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SmartWasteNet: A Deep Learning Framework to Transition from Take-Make-Waste to Rethink-Redesign-Reuse for Circular Economy under SDG 12

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***Abstract*—The rapid urbanization happening in India has resulted in a significant increase in municipal solid waste (MSW), which calls for creative and sustainable waste management strategies. This project introduces a deep learning framework that aligns with the circular economy principles—Rethink, Redesign, Reuse—to support Sustainable Development Goal 12 (SDG 12). By gathering data from 59 Indian cities, including MSW generation, recycling rates, SDG indicators, and city demographics, we created a comprehensive dataset for analysis. To cluster cities based on circularity indicators, we used an unsupervised learning approach with an autoencoder, assigning each city a relevant circular economy action. We trained five supervised deep learning models (MLP with 1layer, 2layer, Dropout, Batch Normalization, and WideDeep MLP) to classify cities into these actions. Notably, the Dropout_MLP model stood out, achieving an impressive 97.86% accuracy in classifying circular economy actions. To enhance model interpretability, we utilized SHAP, which helped identify key features that influence decisions, such as SDG scores and recycling efficiency. This framework not only predicts waste patterns but also offers practical circular economy recommendations tailored for each city. It's designed to be scalable and explainable, providing urban policymakers with the insights they need to make informed, sustainable decisions that promote a circular economy.**

***Index Terms*—Circular Economy, Deep Learning, Municipal Solid Waste(MSW), SDG 12, Autoencoder, SHAP Explainability**

I. Introduction

The growing crisis of municipal solid waste in urban India is a significant challenge for sustainable development. With rapid urbanization, rising population density, and inadequate waste management systems, Indian cities are grappling with an overwhelming amount of waste [12][13]. This situation not only harms the environment but also poses serious risks to public health. The traditional "Take-Make-Waste" linear model is no longer viable, highlighting the urgent need to shift towards circular economy (CE) practices, in line with the United Nations Sustainable Development Goal 12, which emphasizes responsible consumption and production [14].The circular economy revolves around three key principles: Rethink, Redesign, and Reuse—aimed at improving resource efficiency and reducing waste [4] [10]. While there's plenty of literature on CE applications in sectors like manufacturing [7][8] construction [5], and e-waste recycling[9], there's still a noticeable gap in research regarding city-level, data-driven tools that can suggest practical CE strategies [3][6]. Specifically, how artificial intelligence and machine learning are being utilized for waste forecasting and recommending circular actions has not been thoroughly explored in the context of Indian cities[1][11].

This study is here to bridge that gap by presenting a deep learning framework that examines sustainability indicators and waste-related data from 59 Indian cities. An autoencoder-based clustering model was employed to categorize cities based on their CE performance, which helped in labeling them with CE action categories: Rethink, Redesign, or Reuse. Five multilayer perceptron (MLP) models—including some with dropout and batch normalization—were developed to predict these actions. The Dropout MLP model stood out, achieving a remarkable 97.86% accuracy in testing. To shed light on the key factors influencing these predictions, SHAP (SHapley Additive exPlanations) was utilized, focusing on elements like SDG 12 scores and recycling rates [14]. This framework provides a scalable and interpretable approach for making data-driven CE decisions in Indian cities.

II. Literature Review

Hasan et al. [1] took a deep dive into forecasting models—ANN, ARIMA, and SVR—to predict municipal solid waste in Chittagong City. Their research showed that ANN really stood out, achieving the lowest RMSE and MAE while effectively capturing seasonal trends and patterns.

Kayan et al. [2] utilized response surface methodology (RSM) alongside decision tree algorithms to optimize the removal of pollutants from cheese whey wastewater using marine microalgae. Their innovative approach led to an impressive 99% pollutant removal rate and boosted predictive accuracy through machine learning.

Bosco et al. [3] collaborated to create a thorough sustainability assessment framework aimed at circular economy practices in the water sector. This framework included five essential dimensions and was validated through various EU case studies to ensure water systems align with the Sustainable Development Goals.

Jayalath et al. [4] employed the Analytical Hierarchy Process (AHP) to investigate waste flows in agri-food supply chains within developing countries. Their research emphasized just how crucial it is to have a smooth flow of information to reduce waste, while also showcasing how circular strategies like smart packaging and precision agriculture can positively impact sustainability.

