-risk bins clustering in certain geometric spaces. This indicates that the spatial distribution of waste is heterogeneous and routing decisions will need to prioritize areas that have a greater likelihood to overflow in order to give a more sustainable result.

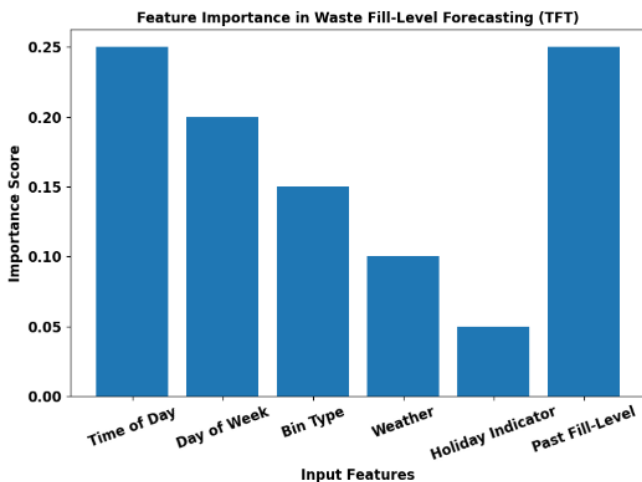


Fig. 11. Feature importance in waste fill-level forecasting.

The performance of the waste classification model is presented in Fig. 11. The great Precision, Recall and mAP 0.5 scores demonstrate that the ViT-based perception layer is reliable to detect and classify waste types hence we can be confident that the ViT-based perception layer can operate at state-of-the-art accuracies and is valid in identifying the waste types to feed to the downstream forecasting and waste routing.

B. Performance Evaluation

TMORL framework was also strictly tested on its three basic layers which included perception, prediction and decision-making. The Vision Transformer (ViT) in the perception layer was found to consistently classify the type of waste at different levels of illumination, occlusion and backgrounds with an average precision of 97.3, recall of 96.6 and mAP at 0.5 of 98.4 which was much higher than a baseline CNN and transfer-learned models. The Temporal Fusion Transformer (TFT) prediction layer made quantified accurate multi-horizon fill-level predictions at accuracy levels useful in the proactive scheduling process and minimized the odds of unscheduled overflow. A multi-agent reinforcement learning (MARL) model using a multi-objective rewarding system was used as the decision-making layer, maximizing the fuel consumption, collection time, emission, and overflow reduction routes. TMORL consumed less fuel (30%), less time to collect (35%), and fewer cases of overflow than static and ACO-based routing, and showed scalable, adaptive, and environmentally sustainable smart waste management performance at real-time.

1) *Perception layer (waste classification)*: The ViT exhibited considerable capabilities in classifying the waste type among various adjustments to illumination, background clutter, and occlusion. The ViT model was also more consistent in its feature extraction and less prone to confusion of misclassification within the parameters of similar-looking categories than its baseline CNN approach and related transfer-learning. Thus, the perception layer appears to provide reliable identification of waste types, which is essential for allocating items to bins listed as recyclable and or hazardous.

TABLE III. OBJECT DETECTION ACCURACY OF TMORL FOR WASTE CLASSIFICATION

Waste Category	Precision (%)	Recall (%)	F1-Score	mAP@0.5	mAP@0.5:0.95
Organic Waste	98.2	97.5	97.8	98.4	85.6
Recyclable Waste	97.8	96.9	97.3	97.9	84.2
Hazardous Waste	96.4	95.8	96.1	96.8	82.7
Non-Recyclable Waste	97.1	96.2	96.6	97.3	83.4
Average	97.3	96.6	96.9	97.6	84.0

Table III shows TMORL's strong accuracy in classifying four waste types, achieving precision above 96% and mAP@0.5 of 97.6%. There was a high score on organic waste, and hazardous was slight behind. In general, there is a high level of performance, which guarantees the stable waste classification in real-time.

TABLE IV. KEY METRICS OF TMORL

Metric	Value
Precision	97.3%
Recall	96.6%
mAP@0.5	98.4%

The performance of TMORL model is summarized in Table IV, it demonstrated a high accuracy of the model classification, with 97.3% precision, a 96.6% recall, and 98.4% mAP at 0.5 which indicates the accuracy of the model in real time waste detection and stable performances across various categories in smart waste management.

