AI Based Prediction Algorithms for Enhancing the Waste Management System: A Comparative Analysis

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Abstract. Waste management has become an increasingly pressing issue due to urbanization, population growth, and economic development. According to World Bank projections, waste production will reach 3.4 billion tonnes by 2050. The paper is focused on detailed analysis of waste management techniques that has to be improved and resources to be maximized, to be able to deal with various types of waste, including agricultural waste, industrial waste, municipal solid waste (MSW), and electronic waste (e-waste). The advancement in the artificial intelligence in various fields has drawn the attention towards utilizing its benefits in achieving optimized management of different types of wastes also. The paper is focused on description of on-recyclable waste materials which can be transformed into energy by using waste-to-energy (WTE) technologies. The different types of wastes generated in different sectors are being studied with details on their quantity and challenges in handling the wastes. The literature highlights the performance analysis of various methodologies of waste handling in terms of their efficiency, economic impacts and ecological implications. The prediction models and their performance was discussed with respect to the R^2 value and mean absolute error (MAE) root mean square error (RMSE) to find the most suitable algorithm. The conclusion suggested that these AI based optimization methods can bring about enhancement in the various waste to energy conversion process making the management of waste materials more sustainable and reliable.

Keyword-: Waste-Management strategies, waste sorting, Artificial Intelligence, Prediction models, RMSE, MAE

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1 Introduction

In different sectors and regions, different amounts and compositions of waste are produced, making waste management a pressing environmental concern. Economic growth and consumption patterns will influence the generation of waste by 2050, according to the World Bank. Urban settings produce a wide variety of waste, including municipal solid waste (MSW) containing food waste, plastics, paper, and other materials, as well as industrial waste (IW), which includes chemicals used in manufacturing processes and electronic waste (e-waste), which is generated from discarded electronics. E-waste production in India in 2010 was around 0.4 million tonnes, and is predicted to reach 0.5 to 0.6 million tonnes in 2013-2014. Another significant category of waste is agricultural waste, which includes animal waste and crop residues. If not managed properly, agricultural waste can significantly pollute soil and water. About 18,000 Megawatts of energy could be generated from agricultural and forestry residues in India according to the Ministry of New and Renewable Energy (MNRE). Biogas plants offer a sustainable solution, not only producing energy from biomass but also utilizing agri-food processing waste and creating valuable natural fertilizers post-fermentation. This highlights the need for integrated efforts between individuals, businesses, and governments to optimize resource use, enhance waste management practices, and explore innovative solutions like AI for waste reduction across all sectors.

Municipal Solid Waste
- **Expected to reach 3.4 billion tons by 2050.**

Industrial Waste
- **Industrialized countries generate about 2.5 billion tons**
- **Developing countries generate about 1.5 billion tons**

Healthcare Waste
- **Estimated to be around 2 million tons per year**

Electronic Waste
- **Reach 74 million tons by 2030**

Agricultural Waste
- **Estimated to be around 5.3 billion tons**

Fig. 1. Estimated Production of Waste

Due to growing populations, urbanization, and growth in the economy, trash creation worldwide has increased. Municipal solid waste (MSW) generation reached 2.01 billion metric tons in 2016, and by 2050, it is expected to reach 3.40 billion tonnes. Fig. 1 in Waste-to-energy (WTE) techniques present a viable way to transform non-recyclable waste materials into energy forms that can be used, like heat, electricity, and fuels. WTE processes use a variety of methods, including pyrolysis, incineration, and the process of gasification digestion by anaerobic means, landfill exhaust recovery, and gasification. Organic waste can be converted into biogas by the process of biogasification, which uses updraft or downdraft gasifiers. This process reduces released greenhouse gases and improves waste management while also providing energy security. In biogasification, microorganisms break down organic waste in an anaerobic environment, producing biogas containing methane, carbon dioxide, and other gases. Biogas can be utilized for heating, electricity generation, or as a vehicle fuel.

However, factors like feedstock composition, process parameters, environment, and gasifier design influence the efficiency of biogasification, necessitating optimization for optimal biogas production and feedstock utilization.

