

Recent advances in applications of artificial intelligence in solid waste management: A review

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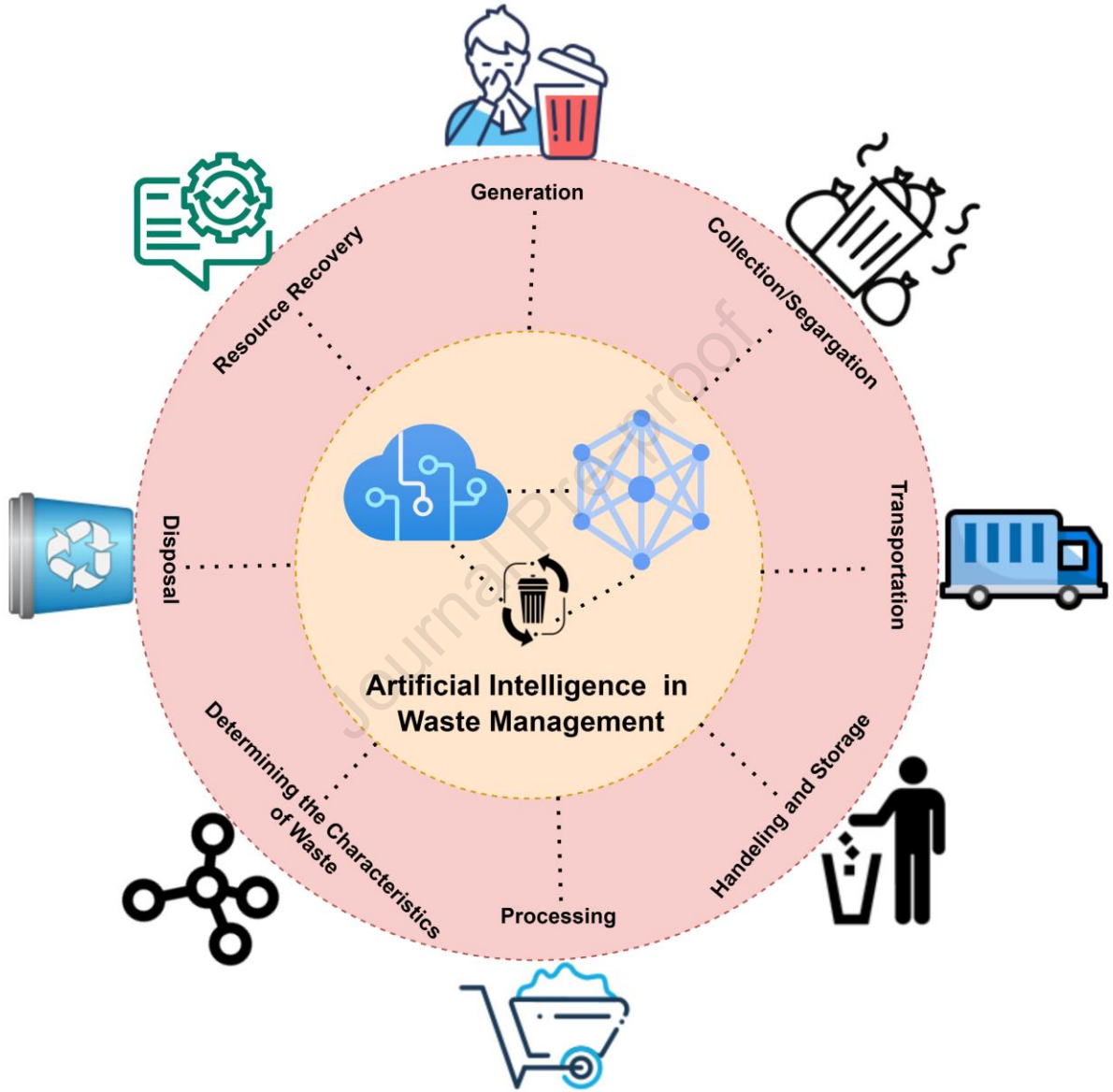
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CRediT authorship contribution statement

I. Ihsanullah: Conceptualization, Writing - original draft, Supervision, Writing-review and editing, **G. Alam:** Writing - original draft, Writing-review and editing, **A. Jamal:** Writing - original draft, Writing-review and editing, **F. Shaik:** Writing-review and editing.

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Recent advances in applications of artificial intelligence in solid waste management: A review

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Abstract

Efficient management of solid waste is essential to lessen its potential health and environmental impacts. However, the current solid waste management practices encounter several challenges. The development of effective waste management systems using advanced technologies is vital to overcome the challenges faced by the current approaches. Artificial Intelligence (AI) has emerged as a powerful tool for applications in various fields. Several studies also reported the applications of AI techniques in the management of solid waste. This article critically reviews the recent advancements in the applications of AI techniques for the management of solid waste. Various AI and hybrid techniques have been successfully employed to predict the performance of various methods used for the generation, segregation, storage, and treatment of solid waste. The key challenges that limit the applications of AI in solid waste are highlighted. These include the availability and selection of applicable data, poor reproducibility, and less evidence of applications in real solid waste. Based on identified gaps and challenges, recommendations for future work are provided. This review is beneficial for all stakeholders in the field of solid waste management, including policy-makers, governments, waste management organizations, municipalities, and researchers.

Keywords: *Artificial intelligence; Waste management; Machine learning; Environmental pollution; Sustainability.*

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1. Introduction

Rapid industrialization and population growth have resulted in a significant hike in the generation of solid waste (Hossein et al., 2022; Lu and Chen, 2022). Solid waste can be generated from the production process or products after use in commercial, industrial, construction, and domestic sectors. Solid waste is a combination of garbage, rubbish, refuse, and litter wastes (Abdel-Shafy and Mansour, 2018). It is usually generated in the form of glass, plastic, organic stuff, and metal. The annual global production of solid waste is between 7 to 9 billion tons, and municipal solid waste accounted for around 2 billion tonnes of total solid waste in 2016 (Chen et al., 2020; Wilson and Velis, 2015). According to previous studies, the amount of municipal solid waste (MSW) produced changes by a factor of 2.6 as a result of the population's rapid growth, enhanced industrialized activities, and hastened urbanization (Tan et al., 2014; Tozlu et al., 2016). A recent study reported that global MSW production will reach 2.59 and 3.40 billion tons by the years 2030 and 2050, respectively (Kaza et al., 2018).

Effective MSW management requires appropriate infrastructure, transportation, and disposal facilities (Ulgiati and Zucaro, 2019). Further, several other obstacles are encountered in the effective management of MSW in developing countries. These include: a) inadequate landfill disposal, b) limited utilization of recycling activities, c) inadequate management of non-industrial hazardous waste, d) inadequate service coverage, and e) operational inefficiencies of services.

Accurate forecasting of MSW is essential for the development of efficient waste management (WM) infrastructure and optimization of existing infrastructure (Kollikkathara et al., 2010; Mohammad K Younes et al., 2015). Traditionally prediction of MSW generation has been supported with the application of different forecasting tools such as descriptive statistical analysis, regression analysis, principal component analysis, time series analysis, and material flow analysis (Beigl et al., 2008; Navarro-Esbrí et al., 2002; Rimaityte et al., 2012; Xia et al., 2021) Regardless

of their efficiencies, all these methods have their strengths and limitations. It is more rational to compare the performance of different methods to identify the best rather than relying on only one. In recent years, owing to unprecedented data availability and technological advancements, predictive models are leaning towards more and more applications of artificial intelligence (AI) approaches. AI-based methods are computationally designed to produce realistic human thinking or cognitive skills in solving complex engineering problems which contain many input/random variables (Wang et al., 2015). AI techniques have emerged as a useful tool for applications in various fields such as water treatment, smart traffic systems, medical sciences, and geosciences (Alam, 2022; Alam et al., 2022; Bugaets et al., 1991; Haleem et al., 2019; Naeem et al., 2020).

In recent years, AI has emerged as a popular tool for predicting MSW. In literature, several AI models have been applied for forecasting and classification of MSW, including artificial neural networks (ANN), support vector machine (SVM), decision trees (DT), genetic algorithms (GA), nearest neighbourhood clustering (kNN), and various other ensemble learning techniques (Abbasi and El Hanandeh, 2016; Ayeleru et al., 2021; Kannangara et al., 2018; Nguyen et al., 2021; Wu et al., 2020).

Although some review articles have been published in the past discussing the applications of AI techniques in waste management (Abdallah et al., 2020; Guo et al., 2021), it is essential to present an up-to-date overview of the current state of research on this topic due to technological advances in recent years. This review is focused on the recent advancements in the applications of AI tools in MSW. A critical overview of numerous AI techniques used for predicting the performance of various methods used for the generation, segregation, storage, and treatment of MSW is provided. Challenges and gaps are identified and recommendations for future research are made. A brief overview of various sections is provided below.

2. Current waste management strategies

MSW is comprised of domestic, community, commercial, construction, and institutional solid waste (Sipra et al., 2018). Current MSW management strategies are faced with multiple challenges, such as rapid population growth, urbanization, and climate change, thereby adding to the dynamics and complexity of the issue. Inappropriate discarding of MSW can generate unhygienic circumstances, and these situations can start toxic waste and pollution in the environment and occur diseases scattered through rodents and insects (S. Khan et al., 2022; Sharma et al., 2020). Solid waste management (SWM) is the assemblage, curing, and settling of solid waste products after being discarded. Due to the toxic flammable, infectious, and radioactive nature of SW, a proper SWM is needed to handle the generated waste and to keep the environment safe (Das et al., 2019; Prajapati et al., 2021). Furthermore, energy recovery, composting, landfill gas recovery, and recycling are attractive options to minimize MSW and convert waste to energy (Deepanraj et al., 2021, 2017a, 2017b, 2015; Elif Gulsen Akbay et al., 2022; A. H. Khan et al., 2022a, 2022b; Qyyum et al., 2022b, 2022a). Resource recovery from waste has gained considerable attention in recent years (Ihsanullah et al., 2022).

