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Artificial Intelligence for Waste Recycling: A Smart Solution for Developing Urban Areas: A case study of Sfax, Tunisia

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***Abstract*: This study applies Artificial Intelligence (AI) to enhance waste sorting in Sfax, Tunisia, addressing the Municipal Solid Waste (MSW) crisis amid landfill saturation and environmental challenges. Using real-world data from the SINE recycling company, several supervised Machine Learning (ML) models—including Logistic Regression (LR), XGBoost, AdaBoost, and Multilayer Perceptron (MLP)—were evaluated. LR achieved the highest and most balanced performance, closely followed by the Support Vector Classifier (SVC). These results demonstrate that even simple ML models can effectively improve waste management efficiency. The validated classification system (≈94% precision) offers a scalable, cost-effective, and sustainable solution for smarter waste sorting, particularly in resource-constrained regions facing environmental pressures.**

***Keywords*— municipal solid waste; machine learning; waste classification; Sfax; recycling.**

I. Introduction

Global Municipal Solid Waste (MSW) generation is rising rapidly, creating significant environmental, health, and economic challenges. Transitioning to a Circular Economy requires maximizing resource recovery through efficient recycling, which fundamentally depends on precise waste sorting. Traditional manual methods are costly, slow, and error-prone, producing inconsistent secondary raw materials.

Artificial Intelligence (AI), particularly Machine Learning (ML), offers a promising solution by automating and optimizing waste classification. While deep learning approaches have been studied in industrialized nations, their applicability and economic feasibility in emerging economies remain underexplored.

This issue is especially pressing in Sfax, Tunisia's second economic and industrial hub, where landfill saturation, inefficient waste logistics, and untapped recycling potential (≈15–20% plastic in the MSW stream) demand urgent solutions. Existing AI models, often adapted from foreign datasets, lack local relevance, failing to capture the diversity of waste streams and operational constraints.

This study develops AI-based predictive models tailored to Sfax, using a real-world dataset from the SINE company. We evaluate multiple supervised ML algorithms, from Logistic Regression to tree-based and neural network models, demonstrating that the simple Logistic Regression model achieves the highest precision (≈94%). Our findings provide a cost-effective, deployable solution for optimizing recycling and advancing circular economy strategies in resource-constrained urban contexts.

II. Literature Review

The global shift toward sustainability has driven innovative approaches in waste management, with automated AI-powered classification systems emerging as a promising solution. Riba et al. (2020)

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implemented automatic sorting to reduce costs, while Bonifazi et al. (2018) used hyperspectral imaging for polymer classification.

Integration of Information and Communication Technologies (ICT), IoT, AI, and Machine Learning (ML) is increasingly applied to optimize waste processes. Hidalgo et al. (2019) showed that IoT and AI can enhance waste collection efficiency.

ML has been successfully used for accurate waste classification: Adedeji and Wang (2019) combined ResNet50 with SVM to achieve 98.92% accuracy across glass, metal, paper, and plastic; Akhand et al. (2023) found fine-tuned Vision Transformers exceeded 95% accuracy on plastic waste; Chhabra et al. (2024) achieved 93.28% accuracy for organic vs. recyclable waste using an enhanced CNN; Sayes et al. (2024) optimized InceptionV3 for high precision on TrashNet. Hashemi-Amiri et al. (2023) and Zhu et al. (2023) highlighted ML's value for logistics and ecological assessment.

These studies collectively demonstrate AI and ML's potential to improve waste classification and overall system efficiency.

III. METHODOLOGY

III.1 DATASET:

The dataset was provided by SINE, a waste management company based in Sfax. For this study, a subset of 500 labeled samples was used, evenly distributed across four classes. The distribution of the classified waste samples is summarized in Table I.

TABLE I
DISTRIBUTION OF SAMPLES

Class	Number of samples
Glass	125
Cardboard	125
Plastic	125
Other	125
Total :	500

III.2 AI MODELS FOR WASTE CLASSIFICATION:

This study employs a structured methodology to investigate the potential of machine learning (ML) models to analyze and optimize waste management strategies, using real-world data provided by SINE

III.2.1 MACHINE LEARNING MODELS:

Several supervised ML algorithms were evaluated for waste classification, including LR, SVC, MLP, RF, XGBoost, AdaBoost, and Gradient Boosting Machine (GBM). LR provides a simple, interpretable baseline; SVC separates linear and nonlinear classes using kernel functions; MLP models complex nonlinear relationships but requires careful tuning. Ensemble methods (RF, AdaBoost, XGBoost, GBM) combine multiple weak learners to enhance predictive accuracy and robustness, with boosting algorithms iteratively reducing bias and variance. These models were compared in terms of interpretability, computational efficiency, and classification performance to identify the most effective and contextually viable solution for optimizing waste sorting in Sfax.

III.2.1 EVALUATION METRICS:

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The performance of the ML models was assessed using standard metrics derived from the confusion matrix:

- **Precision:** The proportion of correctly predicted samples among all samples classified into a given class.
- **Recall (Sensitivity):** The proportion of correctly identified positive instances among all actual positive samples.
- **F1-Score:** The harmonic mean of Precision and Recall, providing a balanced measure of classification performance.
- **Accuracy:** The overall proportion of correctly classified samples out of the total number of samples.

