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A Privacy-First Client-Side Intelligence Framework for Municipal Solid Waste Classification and Economic Valuation: A Case Study of Deolali Pravara

Chhaya S.Yelwande[1], Dr. Prasaddu Peddi[2], Dr. Baban B. Amale[3]

[1]Research Scholar, [2]Research Guide, [3]Research Co-Guide, Department of Computer Science, Shri JJT University, Jhunjhunu, Rajasthan, India

***Abstract*-- The digital transformation of Municipal Solid Waste Management (MSWM) faces significant barriers in resource-constrained regions due to infrastructure costs and data privacy concerns. This study presents an integrated, browser-based intelligent system designed to classify waste types and forecast generation patterns using a zero-infrastructure approach. Following a 7-phase Design Science Research (DSR) methodology, the system evaluates 13 classification and 12 forecasting algorithms using 9,839 real-world records from the DeolaliPravara municipal zone (2022–2024). Results demonstrate that the Random Forest algorithm achieved a peak classification accuracy of 93.1%. For generation forecasting, Support Vector Regression (SVR) and Linear Regression provided high stability ($R^2 = 0.929$). The framework further quantifies a circular economy pathway, identifying a revenue potential of ₹ 13,046,534 from recovered materials. This research democratizes advanced waste analytics by performing all computations on the client-side, ensuring data sovereignty and near-zero operational costs.**

I. Introduction

1.1 Global and National Context

Global waste generation is an escalating crisis, with projections suggesting a rise from the current 2.01 billion tons to 3.40 billion tons by 2050. In India, urban centers generate over 70% of the nation's waste, yet only 20–25% undergoes formal processing. Improper disposal contributes to approximately 11% of global methane emissions, which possess a warming potential 28–36 times higher than carbon dioxide.

1.2 The Analytical Gap

While large municipalities employ server-based AI platforms, small and medium-sized local bodies face an "analytical gap" characterized by:

- *Capability Gap:* Lack of integrated platforms for forecasting and conversion analysis.
- *Accessibility Gap:* High costs of server infrastructure and technical personnel.
- *Privacy Gap:* Concerns regarding the transmission of municipal data to external servers.

1.3 Research Objectives

This study aims to:

1. Evaluate MSW characteristics through data science.
2. Identify resource recovery opportunities via waste-to-product conversion.
3. Apply 25 machine learning algorithms to establish performance benchmarks.
4. Develop a functional, client-side architectural module for municipal use.

II. Literature Review

Data Science in MSWM has seen various specialized applications:

- *The integration of Biodegradable Waste:* García et al. (2005) investigated the use of organic fractions as animal feed, noting that while nutrient-dense, certain fractions require heat treatment to meet safety standards.
- *Energy Recovery:* Kaur et al. (2023) highlighted the potential of biomethanation and gasification in reducing greenhouse gas emissions and fossil fuel demand.
- *Forecasting Models:* Rathod and Patel (2025) reviewed various models, finding that over 30% of recent studies utilized Artificial Neural Networks (ANN) due to their precision in handling complex urban variables.
- *Real-time Segregation:* Pawar et al. (2013) introduced the "SMART SORT" system using audio classification, achieving 94.4% accuracy for materials like glass and plastic.

This research builds upon these works by providing an *integrated* framework that combines these functions into a single accessible platform.

III. Methodology

3.1 Research Framework (DSR)

The study follows a 7-phase implementation process:

1. *Problem Definition:* Identifying stakeholder needs in DeolaliPravara.
2. *Data Collection:* Sourcing 9,839 records spanning 2022–2024.
3. *System Design:* Developing a 3-tier client-side architecture.
4. *Processing Pipeline:* Building the Upload-Edit-Clean workflow.
5. *ML Module:* Implementing 25 algorithms for classification and forecasting.
6. *Analytics/Visualization:* Designing interactive dashboards and revenue models.
7. *Validation:* Evaluating results via RMSE, MAPE, and Accuracy metrics.