There are several treatment alternatives for MSW, which include composting, biomethanation, incineration, pyrolysis and gasification, plasma pyrolysis, and pelletization. Composting refers to the aerobic breakdown of biodegradable organic matter by the action of yeasts, bacteria, fungi, and other organisms in moist and warm environmental conditions. Biomethanation is based on the anaerobic breakdown of organic matter, wherein microbes decompose biodegradable material without oxygen. MSW incineration includes burning garbage, which results in a reduction of its volume with heat recovery. Pyrolysis and gasification involve converting carbonaceous materials (such as biomass) into hydrogen and carbon monoxide with a controlled amount of oxygen at high temperatures. The selection of particular MSW treatment technology is affected by a variety of

123 variables, principally techno-economic viability, environmental safeguards, sustainability, and
124 location-specificity.
125 The main objective of SWM is to reduce and remove the harmful influences of waste resources on
126 human health and the atmosphere to sustain financial growth and better the value of life
127 (Mohsenizadeh et al., 2020; Prajapati et al., 2021). A general schematic of the municipal waste
128 management process is shown in **Fig. 1**.
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Fig. 1. A general schematic of the municipal waste management process

3. AI techniques

In literature, AI-based techniques are used by researchers for solid waste optimization and prediction (Abbasi and El Hanandeh, 2016; Abdallah et al., 2020). Management of SW is aimed at optimizing various activities involved during the process, such as solid waste detection, collection, optimal placement of trash bins, transportation via shortest paths, and disposal. SW

prediction deals with estimating the rate/amount of solid waste generated as a function of various predictors such as population, socioeconomic and demographics, graph data of lanes and streets, type of land use, etc. SW classification involves the application of image processing techniques for classifying solid waste into distinct categories such as glass, plastic, and other biodegradable products. Some of the commonly used AI techniques in solid waste management are neural networks (NN), SVM, GA, particle swarm optimization (PSO), and K Nearest Neighbor (kNN) (Abbasi and El Hanandeh, 2016; Ayeleru et al., 2021; Kannangara et al., 2018; Liang et al., 2021; Nguyen et al., 2021; Soni et al., 2019; Wu et al., 2020). **Table 1** presents a summary of commonly used AI and machine learning (ML) techniques. A description of the general working mechanism of each method and specific applications in solid waste management is also presented.

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149 **Table 1** Advantages and limitations of commonly used AI techniques

AI Technique	Advantages	Limitations	Use
SVM	• Work good in the case of good margin in the splitting amongst classes • Performs efficiently in high-dimensional spaces • Memory effective • Handling nonlinear data effectively	• Not appropriate for large data sets • Not good for noisy data sets • Difficult to select a suitable kernel function • Needed features scaling • Required long time for training	Regression, pattern recognition, and classification
DT	• Needed less effort for data preprocessing and cleaning • No need to normalize the data of the dataset • Not essential to scale the data of the dataset • Easy to understand and interpret	• Required more time for training • Expensive in the case of computational time and complexity • Unable to perform regression and prediction with continuous values • Impacted by noise in the data • Not appropriate for large datasets	Regression and classification
GA	• Easy to understand • Support multi-purpose optimization • Perform well on both discrete and continuous data • Work well related to local minima and maxima • Can easily be modified for other problems	• Computationally expensive and requires more effort and time • Cannot use gradients	Clustering, classification, and regression

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RF	• Improve accuracy and reduce overfitting in DT-based problems • Good for both continuous and categorical variables • Not required features scaling • Can handle nonlinear parameters • Less affected by data noise • Not required data normalization	• Need computational power and resources • Taking more time for training • Perform relatively slow as compared with DT	Regression and classification
Multi-Layer Perceptron (MLP)	• Can be used for large data sets • Good for prediction problems • Support adaptive learning • Good for solving nonlinear problems • East to setup and train	• Needed more computational complexity • Proneness to overfitting • Not suitable for advanced tasks • Cause redundancy due to many parameters	Classification and regression
Artificial Neural Network (ANN)	• ANN learning techniques are vigorous to noise in the training data of a dataset. • ANN have the ability to store information on the complete network • A fault in one or more cells of ANN does not stop it from producing output. • ANN have distributed memory system	• Need more processors and similar processing power. • ANN having unexplained behavior relevant to the network • The time of the network relating to ANN is unspecified • Unable to determine the proper structure of the network	Regression and classification

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Convoluted Neural Network (CNN)	• CNN generates high accuracy, especially in image recognition • CNN can detect the most significant features automatically • CNN have weight sharing approach	• CNN is unable to encode the orientation and position of the object • Required more data for analysis and processing	Segmentation, regression, and classification
Recurrent Neural Network (RNN)	• Good for time series prediction problems • RNN have parameters sharing approach • Recurrent connections are involved in RNN	• Difficult to train RNN • Unable to process long sequences of data in case of activation functions like tanh and relu • RNN has the "gradient exploding and vanishing problems"	Regression and classification
Back Propagation (BP)	• Help to make straightforward network structure and easy to analyze • BP is applicable to deep neural network • Reduces the loss function by updating the weights • No need for special features of the functions	• The performance of BP on a specific issue depends on the data inputs • BP is very sensitive to noisy data • Require matrix-based method instead of mini-batch • Needs more time for training	Classification and regression
K Nearest Neighbor (kNN)	• No training is required before making a prediction • kNN is easy to understand and implement	• Not applicable for large datasets • Not able to work with high-dimensional data • kNN require feature scaling • kNN is very sensitive to noisy data and outliers	Regression and classification
Deep Neural Network (DNN)	• Features are automatically determined • Architecture is adaptable to new problems • Perform parallel computation for huge data	• Need huge amount of data • Difficult to train due to the complex structure • Difficult to understand and describe • Require more computational resources	Prediction, regression, and classification

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Particle Swarm Optimization (PSO)	• Easy to use and implement • Robust control over parameters • Perform parallel computation	• Required mathematical background knowledge for analyses and evaluation • Having weak optimum local searchability	Optimization, regression, clustering, and classification

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The hybrid techniques are the grouping of various AI stand-alone techniques used in a manner to reduce or mitigate the weaknesses of AI stand-alone techniques. The main objective of employing the hybrid or ensemble techniques is to improve the predictive performance of base regressor and classifiers through an intelligent combination of weak learners (Jamal et al., 2022, 2021; Ullah et al., 2021b). In the published literature, hybrid techniques proved in the case of performing better and improving the accuracy of a model as compared to separate AI techniques (Ahmadi et al., 2021; Huang et al., 2021; Mirzadeh et al., 2022; Ullah et al., 2022a). Researchers used ANN in combination with SCA, GA, MLP, and RSM to improve the prediction accuracy of solid waste and municipal solid waste generation (Coskuner et al., 2020; Liang et al., 2021). Similarly, SVM was used in combination with least square (LS), federated learning (FL), wavelet theory (WT), and deep learning-based segmentation (DLS) for hospital waste prediction and forecasting municipal waste generation (Abbasi et al., 2013; Ayeleru et al., 2021; Golbaz et al., 2019). Coskuner et al. (2020) used CNN with Long Short-Term Memory (LSTM) to predict municipal solid waste generation (Coskuner et al., 2020) and Soni et al. (2019) used an artificial neural fuzzy inference system (ANFIS) with discrete wavelet theory (DWT) and GA to forecast municipal solid waste generation (Soni et al., 2019). **Fig. 2** shows the AI hybrid techniques used in solid waste generation prediction and forecasting.

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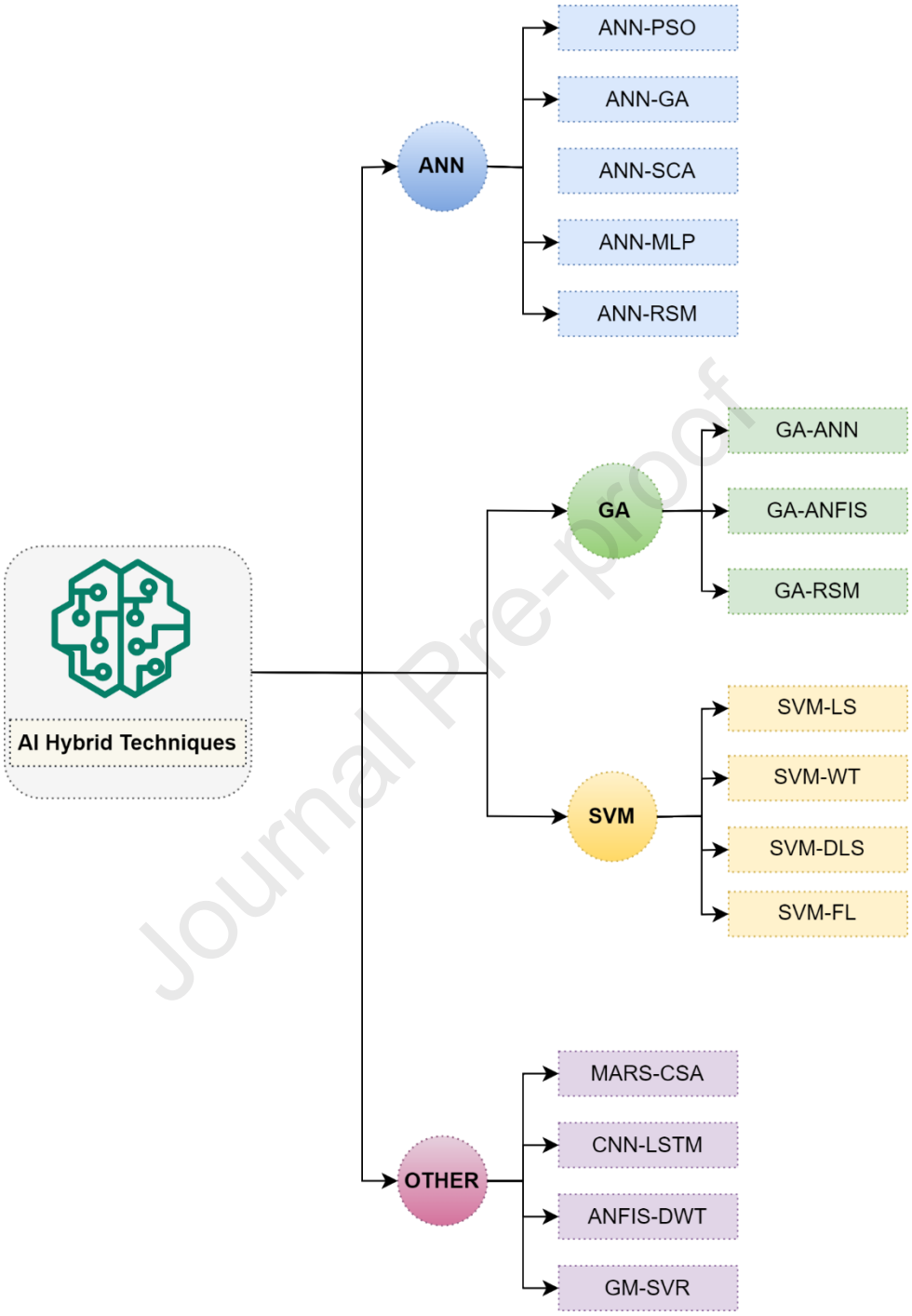


Fig. 2. Classification of AI hybrid techniques used in solid waste generation prediction and forecasting.

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4. Applications of AI in solid waste management

Accurate forecasting of MSW is important for developing an effective waste management plan. In recent years, numerous studies have reported the applications of different ML-based approaches in waste management for the prediction and optimization of generation, detection, collection, classification, and properties of the MSW (Dai et al., 2011; Ramasami and Velumani, 2016; Shyam et al., 2017). AI has the potential to revolutionize the process of waste management in future. An overview of the smart waste collection system for the city of Copenhagen, Denmark, is depicted in **Fig. 3** (Gutierrez et al., 2015).