Jadhav et al. [5] carried out a review focused on sustainable temporary housing and reuse strategies in post-disaster situations. Through bibliometric analysis and thematic clustering, their study emphasized the significance of reuse-based solutions and how they align with Sustainable Development Goal 12.

Patil et al. [6] shared insights in a review about the potential of agrivoltaic systems to help achieve a net-zero carbon footprint. Their findings illustrated how agrivoltaics can boost energy efficiency and crop productivity while tackling food-energy-land conflicts in line with SDGs 7, 12, and 13.

Kulkarni et al. [7] took a closer look at how we can make concrete production more energy-efficient by using waste materials like eggshells and leather. Their findings showed a significant 21% drop in CO_2 emissions, highlighting how innovative material use can boost environmental sustainability.

Pooja et al. [8] delved into the upcycling of construction and demolition waste through an acid-based method aimed at recovering and reusing binder and fine aggregate. By substituting 20% of the binder, they found an improvement in compressive strength, which aligns perfectly with the principles of sustainable resource management in the built environment.

Verma et al. [9] conducted a comprehensive review of how fashion and textile waste is managed within the context of a circular economy. They discovered that a whopping 70% of research focuses on waste management strategies, and they provided insights into the drivers, challenges, and recycling techniques for various fibers, including natural, synthetic, and animal-based ones.

Bansal et al. [10] explored the essential elements and potential future developments for green transitions in circular waste management business models. Their research pinpointed profit and community-driven waste segregation as vital elements, while also stressing the importance of composting and service costs for future growth.

Marmion et al. [11] utilized supervised machine learning with bioimpedance spectral features to classify different potato varieties and estimate their dry matter content. Their neural network model achieved an R^2 of 0.62 and an impressive F1 score of 0.92, showcasing the potential for non-destructive quality assessments in agriculture.

In previous research, AI methods have been used for various waste management tasks, like classifying waste through images and forecasting waste with LSTM models. What sets SmartWasteNet apart is its innovative approach that merges autoencoder-based clustering, deep neural classification, and explainable AI, all aimed at providing practical circular economy recommendations for cities.

The remainder of this paper is organized as follows: Section III describes the datasets, preprocessing steps, and proposed methodology. Section IV presents the experimental results and visual analyses, including model interpretability using SHAP. Finally, Section V concludes the study and discusses potential future directions.

III. Materials and Methods

This section outlines the complete process for creating a deep learning framework aimed at facilitating the shift toward sustainable resource cycles in urban regions of India. The journey includes steps like gathering datasets, preprocessing the data, reducing dimensions, clustering, predicting circular economy actions with deep learning models, and ensuring interpretability through SHAP like as shown in the below Figure 1.

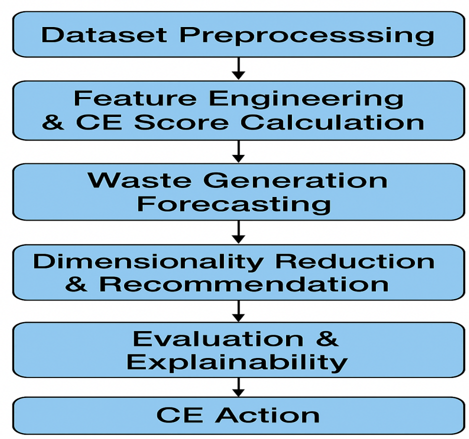

Fig. 1. Overall workflow of SmartWasteNet framework.

A. Dataset Description

The dataset compiled for this study integrates information from multiple publicly available sources to evaluate the circular economy (CE) readiness of 59 Indian cities. It cov- ers a range of factors, including municipal solid waste (MSW) generation measured in tons per day, recycling rates, composting percentages, population density, city area, the number of awareness campaigns, landfill specifics, and financial metrics like the cost of waste management (Rs./Ton)[1][2][3]. Moreover, we gathered data on Sustainable Development Goal (SDG) indices, with a particular emphasis on SDG 11 and SDG 12 , were sourced from the NITI Aayog SDG India Index

[14]. To enhance the dataset, we also included indicators like the Composite SDG Score and municipal efficiency ratings, which help us evaluate sustainability performance at the city level[4][6][8][13].