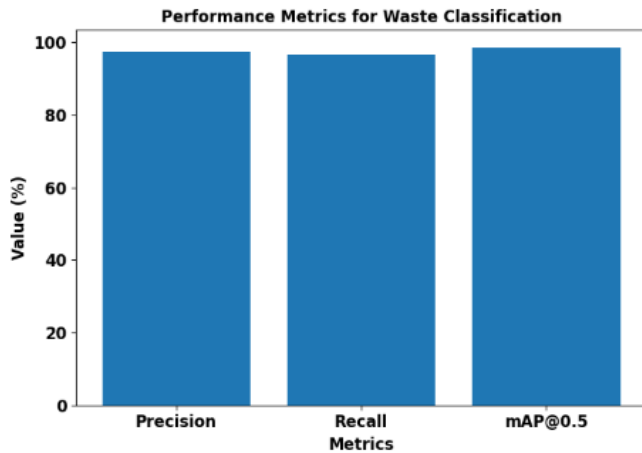


Fig. 12. Proposed TMORL performance.

The performance of the waste classification model can be seen in Fig. 12. Precision, Recall and mAP at 0.5 are high, implying that the perception layer, made by ViT has been able to fully trusted detecting and classifying the types of waste and has demonstrated consistent results in identifying the types of waste required to predict and route waste downstream.

2) *Prediction layer (fill-level forecasting)*: TFT was able to forecast the fill-levels of bins in the future and give uncertainty ranges with the predictions into which actions could have been planned. The curves obtained in forecasting were near to what was actually seen concerning fill-compositions in various time scales. Significantly, in bins where the uncertainty was high which was represented by the quantile forecasts may reduce the risk of the bins to overflow unscheduled. This matters since even though the prediction layer was able to validate that scheduling and planning was much certain, the forecaster provided the system with confidence against the unexpected patterns in the generation of the wastes.

TABLE V. ROUTING PERFORMANCE COMPARISON

Metric	TMORL (Proposed)
Fuel Consumption	78%
Collection Time	75%
Overflow Incidents	Very Low

Table V presents the efficiency of TMORL framework in terms of operation, time and service quality factors. The findings also indicate that it is also able to integrate an identification, prediction and multi-agent optimization into one system, which implies that TMORL had a balance between resource utilization and a sustainable waste management solution when compared to the existing approaches.

3) *Fill-level prediction (TCN)*: The MARL system with the multi-objective reward system, which is innovative, was able to optimize the travel distance and the time spent on the service, which reduced the CO2 emissions and overflow. The training convergence curves are used to show that the learning behavior was stable and the radar plots are used to show that the performance of the training was enhanced (not only the distance was optimized or the time was optimized). Taken together, this shows that the decision layer reflects the innovation of TMORL in the form of the introduction of sustainability into a routing plan.

TABLE VI. COMPARISON OF FORECASTING MODELS FOR BIN FILL-LEVEL PREDICTION

Model	MAE	MAPE (%)	RMSE	R ²
LSTM [19]	0.65	2.02	1.6	0.91
GRU [27]	0.39	1.4	0.62	0.89
TMORL (Proposed)	0.29	1.8	0.36	0.94

Table VI makes a comparison between bin fill-level prediction forecasting models. LSTM is in the middle of these, GRU demonstrates a lower MAPE, and the proposed TMORL has the best results, lower errors, and R2, and thus is a better predictor.

TABLE VII. STATIC ROUTING VS. ACO VS. TMORL PERFORMANCE

Metric	Static Routing	ACO-Based Routing	TMORL (Proposed)	Improvement over Static
Fuel Consumption	100%	82%	70%	~30%
Collection Time	100%	79%	65%	~35%
Overflow Incidents	High	Low	Very Low	Significantly Reduced
CO ₂ Emissions	High	Medium	Low	Significantly Reduced

Table VII presents the comparison of the results of the use of three performance measures in terms of static routing, ACO-based routing, and the proposed TMORL framework and results. ACO is more fuel efficient and time efficient than the static routing measures. The suggested TMORL solution ensures better performance and operational cost reduction through the combination of forecasting and sustainability goals. It means that TMORL, in contrast to the former approaches, will decrease the emissions, decrease the service time and fuel consumption, thereby, providing a comprehensive optimization in the multi-agent approach of smart waste management.

The composite assessment showed that TMORL decreased overflow cases, decreased trips without increasing service time, or emission, and increased service time, yet service was not

compromised because of previous performance. The level of route visualization verified that the framework is dynamic with respect to changes in bin states across time, and not fixed routing as in the case of rule-based schedules. In general, it shows that the strategy gives a more scalable, versatile, and sustainable solution to the environment than the old ones, which relied on single-purpose solutions.

