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Toward smarter management and recovery of municipal solid waste: A critical review on deep learning approaches

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A R T I C L E I N F O

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A B S T R A C T

Increasing generation of municipal solid waste, heterogeneity of waste composition, and complex processes of waste management and recovery have limited the performance of traditional treatment approaches. It is urgent to innovate waste management toward smarter and more efficient modes and break up the bottlenecks of the current system. Recently, deep learning has emerged as a powerful method for revealing hidden patterns or deducing correlations for which traditional treatment approaches face limitations or challenges. However, deep learning concepts and practices have not been widely utilized by researches in municipal solid waste management (MSWM). Herein, this research provides a critical review for deep learning and its application in MSWM. The framework and algorithms of a variety of deep learning methods have been compared and assessed. A body of deep learning applications have been reviewed according to their engagement in waste collection, transportation, and final disposal. Application of deep learning in MSWM stays in its infancy and requires great efforts for further development. The challenges and futures opportunities in the application of deep learning in the MSWM have been discussed to highlight the potential of deep learning in this field.

1. Introduction

A lot of attention is currently devoted to machine learning (ML) methods in environmental fields (Zhong et al., 2021), such as water (Sagan et al., 2020), air (Bellinger et al., 2017), soil (Yaseen, 2021), and energy (Dounis and Caraiscos, 2009). Compared with these fields, the researches on employing ML and artificial intelligence (AI) in municipal solid waste management (MSWM) are less relevant. MSWM plays a crucial role in realizing the goals of sustainable development. The current urbanization, rapid population growth, and economic developments result in large amounts of municipal solid waste (MSW), which needs to be treated and disposed of. The heterogeneity of the composition and complex mechanisms of MSW have limited not only the performance of conventional treatment approaches, which include classified recycling, landfilling, incineration, pyrolysis, gasification,

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Abbreviations

1-D	One-Dimension
2-D	Two-Dimension
3-D	Three-Dimension
AAPRE	average absolute percent relative error
AE	average error
AI	Artificial Intelligence
AARE	Average Absolute Relative Error
BP-NN	Backpropagation- Neural Network
CNN	Convolutional Neural Network
CH_4	Methane
CO_2	Carbon Dioxide
COD	Chemical Oxygen Demand
COVID-19	Corona Virus Disease 2019
D	Discriminator
DNN-TC	Deep Neural Networks for Trash Classification
DBN	Deep Belief Network
DT	Decision Tree
EBGANs	Energy-Based Generative Adversarial Networks
FA	Focus Attention
FID	Fréchet Inception Distance
F-test	Joint hypotheses Test
G	Generator
GA	Genetic Algorithm
GANs	Generative Adversarial Networks
GIS	Geographic Information System
GPU	Graphics Processing Unit
HDPE	High Density Polyethylene
IoT	Internet of Things
IS	Inception Score
KNN	K-Nearest Neighbor
LDPE	low density polyethylene
LHV	Lower Heating Value
LSTM	Long Short-Term Memory
LSVRC	ImageNet Large Scale Visual Recognition Challenge
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MC	Moisture Content
MSE	Mean Square Error
MSW	Municipal Solid Waste
MSWM	Municipal Solid Waste Management
NLP	Natural Language Processing
NRMSE	Normalized Root Mean Square Error
PCA	Principal Component Analysis
PE	Polyethylene
PET	Polyethylene Terephthalate
PM	Particulate Matter
PP	Polypropylene
PS	Polystyrene
PVC	Polyvinyl Chloride
R	Correlation Coefficient
R^2	Coefficient of Determination
R–CNN	Region- Convolutional Neural Network
RE	Relative Error
ResNet	Deep Residual Network
RMSE	Root Mean Square Error
RNN	Recurrent Neural Networks
SBA	Saliency-Based Attention
SGANs	Spatial GANs
SS	Suspended Solids
SVM	Support Vector Machine
SVR	Support Vector Regression
TSS	Total Suspended Solids
VFA	Volatile Fatty Acid
VSS	Volatile Suspended Solids