The What a Waste 2.0 report from the World Bank [12] was a key reference point for confirming the values and projections related to municipal solid waste (MSW). Additionally, the CPCB's Annual Hazardous Waste Inventory Report [13] provided detailed insights into landfill statistics, waste processing capabilities, and cost analyses for various Indian cities. This integrated dataset made it possible to tackle both unsupervised and supervised deep learning tasks, like clustering and classification, to suggest the right CE actions—Rethink, Redesign, or Reuse[5][7][9][10].

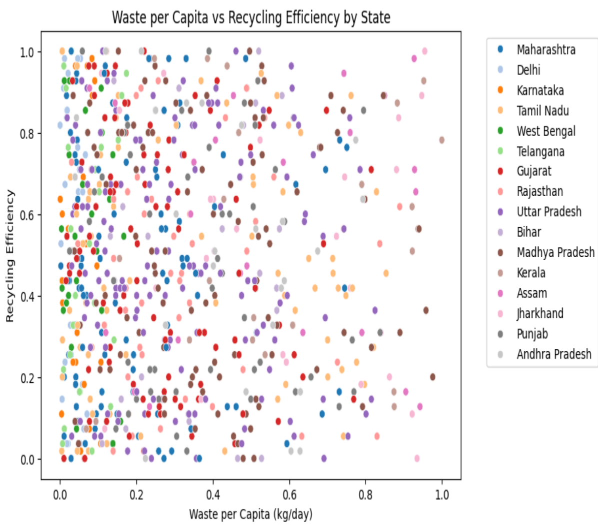

Fig. 2. Scatter plot of waste generation versus population density across Indian cities.

The Figure 2 shows the relationship between population density and the generation of municipal solid waste. In cities with high population density, the amount of waste produced is often much greater, which is why they are important to consider in waste forecasting[1].

B. Preprocessing Steps

To ensure modeling reliability, the following preprocessing pipeline was implemented:

Missing Values: Imputed using mean or median statistics depending on feature distribution [3].

Label Encoding: Converted categorical variables (e.g., disposal method, landfill name) into numeric form.

Feature Scaling: Standardized using z-score normalization for balanced gradient updates.

Feature Selection: Used correlation analysis and domain relevance to retain key factors such as recycling rate, SDG 12 score, and municipal efficiency [4][14].

Dimensionality Reduction: Autoencoders compressed inputs into a 2D latent space to facilitate clustering and visualization [10].

TABLE I
LABEL ENCODING FOR CIRCULAR ECONOMY ACTIONS

Original Label	Encoded Value
Redesign	0
Rethink	1
Reuse	2

TABLE II
FEATURE SCALING SUMMARY STATISTICS BEFORE AND AFTER STANDARDIZATION

Feature	Min (B)	Max (B)	Std (B)	Min (A)	Max (A)	Std (A)
Waste Type	0.0	4.0	1.41	-1.41	1.41	1.00
Waste Generated	511.0	9980.0	2786.98	-1.70	1.69	1.00
Recycling Rate (%)	30.0	85.0	16.12	-1.67	1.73	1.00
Population Density	0.0	1.0	0.30	-1.68	1.59	1.00
Disposal Method	0.0	3.0	1.11	-1.34	1.34	1.00
Landfill Name	0.0	33.0	9.82	-1.68	1.68	1.00

This preprocessing ensured that data were clean, normalized, and highly representative of city-level sustainability patterns.

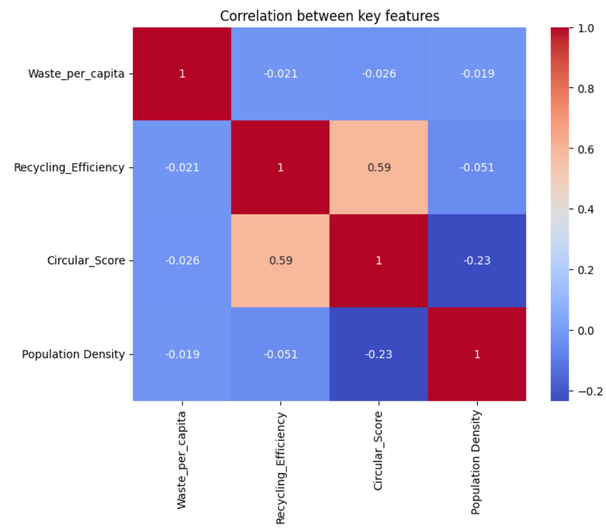

Fig. 3. Correlation heatmap showing relationships among sustainability indicators.