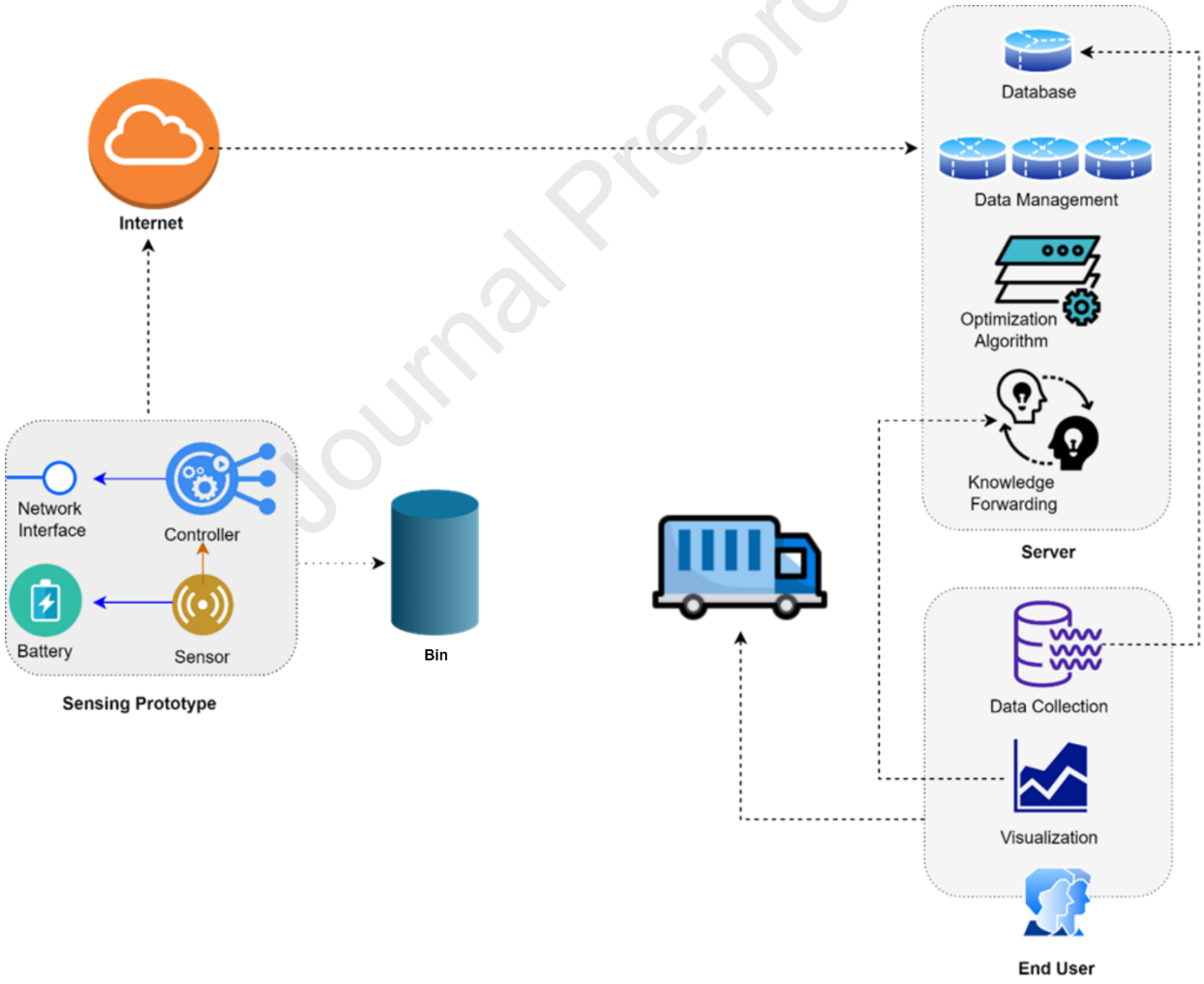


Fig. 3. The proposed smart waste collection system for the city of Copenhagen, Denmark. Reproduced with permission from Ref. (Gutierrez et al., 2015). Copyright (2015), The Authors and Elsevier B.V.

Table 2 and 3 summarizes the application of various AI and hybrid AI techniques, respectively, in SMW, including the generation, detection, collection, classification, and prediction of their composition and properties. The applications of AI tools for forecasting the amount of generated waste, optimizing their collection, classification, and segregation process, and determining the various characteristics of waste are discussed below.

4.1. Generation of waste

Accurate forecasting of future waste generation provides the basis for the development of an effective MSW management plan. Error in the process may lead to several problems in the selection of appropriate management techniques, management policies, the establishment of infrastructure, and related environmental impacts. In literature, numerous AI-based forecasting techniques have been used for predicting the amount of waste generated over time as a function of input predictors.

Golbaz et al. (2019) evaluated the performance of AI and linear regression in predicting hospital waste generation (Golbaz et al., 2019). Several Kernel and Neuron-based ML algorithms were used for analyzing the data of hospitals from the Karaj metropolis (Iran). Models input included several variables such as the activity years of the hospital, number of wards, occupied and active beds, inpatients and staff, and ownership types. Both Kerner and Neuron-based techniques yielded superior performance compared to multiple linear regression, however, the Kernel-based models achieved the best performance based on various performance metrics such as average R^2 (0.82–0.86), average RMSE (0.003-0.008) values.

In another similar study, the authors used three widely used ML models (DT, SVM, and ANN) for forecasting urban solid waste in the city of Bogota, Colombia (Solano Meza et al., 2019). The main predictor used in the analysis were distribution by collection zone in the area, population and

socioeconomic stratification, and quantity of solid waste generated in a predetermined time. The modeling results showed that the SVM is the most appropriate model for such a type of analysis. The research work conducted by Ali et al. (2021) highlighted that integration of different optimization models (like sequential linear regression, minimal optimization multilayer perceptron neural network) could serve as a rapid useful tool for waste-management decision-making involved either during its generation or disposal (Ali et al., 2022).

Ghanbari et al. (2021) attempted to estimate the solid waste generated as a function of detailed socioeconomic components (spanning from 1991 to 2013) of residents in the city of Tehran, Iran (Ghanbari et al., 2021). For estimating the solid waste, three commonly used ML methods, including RF, ANN, and multivariate adaptive regression splines (MARS) were employed. The performance of various models was assessed in terms of various statistics such as correlation coefficient, root means square error (RMSE), absolute error (MAE), Nash coefficient, and the ratio of RMSE to the standard deviation (SD) of measured data. The study also applied the crow search algorithm (CSA) to the selected MARS model to increase its accuracy. The optimized hybrid model (MARS-CSA) outperformed the base model having a correlation coefficient value of 0.82, Nash coefficient of 0.56, and errors RMSE and RSD values of 10.908, and 0.657, respectively.

Kannangara et al. (2018) developed two machine learning models (neural network and decision trees) for accurate prediction of municipal solid waste generation based on diverse socioeconomic and demographic attributes of residents of 220 municipalities in Ontario, Canada (Kannangara et al., 2018). Though both models offered acceptable performance, NN was identified as the best model describing over 72% of the variation in the data. Livani et al. (2013) employed a hybrid machine learning model (combining linear regression and weighted k-means clustering) for municipal solid waste prediction in the city of Calgary, Canada (Livani et al., 2013). Study results

revealed that the proposed hybrid model outperformed the single application of linear regression and k-means clustering both in terms of accuracy of SW prediction and robustness.

As mentioned before, MSW generation is affected by several key factors. The three-dimensional fuzzy interface map is a highly useful tool for visualizing and a better understanding of the intra-relation between independent and dependent variables. Forecasting based on a multi-model is usually more appropriate since it can enhance the practitioner's confidence in relevant policymaking based on the model's output. Chhay et al. (2018) employed multi-model forecasting to investigate the effect of socioeconomic factors on MSWG in China (Chhay et al., 2018). It was found that there is an increasing trend of MSW generation with time. Forecasting by GM and ANN shows roughly similar predictions between 2016 to 2030, while linear regression shows lower MSW generation at the end of the study period (2030). The prediction results of ANN are more reliable and robust compared to other models since it provides non-linear and irregular trends between the years 2005 and 2015, which is consistent with the actual data available for this time period.

Fig. 4 presents scatter plots showing the correlations between MSW generation and various predictors such as population, the fraction of population over 45 years, income level, employment, and proportion of dwelling versus rented apartments (Kannangara et al., 2018). Results showed that there is a negative correlation between the fraction of the population over 45 years and MSW generation, meaning that the population above this age produces less waste. Employment and income have positive trends with MSW generation, while dwelling units have no specific trend.