Municipal solid waste (MSW) and coal are co-fired in a grate-circulating fluidized bed (CFB) combustion at the Changchun the municipal waste power plant in China, which has adopted an inventive waste-to-energy incineration technique. This approach meets emission limits and efficiently processes large volumes of garbage, attaining a fuel-to-electricity (FTE) efficiency of 14.6% despite the low calorie count and high moisture content of the the municipal waste. [1]. Additionally, an evaluated hybrid system integrates waste gasification with coal-fired power generation, capable of generating 16.12 MW net power from waste with a 35.16% waste-to-electricity efficiency. Its investment recovery period is 4.58 years, with a net present value of 40,341.00 k$ [2]. There has been an evaluation of waste-to-energy (WTE) technologies in the global arena, with a particular focus on their contribution to renewable energy and the management of municipal solid waste (MSW). An analysis of waste incineration combined with refuse-derived fuel (RDF) in the Kingdom of Saudi Arabia (KSA) from 2012 to 2035 is provided. In light of the high availability of food waste, efficiency, and low operating costs, biomethanation appears to be the most suitable option. While incineration is efficient, there are challenges associated with the management of pollutants that are associated with it [3]. In addition, four WTE technologies have been assessed for sustainability: incineration, gasification, pyrolysis, and anaerobic digestion. Techniques that transform non-recyclable trash into useful energy sources, such as heat, fuel, and power, are referred to as waste to energy (WTE) technologies. Since incinerator burns waste at high temperatures, it is probably the most practical WTE technology both financially and operationally.

sA more sustainable option is AD, while incineration is the least sustainable. It is evident that gasification and pyrolysis are more sustainable than incineration, which provides insights for developing countries like Bangladesh when it comes to waste management and renewable energy policy decisions. WtE plants in twelve Nigerian cities have also been evaluated for their ability to generate electricity, their global warming potential (GWP), their acidification potential (AP), and their dioxin/furan emissions through a life cycle assessment (LCA). Among the hybrids studied, INC/AD is most capable of reducing GWP and AP, and LFGTE is most capable of reducing carcinogenicity [5]. WTE conversion methods are discussed in this paper, with an emphasis on operational efficiency and environmental impacts. Among the topics covered are waste management methodologies, legislative frameworks, and the status of waste incinerators in the Czech Republic. In addition, it discusses energy production routes, byproduct management, and challenges in the field of waste to energy [6]. As well, it estimates that Indonesia could generate 1.7 million kWh of electricity from biogas produced from animal waste in order to meet sustainable energy goals. The difficulties faced by Indonesia while scaling up the production of biogas are also discussed in the article [7]. Further, it examines thermal waste treatment with energy recovery, emphasizing the environmental benefits and primary energy savings associated with municipal solid waste incinerators. A new method of calculating these savings is introduced in the study, and its performance is compared with that of other utility systems [8]. Another study simulates the operation of a municipal waste material incinerator in Tehran. Through optimization, the plant's ability to generate energy was boosted from 4 MW to 19 MW, demonstrating both efficiency gains and environmental advantages [9]. Last but not least, a cutting-edge strategy suggests combining a hybrid waste-to-energy system with a coal-fired power station to improve solid waste from municipality's efficiency when it comes to energy. By integrating it, WTE efficiency is increased by 9.16%, resulting in an extra 3.71 MW of net power. According to the economic analysis, there are both operational and financial benefits to using this technology over conventional waste-to-energy models, with a dynamic payback period of 3.55 years [10] as shown in Table 1.

