MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 1853-1856

A Multi-Model Machine Learning Framework for Waste Intelligence: Classification and Predictive Analytics for Smart Waste Management

Dr.Manjula Devarakonda Venkata[1],
Department of Computer Science and Engineering
Pragati Engineering College (A) , Surampalem.
dv.manjula@gmail.com

Dr.Alugolu Avinash[2*],
Department of Computer Science and Engineering
Pragati Engineering College (A) , Surampalem.
agoyal514@gmail.com

P.Kanaka Tulasi[3],
Department of Computer Science and Engineering
Pragati Engineering College (A) , Surampalem.
pkanakatulasi86@gmail.com

S.K.Sankar[4],
Department of Computer Science and Engineering
Pragati Engineering College (A) , Surampalem.
sksankar2023@gmail.com

Abstract:

A swift expansion of urban environments and industrial sectors is contributing to a rise in the volume and complexity of solid waste, posing significant challenges for current waste management systems. Traditional waste collection methods are heavily reliant on manual sorting and fixed collection schedules, leading to increased handling costs and adverse environmental impacts. In this context, machine learning presents an opportunity to enhance waste management through intelligent data systems. We introduce a multi-algorithm Machine Intelligence framework designed to tackle the complexities of waste management by leveraging various machine learning techniques, data classification, and predictive analytics. Our approach incorporates four distinct machine learning models: Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbours (KNN), and Extreme Gradient Boosting (XGBoost). We employ these models within a comprehensive analysis framework to facilitate comparisons among them.The proposed methodology encompasses data preparation, feature encoding, and performance optimization strategies aimed at enhancing both accuracy and reliability for predictive applications. Our experimental results indicate that an ensemble model combining XGBoost with Random Forest outperforms traditional models in predictive tasks, with Random Forest demonstrating consistent superiority in classification accuracy. This research illustrates that integrating multiple machine learning models can lead to more cost-effective and adaptable waste management systems, ultimately supporting sustainability goals.

Keywords: Machine Learning, Waste Management, Waste Classification, Predictive Analytics, XGBoost, Random Forest, Smart Waste Systems, Data-Driven Decision Making.

INTRODUCTION

Waste management has recently become increasingly challenging due to the ongoing trends of urbanization, industrialization, and evolving consumption behaviours worldwide [1],[2]. The continuous generation of waste has posed significant challenges to existing waste management systems, which are now often overwhelmed and inadequately designed to handle the volume of waste produced [2]. Many traditional systems rely on manual segregation and have outdated collection schedules that fail to adapt to changing demands, leading to issues such as overflowing bins, inefficient resource utilization, and heightened pollution levels [10]. Consequently, there is a pressing need for advanced and effective waste management systems.

As illustrated by industry growth, machine learning presents a potential solution for addressing complex data-related challenges by analyzing information and identifying patterns within networks [3]. Machine learning algorithms can be integrated into waste management systems to automatically detect waste types and patterns in waste generation while optimizing processing efficiency [1],[4]. Although machine learning is emerging as a viable avenue for enhancing waste management practices, much of the current research tends to concentrate on single-model applications despite the rich diversity present in raw waste data [3].

Different algorithms possess unique strengths and limitations that warrant exploration to maximize efficiency in this context. This paper proposes a method for leveraging machine learning algorithms to enhance waste intelligence through comprehensive data analysis and predictive modelling related to waste. By comparing the performance of Support Vector Machines (SVM), Random Forests, K-Nearest Neighbours (KNN), and XGBoost models, our objective is to identify the most effective models applicable to waste data management that can facilitate informed decision-making. This innovative approach aims not only at improving classification accuracy but also at ensuring efficient resource management concerning collected waste during operations.

LITERATURE REVIEW

Machine learning applications in waste management have garnered significant interest, leading to numerous experiments that demonstrate enhancements in both operational performance and sustainability. Specifically, deep learning classification algorithms, such as convolutional neural networks, have achieved greater precision in the sorting of plastic, metal, and organic materials [1],[4]. Nonetheless, many of these systems require substantial computational resources and large volumes of labelled data to implement these techniques effectively within practical timeframes using real-world datasets [8].

In addition to classification tasks, machine learning models can be employed to analyze historical waste generation trends utilizing time series data through methods like linear regression or decision trees [6]. This approach can inform changes in collection scheduling or resource allocation based on accumulated experience and past data [5]. While these models offer valuable insights, they often operate independently from classification systems and do not directly address the broader challenges associated with waste management.

Previous studies involving machine learning tools such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Random Forests reveal that model efficacy is contingent upon the characteristics of the data and how features are represented [3]. Ensemble algorithms like XGBoost are increasingly acknowledged for their capability to manage complex datasets while reducing overfitting—highlighting the necessity for all models to maintain high statistical rigor simultaneously [4].