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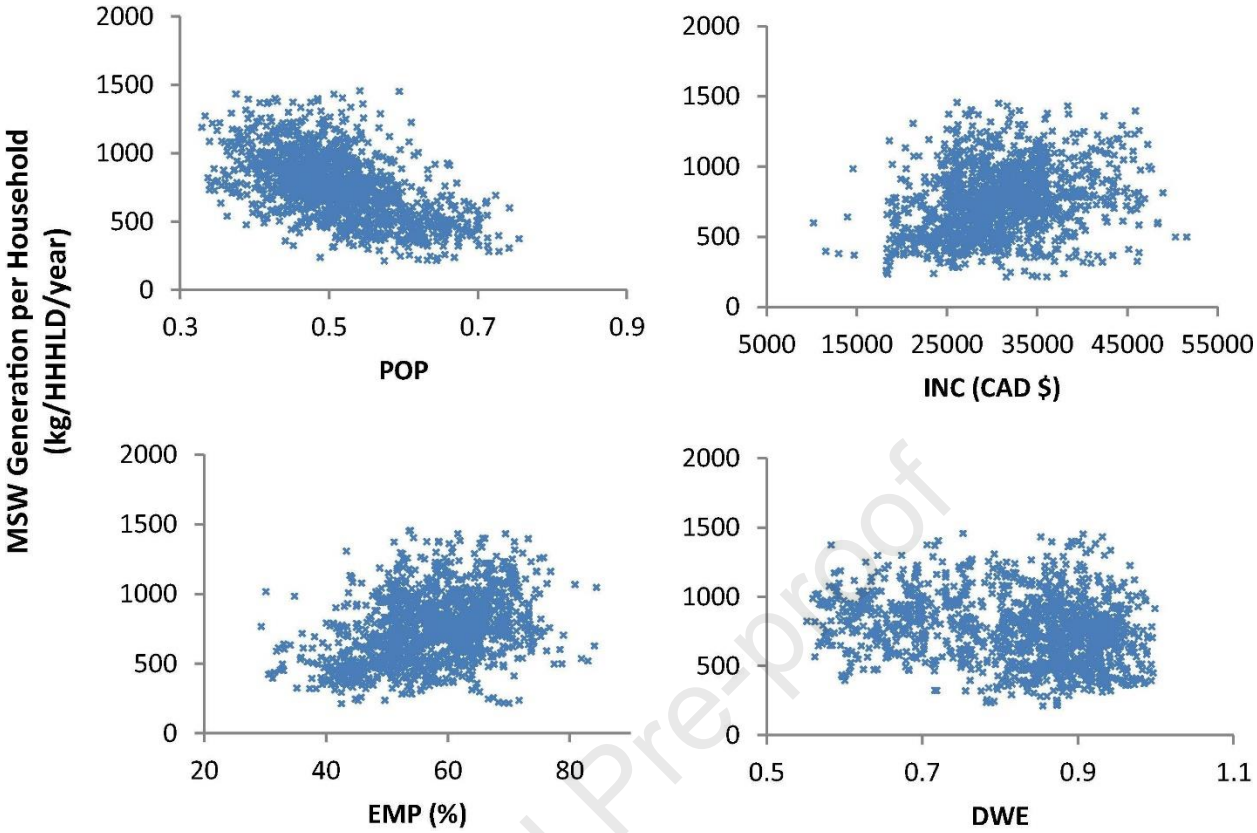
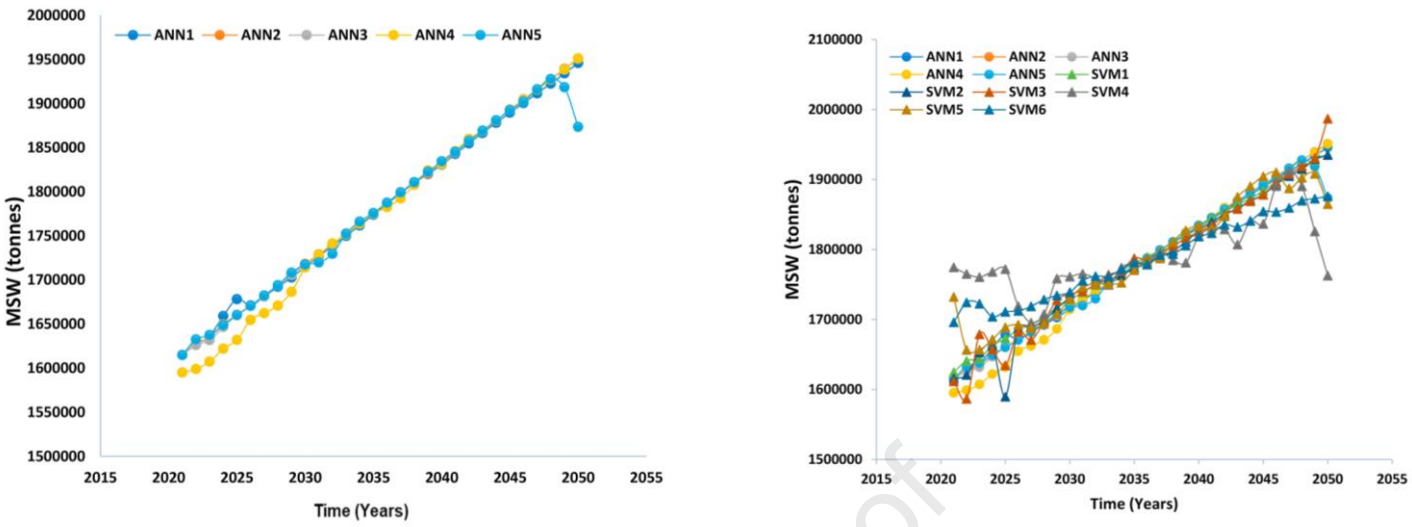


Fig. 4. Scatter plots showing a correlation between MSW generated per household and POP, INC, EMP and DWE. Reprinted with permission from Ref. (Kannangara et al., 2018). Crown Copyright (2018), Elsevier Ltd.

Fig. 5a shows a comparison of MSW generation output between different ANN architectures over a 30 years period (Ayeleru et al., 2021). It is evident from the plot that an approximately linear increment in MSW generation is expected over time. **Fig. 5b** depicts the MSW predictions of 11 machine learning models (6 SVMs and 5 ANNs) over a 30 years period for the city of Johannesburg, South Africa. ANN10 (with ten neurons structure) and linear SVM (SVM1) were identified as the best models. The annual forecast from SVM1 and ANN10 models was estimated to be 1.784×10^6 and 1.782×10^6 tonnes, respectively.



(a) **(b)**

Fig. 5. (a) ANN 30 years forecast of MSW generation. **(b)** City of Johannesburg MSW generation forecast (ANN and SVM model comparison). Reprinted with permission from Ref. (Ayeleru et al., 2021). Copyright (2020), Elsevier Ltd.

A recent study compared the predictive performance of three different machine learning algorithms, including one-dimension Convolutional Neural Network (1D-CNN) Attention, and LSTM for predicting the MSW Amount in Shanghai (Lin et al., 2021). **Fig. 6a** presents the train and validation loss at various epochs for the attention algorithm. It is evident that MSE tends to decrease with increasing epochs for both training and testing datasets. MSE reaches the convergence state at epochs between 110th to 120th epochs, and its value for train and validation loss are around 0.006 and 0.012, respectively. **Fig. 6b** shows the correlation efficiency results for predicted and actual values of MSW amount. The R^2 values of 0.78 proved the feasibility and practicability of employing an attention algorithm for predicting MSW amount in the study area. **Fig. 6c** plots the train and validation loss for the CNN model with increasing epochs. The MSE for both decreases with increasing epoch, with train loss attaining a steady MSE value of 0.0086 at the 120th epoch while validation loss converged to a final MSE of 0.052 at approximately the same epochs (120). Further, the correlation coefficient (**Fig. 6d**) is 0.864, indicating that the CNN

model is also good for estimating MSW amount. **Fig. 6(e,f)** shows the LSTM model performance in predicting the MSW amount. **Fig. 6e** again presents the train and validation loss, while **Fig. 6f** depicts the correlation efficiency analysis. Both the train and validation loss curves reached the convergence state at a much earlier epoch, while the R^2 value of approximately 0.9 shows that LSTM outperformed both the attention algorithm and CNN models.

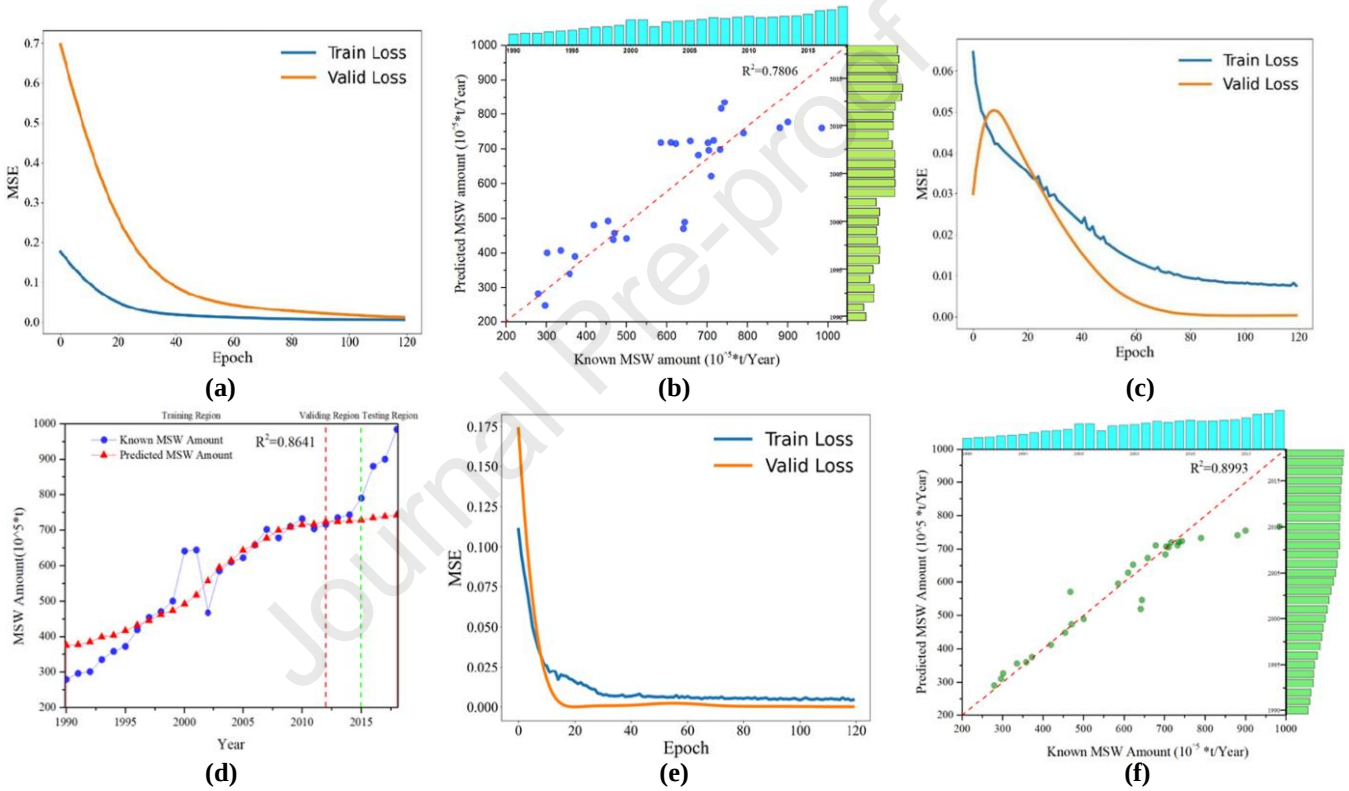


Fig. 6. Determination of Attention model performance: (**a)** Loss of the proposed approach versus different epochs**; (b)** Joint-plot (Scatter and Bar plot) of predicted VS known MSW amount in Shanghai ranged from 1990 to 2018. CNN model performance evaluation: **(c)** MSE with different epoch for 1D-CNN on the estimation of MSW amount in Shanghai; **(d)** Comparison of predicted and actual MSW Amount in Shanghai Prediction performance by proposed LSTM for MSW quantity in Shanghai: **(e)** loss VS epoch; **(f)** Correlation with predicted and known MSW amount. Reprinted with permission from Ref. (Lin et al., 2021). Copyright (2021), Elsevier B.V.

4.2. Collection and segregation of waste

Collection and segregation of MSW are crucial for effective and efficient management as well as recycling. Recently, various studies have investigated the applicability of AI-related technology applications for waste classification and segregation.

Various soft computing techniques can be employed to optimize the process of collection and recycling of garbage bins in residential areas (Gupta et al., 2019). Khoa et al. (2020) proposed a hybrid graph theory and machine learning-based framework to optimize solid waste collection by identifying the shortest path (Anh Khoa et al., 2020). The proposed framework was also implemented in a real-world case study (Ton Duc Thang University) and the obtained results were promising in terms of time saved in waste collection and management.

Aishwarya et al. (2021) suggested the application of image processing based on YOLO and machine learning algorithms for detecting and separating non-biodegradable waste from the trash bins (Aishwarya et al., 2021). Data was divided into three major waste categories: plastic, metal, and glass with at least 450 images of each for training the model. The accuracy of the models was validated using the raspberry pi camera.