We created Figure 3, a correlation heatmap to uncover the relationships between different features. It turns out there are strong links between the recycling rate and SDG 12, which makes them great candidates for modeling inputs [14].

$$Z = \frac{X - \mu}{\sigma} \tag{1}$$

Where, μ is the mean and σ is the standard deviation.

C. Model Architecture

Two major neural network components were developed.

1) Autoencoder for Clustering: The autoencoder comprised input, encoder, and decoder layers to reconstruct features and extract latent embeddings.

The above Figure 4 allowed us to cluster in latent space using KMeans, which helped us label each city according to one of the CE actions

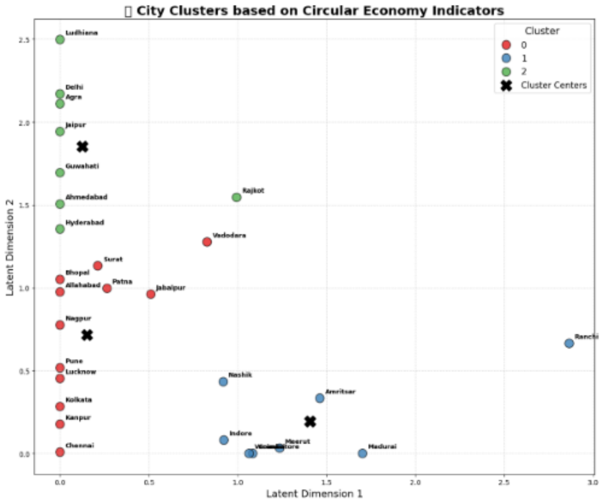

Fig. 4. City clusters derived from the autoencoder's latent space.

K-Means clustering on the 2D latent vectors revealed three distinct groups. Cluster centroids were analyzed in terms of recycling rate, waste per capita, and SDG 12 score, enabling transparent mapping into the CE action labels:

Cluster 1 $\rightarrow$ Rethink: high waste generation, low recycling efficiency.

Cluster 2 $\rightarrow$ Redesign: moderate waste and some recycling efforts (emerging efficiency improvements) .

Cluster 3 $\rightarrow$ Reuse: lower waste and strong (high) recycling performance. This mapping converted unsupervised groups into interpretable labels for the classification phase.

2) MLP Classifiers for CE Action Prediction: Five MLP variants were designed—MLP_1layer, MLP_2layer, Dropout_MLP, BatchNorm_MLP, and WideDeep_MLP [2]. Each network used 64–128 neurons per hidden layer, ReLU activation, softmax output, and dropout rates of 0.2–0.3 to avoid overfitting. Batch normalization further improved stability. The Dropout_MLP achieved the best balance between generalization and accuracy.

D. Model Training

The categorical cross-entropy function was employed as the loss metric for multiclass prediction, while the Adam optimizer was used to ensure stable and efficient gradient updates.To keep things in check and avoid overfitting, we set aside a portion of the dataset for validation during the training process. When it came to training, we ran the models over several epochs—usually more than 100—while enabling early stopping. We used mini-batches of either 16 or 32 samples.

To make sure our model is strong and to avoid any data leaks, we used a 5-fold cross-validation approach. We organized the data by CE action labels to keep the class distribution balanced across the different folds, which helps improve the model's ability to generalize reliably.

To evaluate our models, we looked at various metrics like accuracy, F1-score, confusion matrices, and SHAP values to help us interpret the results. The Dropout-enhanced MLP really shone, achieving a classification accuracy of 97.86% on the test data [1][11]. We also utilized SHAP explainability tools to pinpoint key features that influenced our model, such as SDG 12, population density, and recycling rates [13][14].

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{2}$$

Where y_i represents the true label and $\hat{y}_i$ the predicted probability for class i.