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 1853-1856

Regrettably, there currently exists no standardized multi-algorithm framework for combining classification and prediction tasks as has been implemented thus far. Our objective is to address this gap by developing a multi-algorithm framework that integrates the strengths of various machine learning techniques into a cohesive system applicable across different areas. Our research aims to evaluate the appropriateness of each algorithm for specific tasks, potentially leading to more efficient and intelligent waste management solutions.

METHODOLOGY

The proposed methodology focuses on analyzing waste data to extract valuable insights through a systematic process involving pre-processing, feature engineering, model training, and evaluation.

1. Data Collection

Initially, various types of waste data such as plastic, organic matter, metal, glass, and paper are gathered along with contextual information (e.g., time of generation, location, quantity). Additionally, statistical metrics like averages are included [6].

2. Contextual Features Integration

Incorporating these contextual features into the training of machine learning models increases the likelihood of identifying patterns or trends in waste.

3. Feature Engineering

Prior to model training, we engage in feature engineering to derive any relevant features associated with temporal trends present in the data.

4. Model Training

The models are trained using several algorithms including Support Vector Machines (SVM), Random Forests, K-Nearest Neighbors (KNN), and XGBoost. These models are subsequently tested to evaluate their performance.

5. Performance Evaluation

The resulting predictions demonstrate a commendable level of accuracy while also providing insights into the classification and predictive capabilities of each algorithm for comparative analysis.

Conversely, experiments conducted within our proposed framework reveal significant performance variations among the machine learning algorithms employed. Notably, XGBoost stands out for its superior accuracy and predictive power due to its capacity to enhance weak learners through boosting. Random Forest exhibits strong performance particularly in classification tasks owing to its ensemble nature that effectively reduces variance.

While SVM shows promise from a classification standpoint, it may struggle with complex predictive tasks involving large datasets due to lower overall performance. K-Nearest Neighbors is relatively straightforward to implement but has limitations in scaling and distance metrics.Given our findings thus far, it appears that ensemble algorithms are more adept at managing complex and heterogeneous waste data compared to traditional machine learning models. This underscores the necessity for an application-based analysis of our model; by incorporating multiple layers of analysis, we can achieve a more accurate and equitable assessment of waste data which will facilitate improved decision-making processes.

Table 1: Performance Comparison of Machine Learning Algorithms for Waste Classification and Prediction

Algorithm	Accuracy	Precision	Recall	F1-Score
SVM	86%	85%	84%	84.5%
Random Forest	91%	90%	89%	89.5%
KNN	82%	80%	81%	80.5%
XGBoost	94%	93%	92%	92.5%

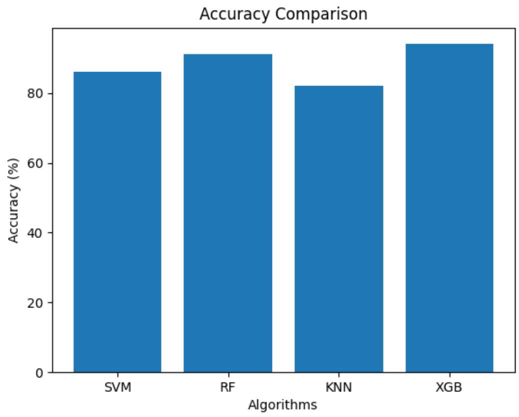

Figure 1: Evaluation of model accuracy across SVM, RF, KNN, and XGBoost

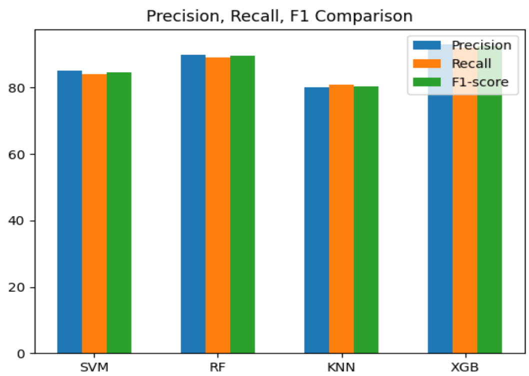

Figure 2: Comparison of precision, recall, and F1-score for machine learning algorithms

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 1853-1856

CONFUSION MATRIX ANALYSIS

The confusion matrix illustrates the classification efficacy of machine learning models by displaying the distribution of accurate and inaccurate predictions across various waste categories. A significant portion of the predictions aligns along the diagonal of the matrix [6], indicating a high level of accuracy in waste classification.