4.3. Classification of waste

Classification of waste is also essential for proper management, disposal, and recycling of waste. The on-site classification of waste will help to segregate the waste and facilitate its transportation to approved disposal and recycling facility. Various AI techniques have been employed for the classification of various types of MSW in the bin, including quality and quantity of waste (Islam et al., 2014), and their classification into various types/groups/categories (Altikat et al., 2022; Bobulski and Kubanek, 2021; Funch et al., 2021; Qin et al., 2021).

4.4. Factors influencing MSW generation and classification

MSW generation rate is typically influenced by several predictors which are selected as the input variables in AI model development.

The general architecture of the neural network for predicting the MSW generation rate is presented in **Fig. 7** (Alidoust et al., 2021). In the input layer, the available predictors' data is fed to yield the output, which is usually MSW generation rate or MSW classification. Typical inputs considered by previous studies in this regard are the study area population, socioeconomic status, education level, sex ratio, historical waste generation data, GDP, household size, temperature, rainfall, wind strength, day of the week, the month of the year, seasonal patterns, type of land use, energy consumption, electricity demand per capita, floor, space ratio, and trash bin images. The predictive performance of the neural network is influenced by several factors, such as the number of hidden layers, the type of training algorithms, and transfer activation functions. Few studies have reported that the optimal performance of NN in MSW prediction was obtained by employing Levenberg-Marquardt as a training algorithm and Purelin and Tansig as a transfer function (Alidoust et al., 2021; Ayeleru et al., 2021).

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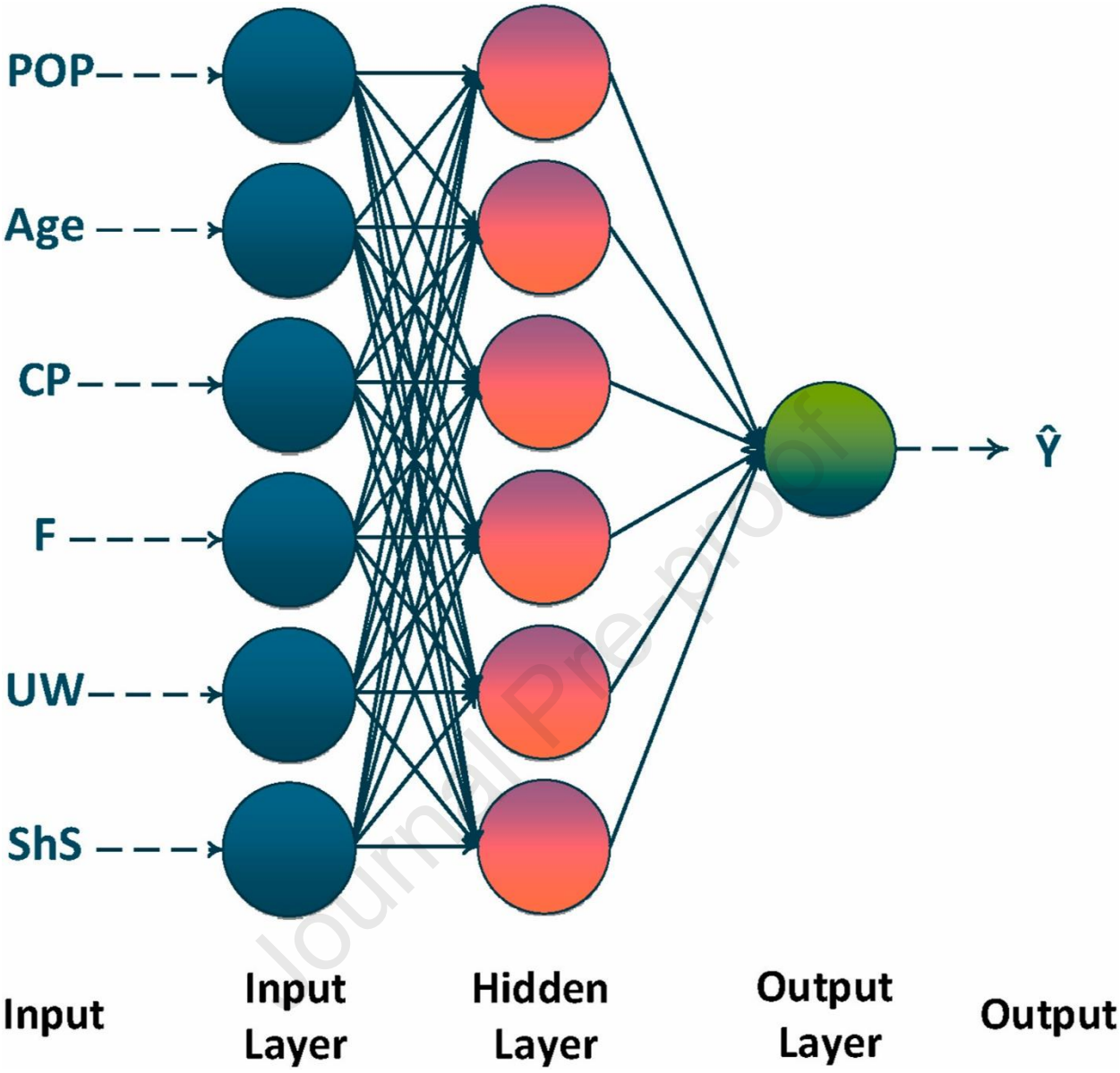
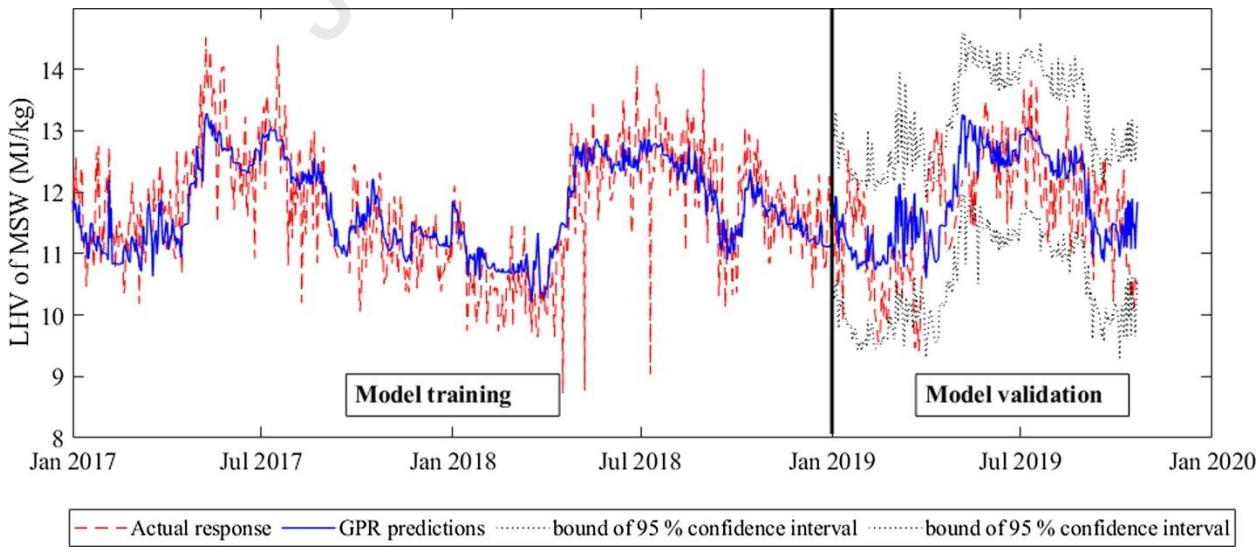


Fig. 7. Typical Neural Network Architecture for predicting the shear modulus of MSW. Reprinted with permission from Ref. (Alidoust et al., 2021). Copyright (2021), Elsevier Ltd.

4.5. Determining the characteristics of waste

MSW is a complex and heterogeneous fuel. To improve the operational performance of waste-to-energy (WtE) plants, previous studies have attempted to investigate the association of several influential factors of MSW generation as environment and socioeconomic characteristics, and land use indicators. However, an important parameter is the heating value (HV) of MSW whose variations has a significant influence on the operational stability of WtE plants. Recently, few

352 studies attempted to model the HV of MSW (Reddy, 2011; Zhou et al., 2014). **Fig. 8** depicts the
353 test datasets scatter plots for observed and predicted HV responses using an optimized Gaussian
354 process regression (GPR) (Birgen et al., 2021). It may be noted from the plot that winter months
355 had LHVs (around 11.12 MJ/kg) while summer months had higher LHVs (around 12.5 MJ/kg).
356 Most of the observed LHVs lie within the 95% confidence interval indicating an excellent GPR
357 model prediction. The predictions had large sample variance and lower noise-to-signal ratios.
358 **Fig. 9** presents the correlation plots for different input variables with LHVs of MSW for the same
359 study (Birgen et al., 2021). Correlation plots are useful in understanding the patterns in the data
360 and identifying the outliers in the data. It is evident from **Fig. 9** that temperature has a positive
361 correlation with LHVs of MSW (**Fig. 9a**). It seems that there is no apparent correlation between
362 precipitation (**Fig. 9b**) and wind strength (**Fig. 9c**) with LHVs. It is also evident that weekdays
363 have higher LHVs compared to weekends, and similarly, holidays have the lowest LHVs (**Fig.**
364 **9d**). Finally, it can be observed from **Fig. 9e** that winter weeks have lower LHVs than summer
365 weeks, which is rational.
366



367

Fig. 8. Actual response and GPR model predictions for training (left) and validation (right) datasets without optimization. Reprinted with permission from Ref. (Birgen et al., 2021). Copyright (2021), Elsevier Ltd.