3.2 Data Model and Study Area

The study area is DeolaliPravara, a municipal town in Maharashtra, India (Population ~30,334). The data is structured using the Waste Data Row interface:

- *Date:* ISO 8601 format.
- *Zone:* 18 wards/geographic identifiers.
- *Waste_Type:* Categorized into Plastic, Organic, Paper, Metal, and Glass.
- *Quantity_kg:* Numeric weight.

3.3 Data Preprocessing Pipeline

To ensure high-integrity analysis, an automated cleaning pipeline was implemented:

- *Duplicate Removal:* A composite key (Date + Zone + Type) is used to identify and remove redundant records ($O(n)$ complexity).
- *Outlier Detection:* The system utilizes the Interquartile Range (IQR) method:
    - $IQR = Q3 - Q1$
    - $Upper Bound = Q3 + 1.5 \times IQR$
    - Any $q_i> Upper Bound$ is flagged as a high-quantity outlier.

IV. Machine Learning Implementation

4.1 Classification Algorithms

The study implemented 13 algorithms to predict waste categories:

- *K-Nearest Neighbors (KNN):* Uses Euclidean distance $d(x, x_i) = \sqrt{\sum (x_j - x_{ij})^2}$ for majority voting.
- *Random Forest (RF):* An ensemble of 100 decision trees using Gini Impurity for splitting.
- *Logistic Regression***:** Employs the Softmax function for multi-class probability:
    - $P(y=k|x) = \frac{\exp(w_k^T x)}{\sum \exp(w_j^T x)}$
- *Support Vector Machine (SVM):* Utilizes RBF kernels to find maximum margin hyperplanes.

4.2 Forecasting Algorithms

Five primary models were evaluated for generation trends:

- *Linear Regression:* Assumes $y = \beta_0 + \beta_1 t + \epsilon$ to model baseline trends.
- *Prophet (Facebook):* Decomposes time series into $y(t) = g(t) + s(t) + h(t) + \epsilon_t$ (Trend, Seasonality, Holidays).
- *LSTM:* A Recurrent Neural Network designed to capture long-term dependencies via forget, input, and output gates.

V. System Architecture

5.1 Client-Side Only Philosophy

The system is built on a **zero-backend** architecture using Next.js 14 and TypeScript.

- *Data Privacy:* Data never leaves the browser, eliminating server breach risks.
- *Storage:* Leverages localStorage and IndexedDB for persistence.
- *Visualization:* Uses **Recharts** for 60 FPS interactive rendering of up to 10,000 records.

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VI. Results And Discussion

6.1 Data Quality Performance

The pipeline successfully processed the raw dataset in 4.2 seconds, identifying 372 flagged issues and achieving a final data quality score of 99.2%.

6.2 Algorithm Performance Benchmarks

- *Classification:* Random Forest was the top performer with 93.1% accuracy. SVM provided the highest Precision (93.6%), while LightGBM achieved the best Recall (95.0%).
- *Forecasting:* SVR and Linear Regression achieved an R^2 of 0.929, indicating they are highly reliable for municipal waste generation patterns. Gradient Boosting provided the best MAPE (6.6%).

6.3 Economic Valuation

The conversion module identified 13 product pathways:

- *Revenue Leaders:* Metal waste contributed ₹ 8,506,183 (65.2% of total value).
- *Plastic Potential:* ₹ 2.1M potential from plastic granules.
- *Environmental Impact:* Diversion of organic waste from landfills could avoid 429.5 tonnes of CO_2e.

VII. Conclusion

This research successfully bridges the "analytical gap" by providing a high-performance, cost-free, and private tool for municipal waste management. By demonstrating that Random Forest and SVR can provide near-state-of-the-art results on local browser hardware, this framework paves the way for data-driven circular economies in developing regions. Future work will focus on integrating real-time IoT sensor inputs to automate the data collection phase.

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Corresponding Author: Chhaya S Yelwande,

Email: csgalande27@gmail.com