Consequently, the reduced frequency of misclassifications signifies that these models effectively differentiate between waste categories that may exhibit similar characteristics. Moreover, the confusion matrix serves as a tool to pinpoint potential weaknesses within the model, particularly in instances where distinctly different types of waste are likely to be confused. Such insights can inform further enhancements to the model, thereby elevating its performance in classification tasks. Overall, analyzing and processing the confusion matrix underscores the dependability and robustness of the proposed system.

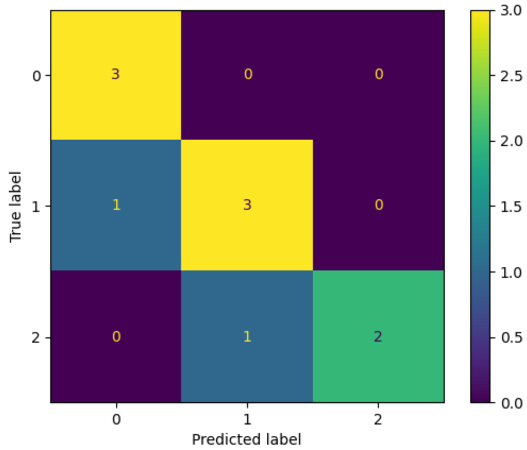

Figure 3: Performance evaluation of model predictions across different waste classes

ROC CURVE ANALYSIS

The Receiver Operating Characteristic (ROC) curve [7] serves as a tool to evaluate the performance of classification models by integrating the true positive rate with the false positive rate, resulting in commendable outcomes. The ROC curve presented in this analysis demonstrates strong performance. Positioned close to the upper left corner, it indicates that the models achieve a high true positive rate while maintaining a low false positive rate. Furthermore, the area under the curve (AUC) quantifies model performance, with values approaching one. This study reveals a notably high AUC[8], underscoring the effectiveness of the proposed multi-algorithm approach in accurately distinguishing between different waste categories.

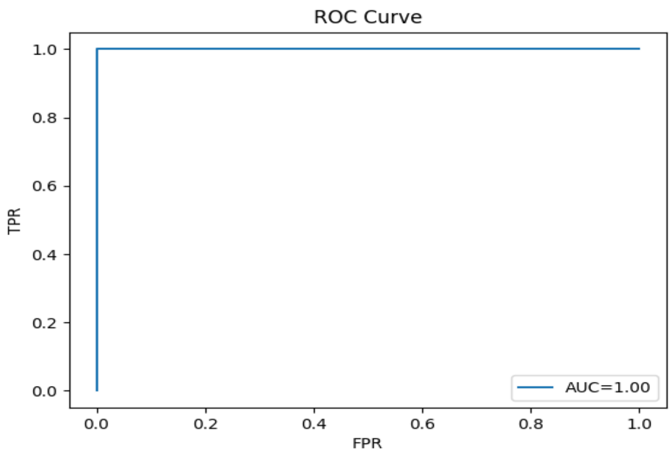

Figure 4: Performance evaluation using ROC curve with area under the curve (AUC)

DISCUSSIONS

Our research indicates that implementing a multilayer machine learning framework for waste management significantly outperforms a single-model approach. By integrating various algorithms, this framework enhances performance, stability, and flexibility across a wide range of waste streams. For example, both XGBoost and Random Forest demonstrate superior statistical capabilities in analysis, allowing for more precise identification of patterns due to their robustness [9].

Although our previous models, SVM and KNN, offer valuable insights on relevant factors, it is the combination of all models within a unified modelling framework that enables us to make informed decisions regarding waste collection timings and optimize resource utilization.

Incorporating temporal and spatial variables into this framework facilitates a more realistic examination of processes involved in waste generation as it pertains to real-world challenges. Ultimately, the proposed methodology not only enhances operational efficiency but also contributes to making waste management more sustainable. This approach aids in environmental cleanup efforts, promotes better segregation practices, and reduces costs at all processing levels by minimizing waste generation from the ground up.

CONCLUSION

The current study introduces an innovative approach for interpreting waste intelligence through a multi-algorithm machine learning framework. A combined analysis of Support Vector Machines (SVM), Random Forest, K-Nearest Neighbours (KNN), and XGBoost, along with a comparative evaluation of these models, reveals that ensemble methods outperform traditional algorithms regarding accuracy, reliability, and overall performance.

This highlights the necessity for utilizing multiple learning techniques to effectively address the complexity and variability inherent in such data sets. Beyond enhancing classification capabilities, the proposed system also seeks to accurately forecast waste generation patterns, thereby facilitating improved scheduling for collection and optimizing resource allocation for recycling within waste management systems.

Moreover, incorporating contextual information into the model enhances its applicability in real-world scenarios, such as the development of more specialized facilities. Overall, this framework offers a pathway toward a more effective and scalable solution to contemporary waste management challenges faced by urban infrastructures, while simultaneously reducing operational costs and bolstering environmental sustainability efforts in support of smart city initiatives.