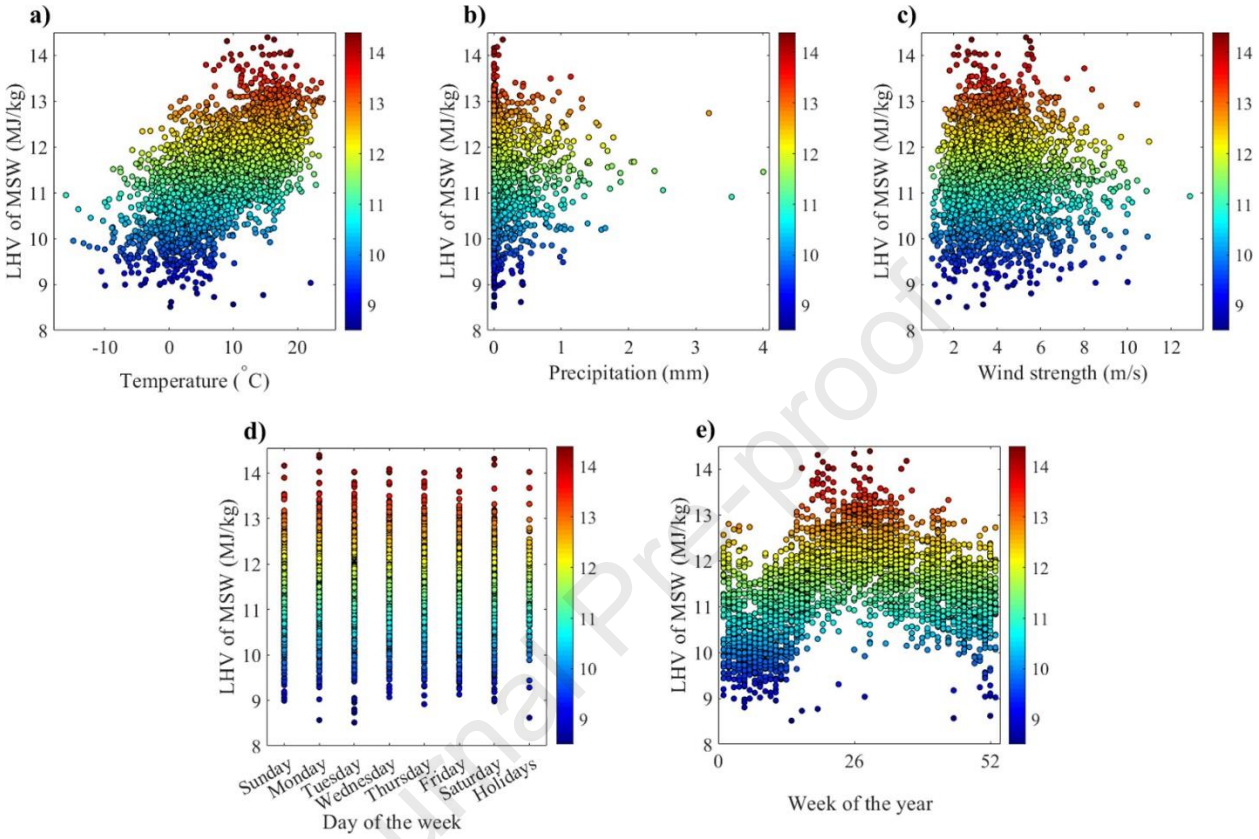


Fig. 9. Daily LHV of MSW (plant data) as a function of the selected predictors **(a–e)**. Reprinted with permission from Ref.(Birgen et al., 2021). Copyright (2021), Elsevier Ltd.

376 **Table 2** A summary of published literature on the applications of AI techniques in SWM

Application	AI technique employed	Input variables/predictors	Output	Key findings	Model performance indicators	Reference
Solid waste detection and classification	MLP	Waste bin Images	Quality and quantity of waste in the bin	The use of Dynamic Time Warping (DTW) in conjunction with Gabor wavelet (GW) for feature extraction and an MLP classifier yielded encouraging results in terms of waste level estimation accuracy of approximately 98.50%.	Sensitivity = 98.00% Specificity = 98.50% Accuracy = 98.50%	(Islam et al., 2014)
MSW generation	SVM, ANN, kNN, ANFIS	Monthly time series MSW generation data (1996 to 2014) over the eighteen years	Peak monthly and annual MSW generated	The ANFIS system yielded the most reliable peak forecasts, whereas kNN effectively predicted average monthly waste quantities.	**ANFIS:** RMSE= 0.002, MAE= 0.001, MAPE=3.39E-06, R^2=0.99 **SVM:** MAE= 203.03, RMSE= 300.70, MAPE= 0.05, R^2=0.93 **ANN:** MAE= 335.03, RMSE= 498.43, MAPE= 0.07, R^2=0.83 k**NN:** MAE= 251.80, RMSE= 387.21, MAPE= 0.06, R^2=0.88	(Abbasi and El Hanandeh, 2016)
MSW generation	DT, ANN	Used cross-sectional residential waste data were collected from 220 municipalities (over nine years) in Ontario region. Residents' socioeconomic and demographic variables were used for the purpose	MSW amount and diversion as a function of demographic and socioeconomic variables at municipal levels.	The best-fit models were the neural network model, which explained 72 percent of the variability in the data. The proposed ML models can be reliably applied to other geographic locations since similar socioeconomic parameters can be easily obtained from census data.	RMSE = 20, 18 MAPE = 18, 15 R^2 = 0.63, 0.83	(Kannangara et al., 2018)
MSW generation	ANN	Socioeconomic predictors, such as GDP per capita permanent resident population (PSP), disposable income (PCDI), and general public budget	MSW amount	The coss-prediction procedure confirmed that while models for the northern or southern regions may be appropriate for MSW prediction in another geographic location with similar sociodemographic	RMSE = 39.682, 83.607, 52.560, 113.719, 131.984, 133.513 R^2 = 0.878, 0.613, 0.778, 0.607, 0.325, 0.320	(Wu et al., 2020)

		expenditure (GPBE), were used as main inputs for solid waste generation		characteristics. Dominant factors for MSW generation were GDP and PSP.		
MSW generation	CNN, LSTM	Twenty-five demographic and socio-economic factors were the predictors. These include population, household, HH size, sex ratio, GDP, budget revenue, public utility investment, municipal project investment, employment, floor space ratio, and population density	MSW amount	The performance of 1D-CLA is superior to that of any single model or combination of models. MSW has Pearson correlation values above 0.9 and is positively related to social production and population characteristics.	**Attention Model:** R^2= 0.78 **1D-CNN:** R^2 = 0.86 **LSTM:** R^2 = 0.90 **1D-CLA:** R^2 = 0.95	(Lin et al., 2021)
MSW generation	RF, kNN, DNN	Eight input variables were utilized including, consumption waste generation characteristics, and demography of the case study from Vietnam	MSW Amount (tons/day)	KNN and random forest (RF) algorithms show a good predictive ability of the training data data), with a mean absolute error (MAE) of 121.5–125. and an R^2 value > 0.96 for the testing data. The most important predictors for MSW predictions were population, total retail sales, and urban average monthly consumption expenditure.	**RF:** MSE = 121.5, RMSE = 202.3, R^2 = 0.96 **kNN:** MSE = 125.0, RMSE = 201.6, R^2 = 0.97 **DNN:** MSE = 177.6, RMSE = 294.6, R^2 = 0.91	(Nguyen et al., 2021)
MSW collection and generation	ANN, FFBPNN (feed-forward back-propagation neural network)	Monthly solid waste quantities and vehicle trips from the weight bridge	landfill area estimation based on solid waste collected and generated	Options for garbage disposal and waste classification and the required landfill volume were calculated, and it was discovered that the landfill authority could save up to 28.6% of the valued urban landfill area requirement by utilizing appropriate options. Due to the scarcity of disposal places, the garbage height in landfills is expected to rise.	R^2 = 0.85, 0.86	(Hoque and Rahman, 2020)

MSW generation	ANN, SVM	Population, the number of family units, formal employment, and data on the unemployed were a few inputs	MSW forecasts/future predictions for the coming three decades	The network structure with 10 neurons in the hidden layer structure (ANN10) performed the best, yielded a determination coefficient (R^2) of 99.9%, whereas the linear SVM model fared among the selected SVM models, attaining an R^2 of about 98.6%. Model estimates suggested that the total annual MSW for the study area (Johannesburg) will reach around 1.78×10^6 tonnes in 2050.	R^2 = 99.9, 98.6	(Ayeleru et al., 2021)
MSW Shear Modulus Prediction	ANN, M5 model Tree (M5Tree) MARS, multi-gene genetic programming (MGGP)	Age of the MSW, Shear strain confining pressure, plastic percentage, loading frequency, and unit weight	Aimed at identifying the factors influencing the shear modulus of MSW followed by model development for shear modulus prediction	Comparing the predictive performance of developed models, it was revealed that the ANN model outperformed the others. The least and most sensitive variables affecting the estimated shear modulus were loading frequencies and shear.	**ANN:** R^2 = 0.9897, RMSE = 146.49, MAE = 106.12, MAPE = 5.34 **MARS:** R^2 = 0.9640 RMSE = 274.49, MAE = 206.20, MAPE = 10.38 **MGGP:** R^2 = 0.9617 RMSE = 282.99, MAE = 205.38, MAPE = 10.38 **M5Tree:** R^2 = 0.8482 RMSE = 564.60, MAE = 385.90, MAPE = 19.42	(Alidoust et al., 2021)
MSW generation	Archimedes Optimization Algorithm (AOA), Sine Cosine Algorithm (SCA), PSO, and ANN-GA GA, ANN-SCA, ANN ANN-AOA, ANN-PSO	Input data such as population, household size, rainfall, average temperature, maximum temperature, number of educated men and women, GDP, and numbers of months from seven mega cities in Iran were used	Monthly SW amount	Empirical results showed that the ANN-AOA and the fuzzy-reasoning-based models performed well at predicting various target variables. The hybrid model outperformed the ANN models.	**ANN:** RMSE = 9.12, MAE = 8.25, NSE = 0.87, R^2 = 0.85 **ANN-AOA:** RMSE = 5.67, MAE = 5.45, NSE = 0.92, R^2 = 0.90 **ANN-SCA:** RMSE = 6.78, MAE = 6.23, NSE = 0.90, R^2 = 0.86 **ANN-PSO:** RMSE = 7.89, MAE = 7.12, NSE = 0.89, R^2 = 0.87 **ANN-GA:** RMSE = 8.95, MAE = 8.12, NSE = 0.88, R^2 = 0.86	(Liang et al., 2021)

MSW generation rate prediction	Support-vector-regression (SVR) optimization model (TSOM)	Total population (TP), GDP and consumption level Of individual residents (CLIR)	Accuracy	The SVR with a polynomial kernel produced the most accurate prediction performance for the MSW production rate. The suggested TSOM could determine the impact of numerous essential indicators on the output solid waste generation rate (TP, CLIR, and GDP).	**SVR model:** Prediction accuracy (PA) = 96.92% Fitting accuracy (FA) = 97.48% Overall accuracy (OA) = 97.39%	(Dai et al., 2011)
MSW classification	Deep convolutional neural network (DCNN)	Trash image dataset, which consisted of 1989 images	Waste classification into different types/groups as paper, plastic glass, and metal	The proposed model was effective in classifying waste into different components (glass, plastic, and organic waste) with reasonable accuracy.	Accuracy: DCNN4 = 0.6167 DCNN5 = 0.7000 Error rate: DCNN4 = 0.3833 DCNN5 = 0.3000 Sensitivity: DCNN4 = 0.5667 DCNN5 = 0.5750 Specificity: DCNN4 = 0.9111 DCNN5 = 0.8111 Precision: DCNN4 = 0.6375 DCNN5 = 0.5750	(Altikat et al., 2022)
MSW classification	CNN	The input dataset included thousands of high-resolution images taken at different rotations	Waste classification into different main groups/types such as plastic, paper, glass, and metal	Experimental results indicated that the 15-layer network achieved better performance considering the photos of 120 120 pixels than that of the 23-layer network for images of 227 227 pixels. The classification of waste into four main classes was consistently at a good level, particularly with the few input parameters.	**CNN:** Accuracy cross-validation classification = 74%	(Bobulski and Kubanek, 2021)
MSW generation/forecasting	ANN	Monthly MSW data for a period of 130 months for the city of Bangkok	Solid waste amount	-	Accuracy = 0.875, MSE = 0.233 and R = 0.629	(Sodanil and Chatthong, 2014)
Solid waste classification	SVM MobileNetV2 Softmaxs	Analysis used 2,527 images of MSW	Aimed at classifying the MSW into different	With SVM and Softmax classifiers, the suggested model outperformed existing	Accuracy: Softmax = 82.48 SVM = 83.46%	(Qin et al., 2021)