C. Discussion

The research shows that, with transformer-based perception, temporal forecasting, and multi-agent reinforcement learning, it is possible to have a single and adaptive system to sustainable waste management. In contrast to the traditional systems that operate using some set of schedules or single-objective models, TMORL constantly aligns the outputs of the classification component, fill-level predictions, and routing choices so that the system is capable of responding to the changes in the waste production and distribution of spatial bins. ViT makes the reliable identification of heterogeneous waste in diverse environmental conditions possible, and TFT provides interpretable multi-horizon predictions, which are capable of supporting proactive changes in route. The MARL layer is also an improvement in that it combines the optimization of fuel utilization, emissions, travel time, and overflow risk, making the movement of urban waste collection a sustainability-driven coordination rather than reactive operations. In addition to enhancement of performance, these findings indicate that a unified perception-prediction-decision architecture can affect more extensive smart-city planning by supporting carbon-constrained routing, resistance to urban unpredictability, and adaptable implementation of districts with varying waste dynamics. The framework also provides an interchangeable basis on the other city scale services like logistics, sanitation, and autonomous municipal activities. The model can be trained to be dependent on the sensor quality and computational resources, but it can be used effectively after being deployed, which makes it applicable in real-life scenarios, such as a large metropolitan environment.

VI. CONCLUSION AND FUTURE WORKS

In this study, TMORL, which is a transformer-based multi-agent reinforcement learning model, has been proposed that integrates perception, prediction, and decision making with regard to intelligent urban waste management. The Vision Transformer can be used to classify waste accurately, and the Temporal Fusion Transformer provides trustworthy and understandable fill-level predictions. The multi-objective MARL layer is the optimization of routing according to the operational efficiency and sustainability criteria, such as minimized fuel use, minimized emission, decreased overflow cases, and increased collection speed. Experimental findings indicate that TMORL is better than traditional methods of standardization and heuristics, with substantial improvement in performance and environmental performance. The results emphasize that deep learning combined with reinforcement learning provides a scalable solution to the dynamic control of urban waste systems, regarding operational optimization instead of sustainability in general. Nevertheless, performance of any system is affected by the availability of and quality of sensors and computational needs of transformer-based models and

MARL policies can limit low-resource environments. After implementation, the framework is highly efficient in real time, offering a way of citywide implementation. These results are directly relevant to the research question since they demonstrate that TMORL is an effective way to integrate classification, forecasting, and adaptive routing in the context of real-time uncertainty in urban waste settings.

Future research will look into edge and federated learning plans to minimize the use of centralized computation, add dynamic traffic and environmental condition to plan better routes, and renewable-powered or electric collection fleets in order to make it more sustainable. Multi-city pilots will be tested in large-scale to assess the adaptability of a wide range of urban waste patterns and permit further deployment. TMORL creates a strong progressive model of sustainable waste management that integrates short-term operational objective with the long-term environmental and social sustainability.

REFERENCES

- [1] K. S. Kumar, C. H. Sulochana, D. Jessintha, T. A. Kumar, M. Gheisari, and C. Ananth, "Spatio-temporal Data Analytics for e-Waste Management System Using Hybrid Deep Belief Networks," in *Spatiotemporal Data Analytics and Modeling: Techniques and Applications*, Springer, 2024, pp. 135–160.
- [2] H. Algethami, "Synergizing Deep Learning and the Internet of Things (IoT) for Smart Waste Management (SWM)," in *2024 IEEE 16th International Conference on Computational Intelligence and Communication Networks (CICN)*, IEEE, 2024, pp. 498–506.
- [3] X. Wei and Y. Xu, "Research on carbon emission prediction and economic policy based on TCN-LSTM combined with attention mechanism," *Frontiers in Ecology and Evolution*, vol. 11, p. 1270248, 2023.
- [4] J. Zhao, T. He, L. Wang, and Y. Wang, "Forecasting Gate-Front Water Levels Using a Coupled GRU-TCN-Transformer Model and Permutation Entropy Algorithm," *Water*, vol. 16, no. 22, p. 3310, 2024.
- [5] M. W. Rahman, R. Islam, A. Hasan, N. I. Bithi, M. M. Hasan, and M. M. Rahman, "Intelligent waste management system using deep learning with IoT," *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 5, pp. 2072–2087, 2022.
- [6] M. I. B. Ahmed et al., "Deep learning approach to recyclable products classification: Towards sustainable waste management," *Sustainability*, vol. 15, no. 14, p. 11138, 2023.
- [7] I. Saukenova, M. Oliskevych, I. Taranic, A. Toktamyssova, D. Aliakbarkyzy, and R. Pelo, "Optimization of schedules for early garbage collection and disposal in the megapolis," *Eastern-European Journal of Enterprise Technologies*, vol. 1, no. 3, p. 115, 2022.
- [8] S. M. Cheema, A. Hannan, and I. M. Pires, "Smart waste management and classification systems using cutting edge approach," *Sustainability*, vol. 14, no. 16, p. 10226, 2022.
- [9] J. Gunaseelan, S. Sundaram, and B. Mariyappan, "A design and implementation using an innovative deep-learning algorithm for garbage segregation," *Sensors*, vol. 23, no. 18, p. 7963, 2023.
- [10] S. Shahab and M. Anjum, "Solid waste management scenario in india and illegal dump detection using deep learning: an AI approach towards the sustainable waste management," *Sustainability*, vol. 14, no. 23, p. 15896, 2022.
- [11] T. Sutikno, I. M. I. Subroto, D. Stiawan, and L. Handayani, "Technologies in Urban Smart Waste Management," *High-tech and Innovative Series*, vol. 1, pp. 27–34, 2024.
- [12] J. Yuan and Y. Li, "Wastewater quality prediction based on channel attention and TCN-BiGRU model," *Environmental Monitoring and Assessment*, vol. 197, no. 2, p. 219, 2025.
- [13] X. Chen, "Machine learning approach for a circular economy with waste recycling in smart cities," *Energy Reports*, vol. 8, pp. 3127–3140, 2022.