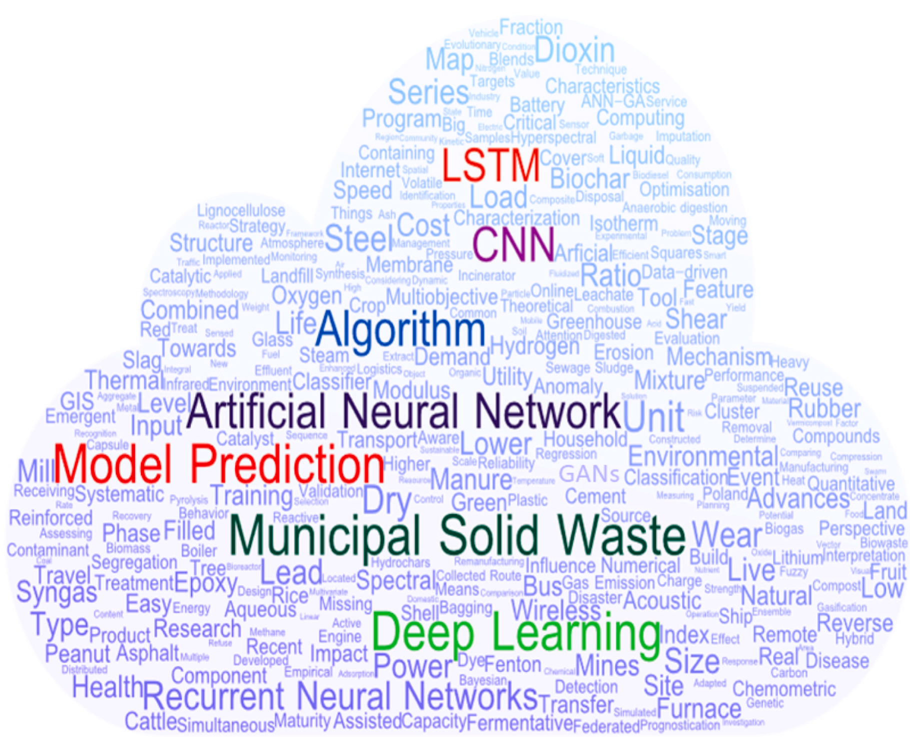

Fig. 1. Keywords cloud about deep learning's application in MSWM.

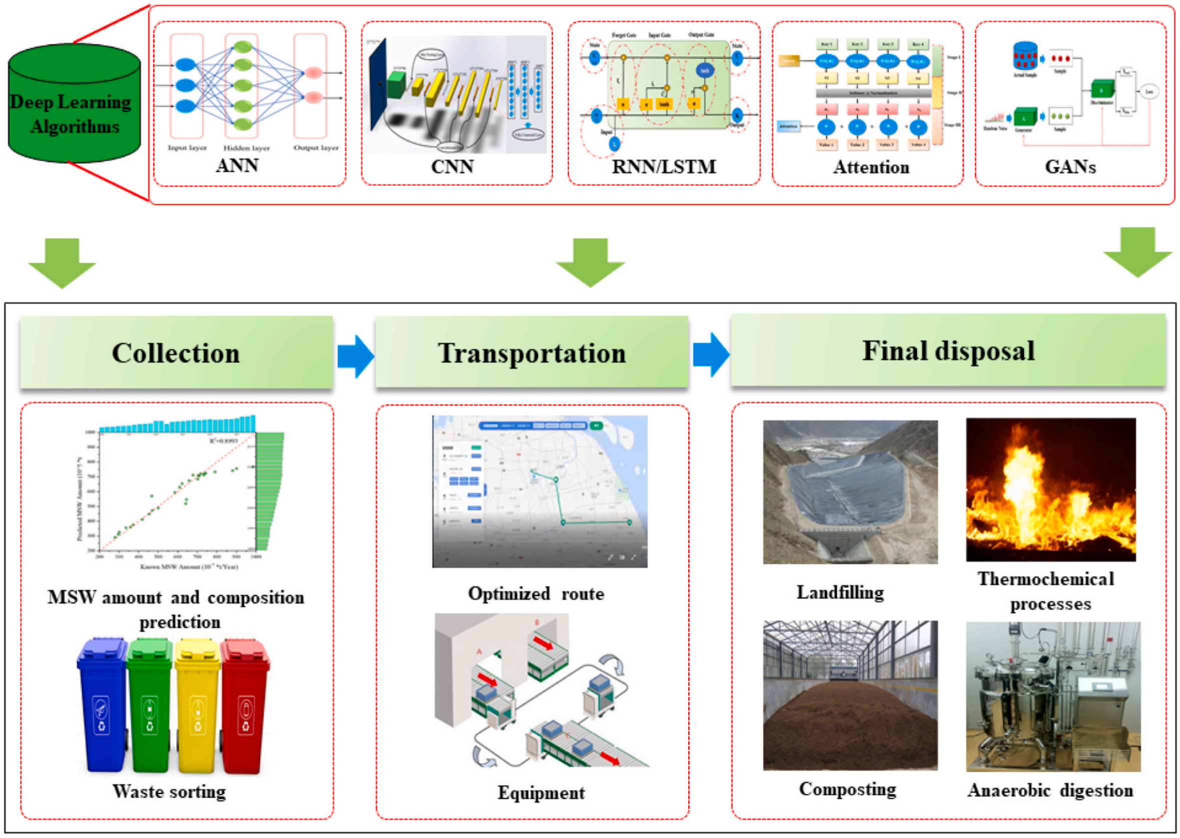

Fig. 2. Algorithms of deep learning and applications in MSWM.