			categories, including metal, glass, cardboard, plastic, paper, and thrash.	similar models, achieving sn accuracy of 82.48 percent and 83.46 percent, respectively. When it comes to image classification, VGG16 was identified as the best model.		
MSW composition	BPNN	Input variables included socioeconomic factors, like geographical location, regional product, city size, gas coverage rate, and year	Aimed at developing quantitative models for analyzing MSW composition	The main impact factors affecting MSW composition were geographic locations, economic activity, gas coverage rate, and per capita gross regional product.	R^2 = 0.26−0.29, MSE = 0.004−0.057, F value = 52.12−59.96	(Ma et al., 2020)
MSW management	Linear regression, MLP, sequential minimal optimization regression (SMOR)	Waste amount data set	Aimed to develop a decision-making framework for MSW in the whole Malaysia region	The linear regression function had a higher correlation coefficient for the training dataset, outperforming other models. The decision-making tool can be used by practitioners for faster and more efficient management of MSW.	R^2: Linear regression = 0.5894, MLP = 0.5837, Sequential minimal optimization regression=0.5854 MAE: Linear regression = 5,660,928,944, MLP = 5,929,172,400, Sequential minimal optimization regression = 5,603,244,223	(Ali et al., 2022)
Lower heating value prediction of MSW	Gaussian processes regression (GPR)	Historical data about various parameters such as temperature, wind strength, week of the year and day of the week	Daily lower-heating value of MSW	The variable temperature was assigned the highest importance by the proposed model, followed by other predictors such as the week of the year and precipitation.	MAE = 0.592 MAPE = 5.23	(Birgen et al., 2021)
MSW generation	ANN	socioeconomic factors (urban population, energy consumption, and GDP	Short-term forecasting of MSW	ANN was identified as the most acceptable model for forecasting MSW generation. Analytical results Revealed that urban population growth was the top influential factor for MSW generation.	R^2 = 0.931RMSE = 450.84, MAPE = 0.0143MAE = 228.53	(Chhay et al., 2018)
MSW generation	ANN	Seasonal patterns, number of trucks, weekly waste generation (WWG),	Weight of MSW generated	-	R^2 = 0.648 mean absolute relative error (MARE) = 2.17%	(Shahabi et al., 2012)

MSW classification	CNN	Trash bags were formed based on six various classes: pure glass (PG), pure metal (PM) glass and mixed waste (GMX), metal and mixed waste (MMX), pure mixed waste (PMX), and glass and metal (GM). Each category consisted of 500 observations.	Detecting metal and glass in consumer trash bags	CNN model was trained for the classification achieved 98 percent prediction accuracy, and the findings encouraged the possible deployment in real garbage collection trucks, allowing for location-specific and long-term monitoring of consumer waste sorting quality, and research on consumer behavior as well as waste management system decision support.	Accuracy = 98.14 Precision = 99.49 Recall = 96.77	(Funch et al., 2021)
Hospital solid waste (HSW) generation	ANFIS, ANN, SVM, FSVM LSSVM,	Active and occupied beds, The number of wards, ownership type, activity staff and inpatients, and years of hospital	Investigated the factor affecting the HSW generation, followed by prediction of HSW generation rate using various ML algorithms	The relationship between trash generation rate and model inputs could be accurately interpreted using machine learning approaches. Results showed that the number of hospital staff and hospital ownership type are the leading factors for the HSW production rate	**ANN:** R^2 = 0.79, MSE = 0.012 **ANFIS:** R^2 = 0.85, MSE = 0.006 **SVM:** R^2 = 0.83, MSE = 0.008 **LSSVM:** R^2 = 0.92, MSE = 0.003 **FSVM:** R^2 = 0.90, MSE = 0.003	(Golbaz et al., 2019)
MSW generation	Nonlinear autoregressive network (NAR), ANN	Population, Gross domestic product (GDP), number, employment and unemployment information, and electricity demand per capita	Annual solid waste generation is expressed in kg/capita/year	Optimum model results revealed that population, GDP, and employment were the critical factors influencing the MSW generation.	R^2 = 0.97, MSE = 2.6	(Mohammad K Younes et al., 2015)
SW generation	(MANFIS (Modified adaptive neural inference system)	Period/year (1981–2013) annual solid waste generation, GDP per capita, population age groups, employment, and unemployment information, and electricity demand per capita	Annual solid waste generation ((kg/capita/year))	Three input variables (as population age groups) are good enough to predict solid waste generation in Malaysia. Humans and their daily activities are directly linked to garbage/waste generation.	R^2 = 0.98. RMSE =3.986, and MAE = 0.673	(Mohammad K. Younes et al., 2015)
MSW generation	LSTM, ANN, and ARIMA (autoregressive	Waste forecasting	Long-term impacts of MSW generation	ANN and ARIMA models provided better accuracy for the training datasets;	**LSTM, ARIMA, ANN:** RMSE = 935.08, 2116.67, 547.14	(Niu et al., 2021)

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	integrated moving average)		temporal fluctuations were investigated.	however, the ARIMA model could not yield reliable and accurate forecasts for testing datasets. LSTM outperformed both the other model.	MAPE = 114.36, 264.05, 50.41, R^2 = 0.92, 0.10, 0.74	
MSW prediction and optimization	DNN	Element composition, fix carbon (Fc) , (C, H, N, O, volatile matter (V), ash (A), and the HTC conditions, including water content (WC), reaction time (t), and temperature (T)	Predicted the hydrochar properties produced from high-moisture MSW	The importance of both temperature to FP (fuel characteristics) and elementary composition and CCS (carbon capture and storage) was revealed by ML-based feature analysis.	R^2 = 0.91 RMSE = 3.29	(Li et al., 2021)
MSW production, collection, and management	DNN	Input factors were classified under different headings as organizational, infrastructure, demographic, and socioeconomic	Proposed a framework for MSW production, collection, and management cost analysis	The influence of combining different services (such as door-to-door and municipal level collection centers) was examined under multiple scenarios.	RMSE = EUR 32.1, and MAE = EUR 24.2	(Fasano et al., 2021)

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387 **Table 3** A summary of published literature on the applications of AI hybrid techniques in SWM

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Application	AI technique used	Input variables	Output	Key findings	Model validation/performance indicators	Reference
MSW generation	AOA, SCA, PSO, GA, ANN, ANN-SCA, ANN-AOA, ANN-GA ANN-PSO	GDP, population, household size maximum temperature, average temperature, rainfall, maximum temperature, and number of educated men and women	Monthly MSW generation	The proposed model has a high ability to predict various target variables for MSW generation. Population, GDP, number of months, and household size, were identified to be the best input combination of predictors for MSW prediction.	**ANN:** RMSE = 9.12, MAE = 8.25, NSE = 0.87, R^2 = 0.85 **ANN-AOA:** RMSE = 5.67, MAE = 5.45, NSE = 0.92, R^2 = 0.90 **ANN-SCA:** RMSE = 6.78, MAE = 6.23, NSE = 0.90, R^2 = 0.86 **ANN-PSO**: RMSE = 7.89, MAE = 7.12, NSE = 0.89, R^2 = 0.87 **ANN-GA: RMSE** = 8.95, MAE = 8.12, NSE = 0.88, R^2 = 0.86	(Liang et al., 2021)
MSW generation	ANN, RF, MARS, MARS-crow search algorithm (CSA)	Population, unemployment rate, rainfall, maximum temperature, household size, educated men, and women, income, and GDP	Prediction of monthly MSW rate	Based on the experimental results, the MARS model was found to be the best-fit model, and the hybrid optimized MARS-CSA model produced better results. For the SWG forecast, four sensitive predictors were chosen based on Pearson correlation: population, income, GDP, and month.	**ANN:** R^2 = 0.74, RMSE = 15.582, MAE = 12.905, E_{NS} = 0.372, RSD = 0.789 **RF:** R^2 = 0.77, RMSE = 12.476, MAE = 9.660, E_{NS} = 0.598, RSD = 0.632 **MARS:**	(Ghanbari et al., 2021)

					R^2 = 0.88, RMSE = 9.014, MAE = 6.901, E_{NS} = 0.790, RSD = 0.456 **MARS-CSA:** R^2 = 0.90, RMSE = 8.452, MAE = 6.453, E_{NS} = 0.815, RSD = 0.428	
MSW generation	DWT-ANN (Discrete wavelet theory–artificial neural network)), GA-ANN DWT-ANFIS, GA-ANFIS	Prediction of waste generation	Amount of garbage generated	The hybrid artificial neural network and genetic algorithm models were reported to have the lowest evaluation metrics values, indicating robust and superior model performance. GA-ANN outperformed other models in terms of MSW forecasting.	**DWT-ANN, GA-ANN DWT-ANFIS, GA-ANFIS**: RMSE = 157, 9507, 155.4, 393.8 **DWT-ANN, GA-ANN DWT-ANFIS, GA-ANFIS**: d index of agreement (IA) = 0.465, 0.864, 0.682, 0.347 **DWT-ANN, GA-ANN DWT-ANFIS, GA-ANFIS**: R^2 = 0.68, 0.67, 0.73, 0.56	(Soni et al., 2019)
MSW generation	ITD-GEP (Intrinsic time-scale decomposition-gene expression programming)	MSW is taken as a function of various parameters such as population, household size, month, rainfall, average temperature, maximum	MSW generation rate	The hybrid models produced higher prediction accuracies and lower errors. Variables such as month, Rainfall, Tave, Tmax, POP, HSS, employment, GDP, and income all had a significant influence on MSW generation.	**ITD-GEP:** RMSE = 12.27, R^2 = 0.735 GEP: RMSE = 13.81, R^2 = 0.61 **MC-GEP:** RMSE = 12.36, R^2 = 0.68	(Fan et al., 2021)