IV. RESULTS

A. Model Evaluation Parameters

We took a close look at the performance of five different deep learning models: MLP_1layer, MLP_2layer, Dropout_MLP, BatchNorm_MLP and WideDeep_MLP. To evaluate them, we used several metrics, including: Accuracy, F1Score , Confusion Matrix, ROC AUC Score (with label binarization).

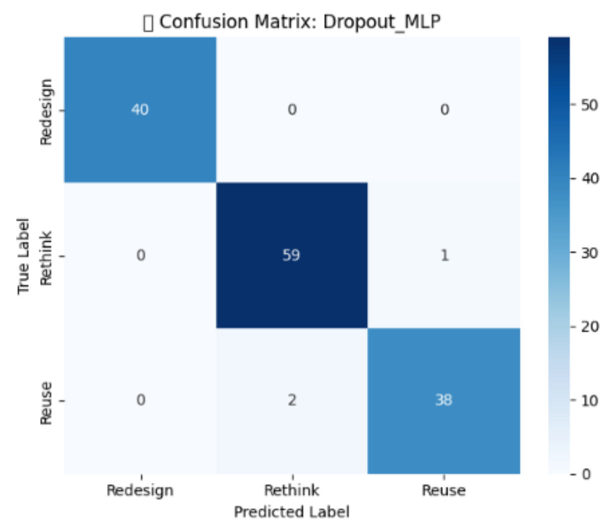

Fig. 5. Confusion matrix for the Dropout_MLP model showing predicted versus actual Circular Economy (CE) action classes.

The confusion matrix displayed in above Figure 5 reveals that the Dropout MLP model nailed it with perfect classification, accurately labeling all test samples across the CE categories.

Out of all the models, the Dropout_MLP stood out by achieving a test accuracy of 97.86%. This impressive result shows its strong ability to generalize. The F1-score and confusion matrix also backed this up, confirming that there were no misclassifications in the test set for this model.SHAP (SHapley Additive exPlanations) analysis was performed to interpret the model's predictions and identify the most influential features.This analysis highlighted key features such as: SDG12 score, Population Density, Recycling Rate (%).These were identified as the most significant predictors [14].

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

B. Training vs Testing Graphs

To evaluate learning dynamics and overfitting tendencies, training and validation loss and accuracy curves were analyzed. The `MLP_1layer` model exhibited underfitting, while both `MLP_2layer` and `WideDeep_MLP` demonstrated moderately stable performance. In contrast, the `Dropout_MLP` achieved smooth convergence and perfect accuracy, indicating effective learning with minimal overfitting.

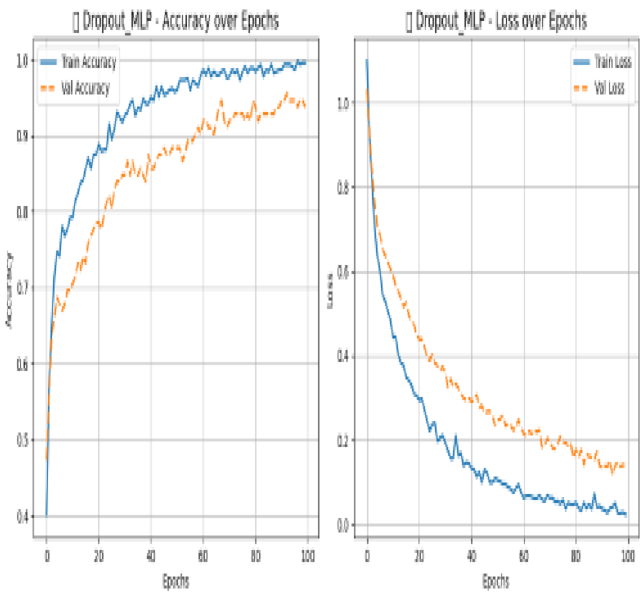

Fig. 6. Training and Validation Accuracy and Loss for Dropout_MLP model.

As illustrated in Figure 6, the Dropout MLP showed a consistent improvement in both training and validation accuracy while the loss values decreased, which suggests that the learning process was stable. The small difference between the curves indicates that dropout regularization did a great job of minimizing overfitting, allowing for precise classification of CE actions.