Table 1. Comparative Analysis of Related Work

Study	Location	Technology Used	Efficiency	Environmental Impact	Economic Analysis	Key Findings
Changchun MSW Power Plant, China [1]	Changchun, China	Co-firing MSW with coal	14.6%	Meets emission standards	Lower costs than imported systems	Effective incineration, saving landfill space
Hybrid Waste-to-Energy System [2]	Not specified	Waste gasification with coal power	35.16%	Not detailed	4.58 years payback, NPV of 40,341.00 k$	Generates 16.12 MW net power from waste
Global WTE Technologies Review - KSA Case Study [3]	Kingdom of Saudi Arabia	Incineration, RDF with biomethanation	Not specified	Challenges with pollutant treatment for incineration	Cost-effectiveness of RDF and biomethanation	Biomethanation most suitable due to high food waste
Sustainability of WTE Technologies [4]	Bangladesh (developing nations context)	Incineration, gasification, pyrolysis, AD	Not specified	AD most environmentally sustainable	Not specified	AD highlighted as the most sustainable option
Life Cycle Assessment of WTE Plants in Nigeria [5]	Nigeria	LFGTE, INC/AD, INC/LFGTE hybrids	Not specified	LFGTE best for carcinogenic reduction	Not specified	INC/AD hybrid most viable in reducing GWP and AP
Thermal Treatment Methods for WTE [6]	Czech Republic	Various thermal treatment methods	Not specified	Detailed analysis of environmental impacts	Not specified	Focus on performance and legislation impact
Producing Biogas in Indonesia Using Livestock Waste material [7]	Indonesia	Biogas production from animal waste	Could generate up to 1.7 × 10^6 KWh/year	Not detailed	Highlights significant potential for electricity generation	Substantial biogas production potential
Thermal Waste Treatment with Energy Recovery [8]	Not specified	Thermal treatment with heat recovery	Not specified	Quantified environmental impact, primary energy savings	Not specified	Case study of municipal solid waste incinerator benefits

Municipal Solid Waste Incineratio n Plant in Tehran [9]	Tehran, Iran	Incineration	Increase d from 4 MW to 19 MW	Not detailed	Not detailed	Optimizatio n increased electricity generation capacity
Coal-fired power plant integrated with a hybrid WTE syste m [10]	Not specified	Integrated WTE and coal power	Increase s efficien cy by 9.16%	Not detailed	Dynamic payback period of 3.55 years	Enhances waste-to-electricity efficiency significantly

2 Artificial Intelligence in waste management Practices

Using AI approaches can make waste management practices easier and more efficient. The collection, processing, transportation, disposal, and monitoring of waste materials all considered to be part of waste management which is shown in Fig. 2. The reduction of garbage's negative impacts on the environment as well as the health of general public is the aim of waste management. Converting garbage into energy is one method of waste management. The process of converting trash into useable types of energy, such as electricity, heat, or fuel, includes using technology to do it. Waste can be turned into energy using a number of different processes, such as anaerobic digestion, gasification, and incineration. Reducing the amount of waste that is disposed of in landfills, lowering greenhouse gas emissions, and producing electricity are just a few benefits of turning waste into renewable energy.

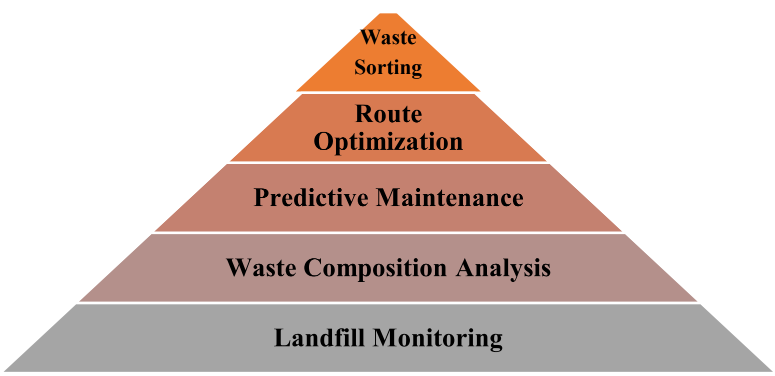

Fig. 2. Different ways AI is being used in waste management

AI-based technologies are currently used in nearly all academic disciplines, comprising medicine, linguistics, and engineering, among others, as an output of the development of AI technology and the constraints of conventional computing techniques [11-13]. The expansion of AI application fields is supported by the modelling techniques used in artificial intelligence's potential to handle noisy, multidimensional data. AI has been universally used in environmental engineering to plan SWM (Solid Waste Management) strategies, simulate soil remediation and ground water contamination, and solve problems relating to air pollution, simulation of soil remediation, water and wastewater treatment modelling, and ground water contamination [14], [15]. Waste management is rapidly using artificial intelligence (AI) to boost sustainability, cut costs, and increase efficiency. Waste management could be transformed by AI by increasing effectiveness, cutting costs, and improving sustainability [16-19].