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		temperature, educated man, and women, and income				
MSW generation	(PLS-SVM (Partial least square-support vector machine)	Weekly time-series MSW data	Weekly prediction of MSW generated for four years (2008 to 2011)	PLS-SVM was more robust than SVM. Further, it had lower sensitivity to variation in input variables than other models.	**PLS-SVM:** RME =1139, RMSE = 1541, R^2 =0.86, MARE = 0.021	(Abbasi et al., 2013)
MSW generation	SVM, ANN, kNN, ANFIS	Model input included monthly time series MSW generation data spanning over eighteen years (1996 to 2014)	Peak monthly and annual MSW generated	The kNN model was successful in predicting average monthly waste quantities, whereas the ANFIS model gave the most accurate peak forecasts of MSW.	**ANFIS:** RMSE= 0.002, MAE= 0.001MAPE=3.39E-06, R^2=0.99 **SVM:** MAE= 203.03, RMSE= 300.70, MAPE= 0.05, R^2=0.93 **ANN:** MAE= 335.03, RMSE= 498.43, MAPE= 0.07, R^2=0.83 **kNN:** MAE= 251.80, RMSE= 387.21, MAPE= 0.06, R^2=0.88	(Abbasi and El Hanandeh, 2016)
MSW generation	MFO (Moth Flame Optimization)-DNN	Carbon (C), hydrogen (H), nitro (N), sulfur (S), oxygen (O), moisture content (MC), ash, equivalence ratio (ER), and	Gas yield prediction from MSW	Through the proposed hybrid model, MSW for waste treatment plants reduces negative effects on the surrounding environment.	**R^2=** 0.981 **RMSE =** 0.230	(Yang et al., 2021)

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		temperature (Temp) generated from MSW				
MSW generation	MLP-ANN RBF (Radial Basis Function)-SVR	Population, gross domestic product, annual tourist numbers, annual electricity consumption and total annual CO_2 emissions	MSW prediction	RBF-SVR gives good prediction results, and this research can implement their roadmap for waste management systems by the policymakers.	MLP-ANN: $\mathbf{R^2}$ = 0.94 RBF-SVR: $\mathbf{R^2}$ = 0.97	(Jassim et al., 2021)
MSW generation	IPSO (Improved Particle Swarm Optimization)-LSTM	Nine factors were selected: permanent resident population (PRP); the number of overseas tourists (NOT); gross domestic product (GDP); tertiary industry (TI); the consumer price index (CPI), the retail price index (RPI); urban per capita consumption expenditure (UPCCE); urban per capita disposable income (UPCDI);	MSW generation forecasting	The proposed IPSO-LSTM had higher accuracy than the other benchmark models, and the MSW generation quantities are expected to respectively increase to 9.971, 9.684, and 9.090 million tons by 2025.	**MAPE:** 6.28% **RMSE:** 60.2500 **MAE:** 52.36 $\mathbf{R^2}$**:** 0.7178	(Wang et al., 2022)

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		and the total investment in fixed assets (TIFA)				
MSW management	PSO-ANFIS-FCM (Fuzzy c-Mean) PSO-ANFIS-SC (Subtractive Clustering) GA-ANFIS-SC GA-ANFIS-GP	Dataset was built based on the relevant meteorological parameters, namely maximum temperature, minimum temperature, wind speed, and humidity	MSW detection and the output variables are organic, paper, plastic, and textile	Both PSO-ANFIS and GA-ANFIS had a good performance in predicting the physical composition of the waste streams with only a marginal variation.	PSO-ANFIS-FCM: **RMSE** = 2.864, **MAPE** = 9.32, **MAD (Mean Absolute Deviation)** = 2.046. PSO-ANFIS-SC: **RMSE** = **2.543**, **MAPE** = 13.24, **MAD** = 2.368. GA-ANFIS-SC: **RMSE** = 4.329, **MAPE** = 10.46, **MAD** = 10.46. GA-ANFIS-GP: **RMSE** = 2.065, **MAPE** = 12.41, **MAD** = 12.41.	(Adeleke et al., 2022)

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5. Key challenges

Some of the key challenges in the applications of AI techniques in MSW management are summarized below.

5.1. Data availability

Machine and deep learning experiments require sufficient amounts of data for useful and informative results. A good example is deep neural networks that need enough data for training and testing, and it is also called data-eating algorithms. The larger the number of neurons and architecture, the large amount of data is considered necessary to get possible results. Sometimes lacking good data and re-using the old data is not appropriate and cannot be generalized to a variety of problems in a domain. The waste management system also faces the same data unavailability challenge (Guo et al., 2021). Data availability can help to build data sets that can be used to perform MSW generation prediction, bin detection, route optimization, and MSW classification (Xia et al., 2021).

5.2. Trust on collected data and data sets available over the internet

Researchers do not follow the standard protocol while collecting data. Most of the data have missing values and errors due to inappropriate collection methods. Similarly, certain data formats and forms are bad and cannot be trusted and used (Facca et al., 2020). Trusted collected data can be used to predict and classify MSW generation, collection and transformation (Song et al., 2022).

5.3. AI appropriate model selection for data processing

Another potential challenge for the researchers is the use of suitable machine learning and deep learning model for data analysis. The model choice is the process of selecting one among many nominee models for a projecting modeling problem. The right choice of model gives fruitful and informative results (Huang and Koroteev, 2021). The appropriate AI models can help to predict

and classify MSW generation, bin detection, route optimization, pollutant emission monitoring and landfill area estimation.

5.4. Blackbox nature of AI

The increasing popularity and growing interest in the applications of AI in the previous decade have also underlined some challenges and issues in the domain, including the major one which is the black box problem (Ijaz et al., 2021). It is a big problem of producing sense in complex machine learning algorithms and trying to explain machine-based decisions (Abdallah et al., 2020). The internal mechanism of most AI models is difficult to understand, and it is challenging to estimate the relative importance of individual input variables, which can bring uncertainty to the application of such models. AI implementation in waste management can help to effectively collect and transport MSW by applying techniques for bin detection, route optimization and waste classification (Stadlmann and Zehetner, 2022; Xia et al., 2021).

5.5. AI implementation in waste industries

Waste products are continuously growing very fast worldwide. Currently, the established waste industries' garbage collection and processing plants do not have an appropriate intelligent technology system to manage waste products smartly. Similarly, waste sorting is a difficult process for humans which needs an automated process based on AI to sort and recover crucial materials and isolation of unwanted massive waste.

5.6. Needed skills for AI in waste organizations

AI needs relevant skills such as programming, data analysis, probability, and statistics. The lack of AI-skilled workers is the main challenge to implementing AI-based smart systems in the waste management industries. In the current situation, industries generate a huge amount of waste that needs to be tackled smartly by hiring AI-based skilled workers in the industry or training existing workers (Abdallah et al., 2020). Arranging training and workshops for the workers in the waste

management industry will help to enhance their skills to effectively employ various AI techniques for efficient MSW management.

6. Recommendations

The following passages provide a brief description of the potential solutions to overcome the challenges highlighted in the section above

6.1. Use of hybrid models

Over-fitting is a commonly encountered issue during the final classification and clustering layer of neural network models. This problem occurs by supplying less data to the system. These kinds of problems can be solved by using hybrid models (Gavrishchaka et al., 2018; Ullah et al., 2021a). The hybrid model is the combination of more than one model to produce high accuracy and reliable results. Similarly, it also assists the researchers and practitioners to succeed in improving performance and explaining the ability of implemented models. According to Soni et al., (Soni et al., 2019) hybrid models use are appropriate and showed better performance for the prediction of municipal solid waste management.

6.2. Application of ML interpretation techniques

To address the interpretability issue of different ML techniques, various interpretation techniques have been recently proposed, such as feature sensitivity, SHAP analysis, and summary plots (Ullah et al., 2022b). These ML interpretation techniques are very useful to understand the latent correlation between the independent and target variables. Despite their applications in other fields, there is a lack of literature on solid waste management in regard. It is suggested that forthcoming studies should focus on this aspect.

6.3. Use of emerging technology for getting data such as IoT

The annual generation of solid waste is growing very fast up to 2 billion tons and one-third of it is not handled in an environmentally cautious manner. According to the world bank report, solid

463 waste will further grow up to 3.4 billion by 2050. Internet of Things (IoT) is one of the emerging
464 technologies to assist in the management of such as the huge amount of solid waste. IoT provides
465 encouraging solutions to streamline the conventional waste management system (Anh Khoa et al.,
466 2020).

467 ***6.4. Application of Image processing for solid waste separation***

468 Detection and separation of different components of MSW is also an essential aspect of
469 effective solid waste management processes. Accurate information about this can efficiently help
470 in garbage collection, disposal, and recycling. In recent years, image processing has drawn
471 widespread attention and implementation across various fields. The application of such techniques
472 in solid waste will be highly beneficial in timely and effective decision-making regarding solid
473 waste management.

474 ***6.5. Implementation of smart solid waste management***

475 The consumption and quantity of solid wastes are increasing rapidly. This is a potential problem
476 that tends towards least developed countries than developing countries. This can be dangerous for
477 the environment as well as for the people living in society. The implementation of a smart bin
478 system can be possible by installing IoT and GSM (Global Systems for Mobile) and GPRS
479 (General Packet Radio Service) based devices to build a smart waste management system.
480 Similarly, by using the android and iOS-based applications for monitoring the system and getting
481 the information relevant to waste management (Jain and Bagherwal, 2017).

482 ***6.6. Installing devices and sensors for data collection***

483 Managing such a huge amount of solid waste can be achieved by the implementation of a smart
484 management system. Installing suitable devices and sensors can help to achieve good-quality data
485 (Omar et al., 2016). Accurate and enough amount and Data can assist in forecasting waste

management in the future and help to implement the same system in under-developed countries to bitterly manage waste management to protect the environment and community.

6.7. Building AI-based tools and framework for easy data analysis

AI-based tools and frameworks are needed to process the data and to manage waste management efficiently. Bilal et al. (2016) (Bilal et al., 2016) developed a big data conceptual framework for the construction of waste analytics. The proposed framework helps to classify the huge amount of construction waste. They further recommended that this model would help researchers and practitioners to build big data-based simulation tools. Similar ideas could be applied to waste management to produce AI-based tools and frameworks.

6.8. Applications of AI-based tools for the conversion of waste to useful products

AI-based techniques can play a critical role in determining the suitability of waste to be converted into useful products. Furthermore, the process of conversion/extraction of precious materials from waste can be optimized using some ML tools prior to performing the real experiments. This can lead to a sustainable environment and a step toward a circular economy.

7. Conclusion

Various AI models (both single and hybrid) have already proven their potential in the prediction and optimization of generation, detection, collection, classification, and properties of the MSW. Designing of smart SWM system for cities will be a fantastic approach to manage properly the produced solid waste. AI techniques also have the potential to predict the environmental impacts of SW and determine the suitability of waste for the recovery of various previous materials from it. However, still, numerous challenges limit the applications of these awesome tools in real SWM. It is expected that most of these challenges will be solved with technological advancements in the near future. Despite these hurdles, it can be safely predicted that AI techniques can revolutionize the solid waste management process. Future studies can focus on AI application in other domains

of MSW such as transportation, disposal, biogas generation, and its environmental impacts. Further, the application of deep learning technologies and metaheuristics can be explored.

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Highlights

- A comprehensive overview of AI applications in waste management is presented.
- The potential of AI in predicting the performance of waste management processes is discussed.
- Hybrid AI techniques have better predictive capabilities than conventional AI methods.
- The major challenges are highlighted and recommendations for future research are provided.
- Applications of AI can revolutionize the waste management process.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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