- [14] S. Nesmachnow, D. Rossit, and P. Moreno-Bernal, "A Literature Review of Recent Advances on Innovative Computational Tools for Waste Management in Smart Cities.," *Urban Science*, vol. 9, no. 1, 2025.
- [15] I. Sosunova and J. Porras, "IoT-enabled smart waste management systems for smart cities: A systematic review," *IEEE Access*, vol. 10, pp. 73326–73363, 2022.
- [16] A. Zaman, "Waste management 4.0: an application of a machine learning model to identify and measure household waste contamination—a case study in Australia," *Sustainability*, vol. 14, no. 5, p. 3061, 2022.
- [17] P. K. Dara, P. K. Gangwar, A. Das, R. Aarthi, K. C. Lakshmi, and J. G. John, "Intelligent Waste Management Systems Using Deep Belief Network in Smart Cities," in *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, IEEE, 2024, pp. 1–5.
- [18] M. Farghali and A. I. Osman, "Revolutionizing waste management: unleashing the power of artificial intelligence and machine learning," in *Advances in Energy from Waste*, Elsevier, 2024, pp. 225–279.
- [19] S. Ahmed, S. Mubarak, J. T. Du, and S. Wibowo, "Forecasting the Status of Municipal Waste in Smart Bins Using Deep Learning," *IJERPH*, vol. 19, no. 24, p. 16798, Dec. 2022, doi: 10.3390/ijerph192416798.
- [20] A. U. Gondal et al., "Real Time Multipurpose Smart Waste Classification Model for Efficient Recycling in Smart Cities Using Multilayer Convolutional Neural Network and Perceptron," *Sensors*, vol. 21, no. 14, p. 4916, Jul. 2021, doi: 10.3390/s21144916.
- [21] U. K. Lilhore, S. Simaiya, S. Dalal, and R. Damaševičius, "A smart waste classification model using hybrid CNN-LSTM with transfer learning for sustainable environment," *Multimed Tools Appl*, vol. 83, no. 10, pp. 29505–29529, Sep. 2023, doi: 10.1007/s11042-023-16677-z.
- [22] C. A. Villanueva, "Integrated Predictive Analysis Framework for Smart Waste Management," 2024.
- [23] S. Kumar, D. Yadav, H. Gupta, O. P. Verma, I. A. Ansari, and C. W. Ahn, "A novel yolov3 algorithm-based deep learning approach for waste segregation: Towards smart waste management," *Electronics*, vol. 10, no. 1, p. 14, 2020.
- [24] M. A. Olawumi, B. I. Oladapo, and R. A. Olawale, "Revolutionising waste management with the impact of Long Short-Term Memory networks on recycling rate predictions," *Waste Management Bulletin*, vol. 2, no. 3, pp. 266–274, 2024.
- [25] "Smart-Waste-Management-Dataset." Accessed: Feb. 20, 2025. [Online]. Available: <https://www.kaggle.com/datasets/viroopaksh/smart-waste-management-dataset>
- [26] "Dataset for Waste management system." Accessed: Sep. 19, 2025. [Online]. Available: <https://www.kaggle.com/datasets/sarasasaikrishna/dataset-for-waste-management-system>
- [27] W. Zhang et al., "AMTCN: An Attention-Based Multivariate Temporal Convolutional Network for Electricity Consumption Prediction," *Electronics*, vol. 13, no. 20, p. 4080, 2024.