composting, and anaerobic digestion, but the management approaches and the collection. These approaches come with some limitations, which are becoming great challenges in the environmental field. For example, traditional waste sorting mainly relies on manual selection, which has some limitations, such as low efficiency and the potential risk of infections, especially during the COVID-19 pandemic (Iyer et al., 2021). Also, in terms of waste transportation, improper and inefficient transport plans and routes consume a lot of human, physical, and financial resources as well as increase greenhouse gas emissions (Nguyen et al., 2020; Roberts et al., 2010). Moreover, incineration, pyrolysis, gasification, anaerobic digestion and landfilling have potential explosion risks during operational processes (Cai et al., 2021). The issues mentioned above in the MSW field are urgent and need to be addressed for sustainable management.

Recently, deep learning has emerged as a powerful method for automatically learning feature representation from data, and it has been widely applied to many domains related to science, business, and government (LeCun et al., 2015). This method has shown excellent performance in solving the problems of nonlinearity, time variation, multisource, and multiple targets (Xu et al., 2021). Therefore, deep learning has great potential to be applied in the MSWM field. However, deep learning concepts and practices have not been widely utilized by researches in MSWM. The aim of this feature is to introduce and compare deep learning algorithms as well as discuss the application of deep learning status, challenges, future opportunities of this tool in MSWM to highlight the potential of deep learning tool in the MSWM field.

Fig. 1 shows a word cloud of the application of deep learning in MSWM, where the size of each word is proportional to its frequency. Scientific research has been established for deep learning applied in MSWM dated backed to 2005. Using the relevant keywords mainly included artificial neural networks, municipal solid waste/MSW generation, municipal solid waste/MSW amount prediction/forecast, municipal solid waste/MSW composition prediction, municipal solid waste/MSW classification, deep learning, convolutional neural networks/CNN, recurrent neural networks/RNN, long short-term memory/LSTM, generative adversarial networks/GANs, landfilling, leachate, gas emission, incineration, composting, and anaerobic digestion in the indexed database of Web of Science, Derwent Innovations Index, KCI-Korean Journal Database, MEDLINE, Russian Science Citation Index, and SciELO Citation Index. 493 research articles were adopted in MSWM for the period of 2000–2021.

This article mainly focuses on reviewing the employment of deep learning in MSWM, as shown in Fig. 2. Section 2 compares the differences between conventional ML and deep learning, introduced the progress of deep learning, and compared the advantages and limitations among some typical deep learning algorithms. Sections 3, 4, and 5 summarize the deep learning techniques applied in the collection, transportation, final treatment, and disposal fields, respectively. Section 6 discusses the challenges and perspectives of deep learning applications in MSWM.

2. Deep learning

It is noteworthy to clarify the relationship among AI, ML, and deep learning. AI was first put forward in 1956 by John McCarthy and Claude Shannon et al. (Crevier, 1993) who aimed to mimic human behaviors, such as making decisions, solving problems, processing images, videos, and speech. AI contains machine learning and deep learning, while deep learning is a subset of machine learning.

2.1. *Difference between conventional machine learning and deep learning*

ML includes conventional ML techniques, such as support vector machine (SVM), decision tree (DT), genetic algorithm (GA), and deep learning, which have great differences concerning extracting features.

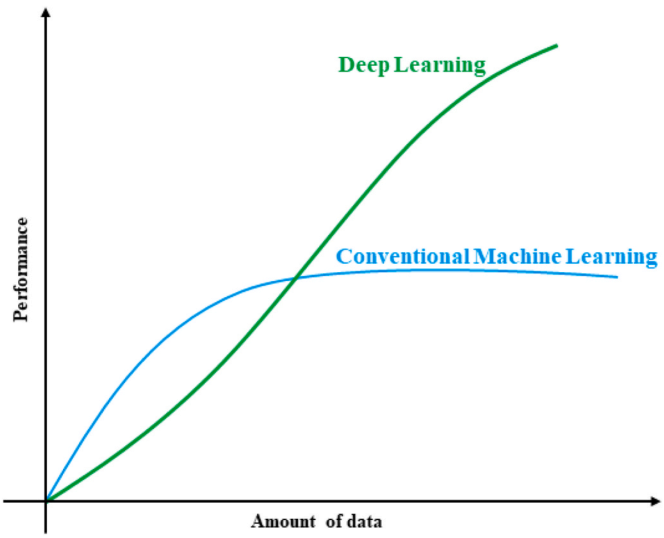

Fig. 3. Performance of conventional machine learning vs. deep learning and their data reliance (Alom et al., 2019).

Deep learning algorithms can automatically extract representations or abstractions from data (Bengio, 2009; Bengio et al., 2013; Najafabadi et al., 2015). A comparison of the performances of deep learning and conventional ML concerning input data is shown in Fig. 3. It can be observed that compared with conventional ML, the performance of the deep learning approach improved with the increase in input data. This is why deep learning approaches are becoming a hot research topic in the big data era. The differences between deep learning and conventional ML can be described in terms of applicability, robustness, generalization, and scalability.