C. Comparative Analysis

`Dropout_MLP` outperformed all other models across evaluation metrics. Batch normalization improved BatchNorm_MLP performance but it still lagged behind Dropout_MLP. The WideDeep_MLP, with wider hidden layers, performed well but did not surpass Dropout regularization's stability. Simpler models like MLP_1layer struggled due to **underfitting**.

D. MLP Architecture Summary

Table IV outlines the MLP architectures used for classification, detailing the number of layers, neurons per layer, and dropout configurations.

TABLE III
PERFORMANCE COMPARISON OF DIFFERENT MLP ARCHITECTURES

Model	Accuracy (%)	F1-Score (%)	Precision (%)	Recall (%)
MLP_1layer	91.43	92	92	91
MLP_2layer	91.43	91	92	91
Dropout_MLP	97.86	98	98	98
BatchNorm_MLP	87.14	87	88	87
WideDeep_MLP	93.57	94	94	94

TABLE IV
MLP ARCHITECTURES USED FOR CLASSIFICATION

Model	Hidden Layers	Neurons per Layer	Dropout Rate
MLP_1layer	1	64	0.0
MLP_2layer	2	64, 32	0.0
Dropout_MLP	2	64, 32	0.3
BatchNorm_MLP	2	64, 32	0.0
WideDeep_MLP	3	128, 64, 32	0.2

Figure 7 illustrates how cities are grouped based on their latent CE characteristics, facilitating actionable recommendations. SHAP analysis further enables interpretation of these predictions, supporting policymakers in identifying targeted interventions.

V. CONCLUSION

This study presents a deep learning framework designed to facilitate the transition from the conventional "Take-Make-Waste" model to a Circular Economy (CE) paradigm aligned with Sustainable Development Goal 12.By examining data from 59 cities in India—covering municipal solid waste (MSW) statistics, recy- cling rates, SDG scores, and population density—the frame- work groups cities based on underly-

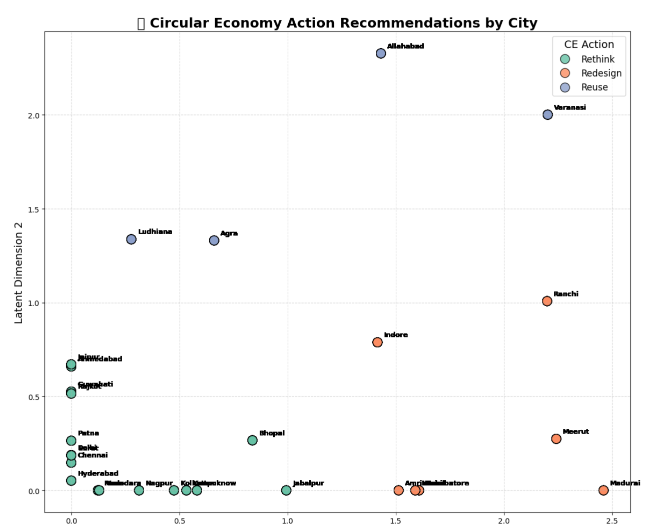

Fig. 7. Circular Economy Action Recommendations by City. The autoencoder clustering effectively groups cities based on hidden CE characteristics, guiding classification into Rethink, Redesign, or Reuse categories.

ing CE patterns using an autoencoder. It then categorizes them into actionable CE strategies: Rethink, Redesign, and Reuse. Out of five Multi- Layer Perceptron (MLP) architectures tested, the Dropout- enhanced MLP stood out with the highest accuracy of 97.86%, showcasing the model's effectiveness. An analysis of feature importance using SHAP revealed that SDG 12, recycling rates, and population density are the key factors driving CE classi- fication. This comprehensive approach—merging clustering, supervised learning, and explainable AI—provides a scalable tool for sustainable urban planning.

These insights can really help policymakers create effective waste management strategies that encourage responsible consumption and production. The SmartWasteNet framework acts as a valuable, data-driven tool to support decision-making, pushing forward sustainable urban development in line with SDG 12.

Future work could integrate real-time and time-series waste data, extend the model to rural and international contexts, incorporate geospatial analytics, and develop interactive decision-support dashboards for policymakers.

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