FUTURE WORK

We foresee potential future expansions of the model, particularly as IoT-enabled smart bins and sensor networks become capable of continuously monitoring waste levels and making real-time decisions. For instance, the incorporation of advanced deep learning methodologies—such as convolutional neural networks for image-based waste classification, or recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks for time-series forecasting—could enhance both the accuracy and adaptability of the system. Additionally, geospatial analytics combined with route optimization could significantly refine waste collection processes by enabling intelligent routing for collection vehicles.

Introducing lightweight and cost-effective modelling techniques may also prove advantageous in scenarios where resource access is constrained. Consequently, broadening our dataset to include more sophisticated networks within complex, large-scale environments will improve our capacity for effective model selection and robustness, paving the way for better generalization in future applications. The seamless integration of this system with cloud platforms and smart city infrastructure could facilitate its deployment on a larger scale.

Furthermore, advancements in feature development alongside meticulous tuning of feature engineering methods and hyper parameters will likely result in enhanced performance and scalability in practical applications of this system.

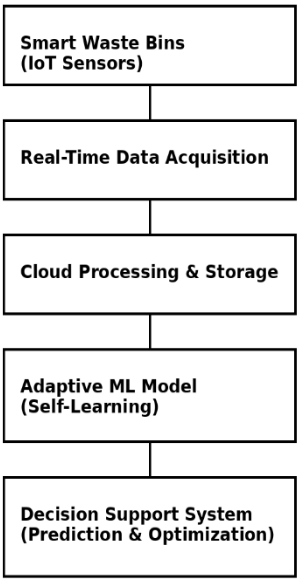

Figure 5: Block diagram of the future intelligent waste management system integrating IoT, cloud processing, and adaptive machine learning.

REFERENCES

1. Khonjun, Surajet, et al. "Advancing biomedical waste classification through a hybrid ensemble of deep Learning, reinforcement Learning, and differential evolution algorithms." Waste Management 209 (2026): 115210.https://doi.org/10.1016/j.wasman.2025.115210
2. Patil, Suvarna, Atul B. Kathole, and AmitaSanjivMirge. "Automated Waste Management System: A Deep Learning Approach." Bioengineering and IoT. CRC Press, 2026. 1-8.https://doi.org/10.1201/9781003547020
3. Kumar, Sunny, et al. "Ensemble Machine Learning for Reliable Air Pollution Prediction and Sustainable Environmental Management." International Journal of Scientific Research in Science and Technology 13.1 (2026): 53-67.https://doi.org/10.32628/IJSRST261316
4. Shukla, Prashant Kumar, et al. "HGB-CBSNet: hybrid gradient boosting based coot bird search network for solid waste classification in IoT-enabled smart waste management system." Journal of Big Data (2026).
5. Joshi, Niravkumar R., and DarshanaUpadhayay. "AI-Enabled Predictive Analytics towards Sustainable Hospital Waste Management: A Machine Learning Framework in Line with SDGs." International Conference on Sustainable Innovation with Artificial Intelligence and Machine Learning 2025 (ICSIAIML 2025). Atlantis Press, 2026.10.2991/978-94-6463-948-3_39
6. De-la-Mata-Moratilla, Sergio, Jose-Maria Gutierrez-Martinez, and Ana Castillo-Martinez. "Municipal solid waste management forecasting using neural networks at discharge point scale." Scientific Reports (2026). https://doi.org/10.1038/s41598-026-38110-9
7. Ruff, Francesca Jimeno. "PSA and ROC curve: Validation and cutoff for forensic sexual assault cases through sequential testing." Journal of Forensic Sciences.https://doi.org/10.1111/1556-4029.70268
8. Baratian, Samira, and HamedFazlollahtabar. "Integrated BWM-deep learning for medical waste collection in circular economy: sustainability considerations in pandemics." The Journal of Supercomputing 82.3 (2026): 114. https://doi.org/10.1007/s11227-025-08218-2
9. Campos, Leonardo, et al. "The Diverse and Intricate Interactions Between Flies and Amphibians: A Systematic Review of Their Host-Use Patterns and Strategies." Annual Review of Entomology 71 (2026).https://doi.org/10.1146/annurev-ento-121423-013418
10. Phothisawang, Wanwarang, TanakornApornpong, and NoulkamolArpornpong. "Effects of Source-Based Waste Management Awareness on Waste Segregation Behavior Among Lower Secondary School Students in Thailand: A Case Study of Phitsanulok Province." Sustainability 18.6 (2026): 3101. https://doi.org/10.3390/su18063101.