3 Utilizing predictive analytics to optimize waste management

Through the resolution of issues such as automated sorting, public instruction, and continuous tracking, artificial intelligence (AI) can enhance the management of municipal solid waste [20]. It has the ability to foresee garbage generation, plan routes for collection, and stop illegal dumping. Still, for sustainable waste management, integration with other plans and policies is essential. To assess the efficiency of algorithms in handling waste, more investigation is required [21]. The study in [22] investigates the application of IoT and analytics to trash management and finds notable gains in the effectiveness of waste collection, financial savings, and preservation of the environment [23]. While data-driven route optimization decreased trip distance by 25%, decreased fuel consumption, and enhanced reuse and recycling, real-time collection of information cut overfilled garbage cans by 20% and collected frequencies by 15%. In order to accurately forecast the weekly production of waste in metropolitan areas, research in [24-26] created an ensemble learning approach which incorporates hyper parametric optimization with a meta regressor framework. This technique outperformed other current algorithms such as SARIMA, NARX, LightGBM, KNN, SVR, ETS, RF, XGBoosting, and ANN, with an R2 score of 0.8 and a median percentage error of 0.26 [27-29]. The results indicate that the application of the ensemble learning technique can lead to a significant improvement in the model's effectiveness in predicting future home trash generation. Compared to individual ML approaches, ensemble results beat average ensemble outcomes. Rajshahi City Corporation (RCC), Bangladesh, uses ineffective waste management procedures, which needs to be improved using Android apps, IoTs, and AI, says [30]. The demand for a sustainable strategy, which helps to optimize sorting procedures, especially for individuals, and to lower trash production generally [31]. According to the study, there is an inadequate infrastructure, irregular collection schedules, and a complicated waste management system that contributes to insufficient waste collection [32]. To increase output and reduce environmental impact, proactive measures such as regular drainage cleaning, continuous garbage collection, and monitoring are recommended. To maximize the treatment of medical waste, a revolutionary device called Catboost has been developed [33-35]. It is possible to optimize garbage sorting, storage, and treatment by using smart containers, GPS technology, temperature sensors, and humidity sensors. This system incorporates data analytics and explainable artificial intelligence (XAI) to improve decision-making and optimize processes [36]. As a result of this innovative strategy, both the environment and the public health can benefit. DenseNet121 convolutional neural networks (CNNs) are employed by [22] in order to improve trash classification accuracy. In the course of refining the model, we used a genetic algorithm (GA) to refine it and the model was tested on the benchmark data set provided by TrashNet. Based on the recording of 99.6% accuracy of the optimized DenseNet121, it is clear that GA has proved to be very effective in maximizing the number of neurons in a fully-connected layer and in reducing the dropout rate as well [37]. A gradient-weighted class reactivation mapping method was used to bring to light the coarse features of the trash image, which also shed light on the comprehensibility of the image [38]. The coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE) measurements for four support vector macine (SVM), Bayesian Artificial Neural Network (ANN), Cubist and Random forest (RF) models in the training and testing phase have been summarized in Table 2 which was performed for groundwater nitrate concentration prediction [39-41].

Table 2. Comparative analysis of different predictive models

Parameters/Models	Cubist	SVM	RF	Bayesian ANN
RMSE	3.52	4.24	3.66	5.89
MAE	2.52	2.73	2.72	4.56
R^2	0.96	0.94	0.96	0.88