IV. Experimental Results and Discussion :

Table II presents model performance across all waste classes in terms of Precision, Recall, and F1-score. Logistic Regression (LR) and Support Vector Classifier (SVC) achieved the highest results, with LR performing best overall, followed by SVC. The Multilayer Perceptron (MLP) ranked third, while AdaBoost, though less accurate, outperformed Gradient Boosting Machine (GBM) and XGBoost. These results indicate that even simple models like LR can deliver high predictive accuracy, computational efficiency, and practical applicability in resource-constrained settings.

Table II: MODEL PERFORMANCE METRICS BY CLASS

ML algorithm	**Types**	**Precision**	**Recall**	**F1-score**
SVC	Glass	1.00	0.95	0.97
	Garboard	0.94	0.86	0.90
	Plastic	0.86	0.97	0.91
	Other	0.95	0.95	0.95
Random Forest	Glass	0.6	0.79	0.68
	Garboard	0.55	0.65	0.59
	Plastic	0.52	0.39	0.45
	Other	0.52	0.38	0.44
MLP	Glass	0.89	0.82	0.85
	Garboard	0.72	0.78	0.75
	Plastic	0.68	0.71	0.69
	Other	0.77	0.73	0.75
XGBoost	Glass	0.66	0.71	0.68
	Garboard	0.54	0.59	0.56
	Plastic	0.46	0.50	0.48
	Other	0.59	0.43	0.50
Adaboost	Glass	0.86	0.66	0.75
	Garboard	0.59	0.46	0.52
	Plastic	0.46	0.45	0.45
	Other	0.33	0.49	0.39
Gardient Boosting	Glass	0.68	0.71	0.69
	Garboard	0.61	0.59	0.60
	Plastic	0.52	0.71	0.60
	Other	0.77	0.46	0.58
Logistic Regression	Glass	1.00	0.95	0.97
	Garboard	0.92	0.92	0.92
	Plastic	0.88	0.95	0.91
	Other	0.97	0.95	0.96

A summary of overall performance (Accuracy and weighted average F1-score) is presented in Table III and Fig.1.

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TABLE III : COMPARISON OF MODEL PERFORMANCE

Model	Accuracy	F1-score
SVC	0.933333	0.933608
Random Forest	0.553333	0.540250
MLP	0.760000	0.761345
XGBoost	0.560000	0.557500
AdaBoost	.513333	0.527492
Gradient Boosting	0.620000	0.618207
Logistic Regression	0.940000	0.940569

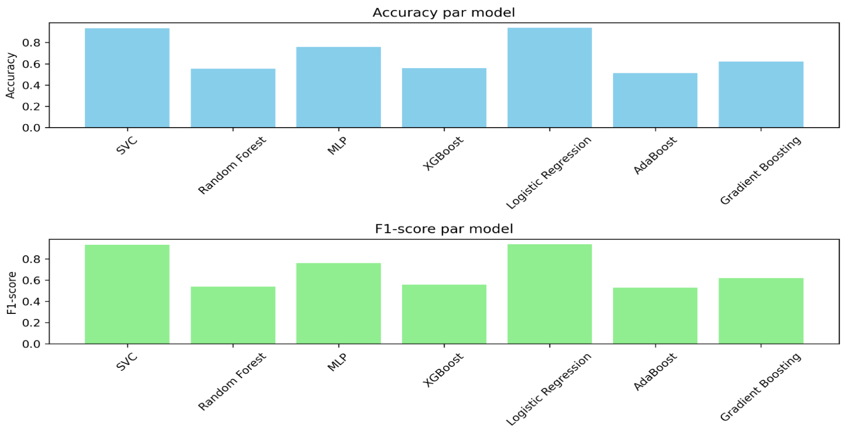

Fig.1: Comparison of Model Performance

Table III and Fig. 1 summarize the overall model performance, including Accuracy and weighted F1-score. Consistent with class-specific results, Logistic Regression (LR) and Support Vector Classifier (SVC) achieved the highest performance, with LR delivering the most balanced results across all waste categories, followed by SVC. The Multilayer Perceptron (MLP) ranked third, capturing complex patterns but performing slightly lower than the linear models.

More complex tree-based algorithms—Random Forest, XGBoost, AdaBoost, and Gradient Boosting—underperformed, likely due to the dataset's size and characteristics, which may have limited their potential and risked overfitting. LR achieved the highest performance (Accuracy: 94%, F1-score: 94.06%), while SVC followed closely (Accuracy = 0.933, F1-score = 0.9336), confirming that simple, well-regularized models can outperform more complex architectures for this task (Table III).

V- CONCLUSION:

This study highlights the transformative potential of Artificial Intelligence (AI), particularly Machine Learning (ML), in addressing the municipal waste crisis in Sfax, Tunisia. With approximately 250,000 tons of waste generated annually—15–20% of which are valuable recyclables—optimizing waste sorting is essential for effective resource recovery.

Using real-world data from SINE, simple, computationally efficient models such as Logistic Regression (Accuracy: 94%, F1-score: 94.06%) and Support Vector Classifier (~94% accuracy) achieved high classification accuracy, distinguishing between glass, cardboard, plastic, and other categories. These results

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demonstrate the feasibility of cost-effective automated sorting systems, enhancing recycling rates and material purity while reducing labor costs.

To maximize impact, AI-based sorting should be integrated into a holistic circular economy strategy, including IoT-enabled collection, public awareness campaigns, and fiscal incentives. Expanding datasets to include more waste types and varied imaging conditions, and piloting automated sorting facilities using LR or SVC, is recommended to validate and scale sustainable waste management practices in Sfax and similar urban areas.

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