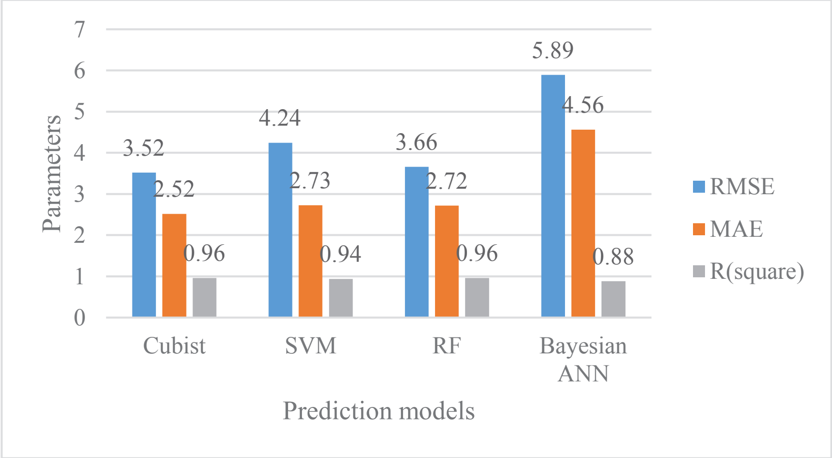

Fig. 3. Comparative study of the prediction model performance

The performance of the different prediction models for a ground water is described in the Fig.3: The analysis conducted that the RMSE was found to be maximum in the ANN based model and minimum in the cubist mode [42]. The MAE was minimum in the prediction done by the cubist model which was 2.52 and maximum in the ANN model which was 4.56 [43]. The conclusion was made that the cubist model had the best predication capability with maximum R^2 value of 0.96 and minimum errors. The R^2 value of random forest method was also found to be 0.96 but it had more RMSE and MAE value 3.66 and 2.72 respectively [44].

4 Autonomous Vehicles and Robotics in Waste Collection

Autonomous vehicles, specifically geared towards garbage collection, are emerging as frontline innovations in waste management, with the potential to revolutionize how residential areas handle waste collection. The spree of advancements in robotics and autonomous vehicles positions them as pivotal in driving operational efficiency and environmental sustainability in garbage and waste collection in the near future [45]. In 2022, a leap forward was taken as a specialty truck manufacturer secured contracts to pioneer the production of autonomous postal and garbage trucks, hinting at a transformative decade ahead for waste management and garbage collection through robotics and automation [46-48]. This surge in robotics engineering and autonomous vehicles emphasizes the evolving landscape of waste collection, where robotics types are tailored for enhanced waste management practices [49]. In exploring the current technologies in autonomous waste collection, several innovations stand out for their efficiency and environmental benefits:

- **Dynamic Autonomous Systems**: These systems can adapt to unexpected events, utilizing advanced algorithms like YOLOV8 for rapid object detection and the Floyd-Warshall Algorithm for optimal route planning. The integration of cameras, LiDAR, radar, and ultrasonic sensors enables precise environmental perception [50].
- **Eco-friendly Design**: Vehicles are battery-powered, supported by Polycrystalline solar cells for on-board charging, and employ Lithium-Ion batteries for energy storage. This design minimizes pollution and supports sustainable operations [51].
- **Advanced Robotics and AI in Recycling**: A robotic system controlled by artificial intelligence, such as that developed by AMP Robotics, improves recycling center efficiency and safety. Through machine learning models, these robots can sort waste safely alongside humans and adapt to new types of packaging and waste. Pneumatic waste systems and intelligent bins facilitate waste collection, reducing emissions and improving operational efficiency [52-53].

There are many benefits that robotics and driverless trucks can bring to waste management, such as enhancing its efficiency, environmental consciousness, and safety. GPS-equipped vehicles take care of optimizing waste collection routes, and robotic waste sorting provides speed and precision to the waste collection process. On this way, carbon dioxide is much less probable to be released into the atmosphere and air pollutants is significantly decreased. Powered by using renewable sources, which include solar energy, these robots are powered by way of power sources which might be renewable. Aside from the fact that automation reduces hard work requirements, operating costs, and worker exposure to hazardous materials, it additionally reduces hard work necessities. This reduces the environmental effect and promotes the health of the surroundings by means of lowering the pressure at the surroundings.

6 Conclusion

In terms of waste control, artificial intelligence (AI) is revolutionizing the industry with an increase in sustainability, efficiency, and safety. By means of making use of this technology, routes may be better planned, computerized sorting is accomplished, and illegal dumping may be stopped, leading to better resource use and a lesser effect at the surroundings. A predictive analytics platform powered by means of artificial intelligence (AI) can help to allocate sources and plan techniques for an organization. A comparative analysis was made where the minimum RMSE of 3.52 was found in the cubist made prediction model and maximum R^2 value of 0.96. Incorporating AI and IoT technology right into a garbage collection system can advantage the environment, minimizes the cost of operations, and boom the efficiency of collection. This is also the case that robotics and driverless vehicles are improving the techniques for recycling and accumulating waste in our society. It is nonetheless essential to conduct further studies in order to correctly determine AI's effectiveness and ensure its longevity within the future.

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