State-of-the-art ML is sometimes called universal learning. Deep learning can be employed in almost any application domain (Alom et al., 2019). While conventional ML has its limitations. High-dimensional informative data with noise or uninformative data constrain feature extractions by conventional ML due to the poor robustness of the conventional ML methods (Zhang et al., 2021). In contrast, by automating the extraction of representations, deep learning algorithms have strong robustness to stand up against noise. In addition, the models based on shallow learning architectures, such as GA or DT, can easily fall short when trying to extract useful information from complex structures and relationships in input corpora (Najafabadi et al., 2015). While the state-of-the-art model can avoid this problem, its structures can be generalized in nonlocal and global ways. As for the generalization of deep learning, it has already been discussed in previous studies (Marco, 2020; Zhou and Wang, 2020). In terms of scalability, deep learning approaches are highly scalable, and the classical convolutional neural network (CNN) structure like deep residual network (ResNet) takes a good example, which is often implemented at a supercomputing scale (He et al., 2016). In addition, Chauhan et al. provided a review on conventional ML versus deep learning (Chauhan and Singh, 2018).

2.2. Taxonomy of deep learning

Deep learning approaches can be classified into supervised learning, semi-supervised learning, and unsupervised learning. The dataset of supervised deep learning has been labelled. In other words, the system has a set of inputs and corresponding outputs (x_t, y_t). CNN and long short-term memory (LSTM) are the typical algorithms for supervised learning. While the training process of semi-supervised deep learning partially relies on labelled datasets. Generative adversarial networks (GANs) take a good example for semi-supervised deep learning. Finally, the environment of unsupervised deep learning does not have data labels. Usually, this technology is applied in clustering, dimensionality reduction, and generative techniques (Alom et al., 2019). Supplementary materials (S1) introduced the progress of deep learning.

Table 1
Comparison of the typical deep learning algorithms.

Algorithms	Advantages	Limitations
ANN (BP-NN)	● Good performer for non-linear dataset ● Less computational time ● Work with noisy and incomplete data	● Overfitting or underfitting ● Black box
CNN	● Being more like the human visual processing system ● Being effective at learning and extracting abstraction of 2-D and 3-D features ● Producing highly weights	● Overfitting ● Larger consumption of computation or memory ● Longer run-time ● Limitation of transparency and explanations
LSTM	● Avoid the problems of gradient degradation ● Learning long-term temporal dependencies ● Being able to learn high-dimensional and continuous actions with backpropagation's focused credit assignment mechanism	● Slow convergence ● Lack of parallel computing ● Failure spectacularly disgracefully without warning or explanation
Attention	● Solving the problem of information overload ● Using as a tool to explain incomprehensible neural architecture behavior	● Lack of interpretability
GANS	● Just using backpropagation rather than Markov Chain ● Updating the parameters in G that was from D	● Model collapse ● Non-convergence ● Instability ● Complexity

2.3. Comparison of typical deep learning algorithms

The framework and algorithms of a variety of deep learning methods have been described in Supplementary materials (S2). Table 1 shows a comparison of the typical deep learning algorithms in terms of their advantages and disadvantages. ANN, based on backpropagation, demonstrates the outstanding capability of using less computational time and establishing highly nonlinear relationships among dispersed and noise additive data (Oliveira et al., 2019). However, the phenomena of overfitting or under-fitting limit the performance of the application of ANN. More like the human visual processing system, CNN has many advantages. For instance, it is more effective in learning and extracting the abstraction of 2-D and 3-D features and producing high weight sharing (Lin et al., 2021). Although CNN has become one of the most important models for image recognition and classification. Large amounts of datasets are used as a precondition for the good performance of CNN, which results in low training efficiency, increased computation and memory consumption, and longer run time. (Qiao et al., 2017).

In contrast to the other algorithms, the LSTM can avoid the gradient degradation and explosion phenomena, and learn long-term temporal dependencies to learn high dimensional and continuous actions with credit assignment mechanisms focused on backpropagation (Yu et al., 2019). However, the drawbacks of the LSTM model which include slow convergence, lack of ability of parallel computing, and disgraceful failure without warnings or explanation, cannot be neglected (Bram, 2007). In terms of attention-based models, they can effectively address the information overload problem and be used as available tools to explain the behaviors of incomprehensible neural architectures (Niu et al., 2021b). Finally, there are some major challenges in the training of GANs such as model collapse, non-convergence, instability, and complexity (Saxena and Cao, 2021). The merits of GANs are just using backpropagation rather than Markov Chain and updating the parameters in the generator, which is originated from the discriminator. This is mainly different from

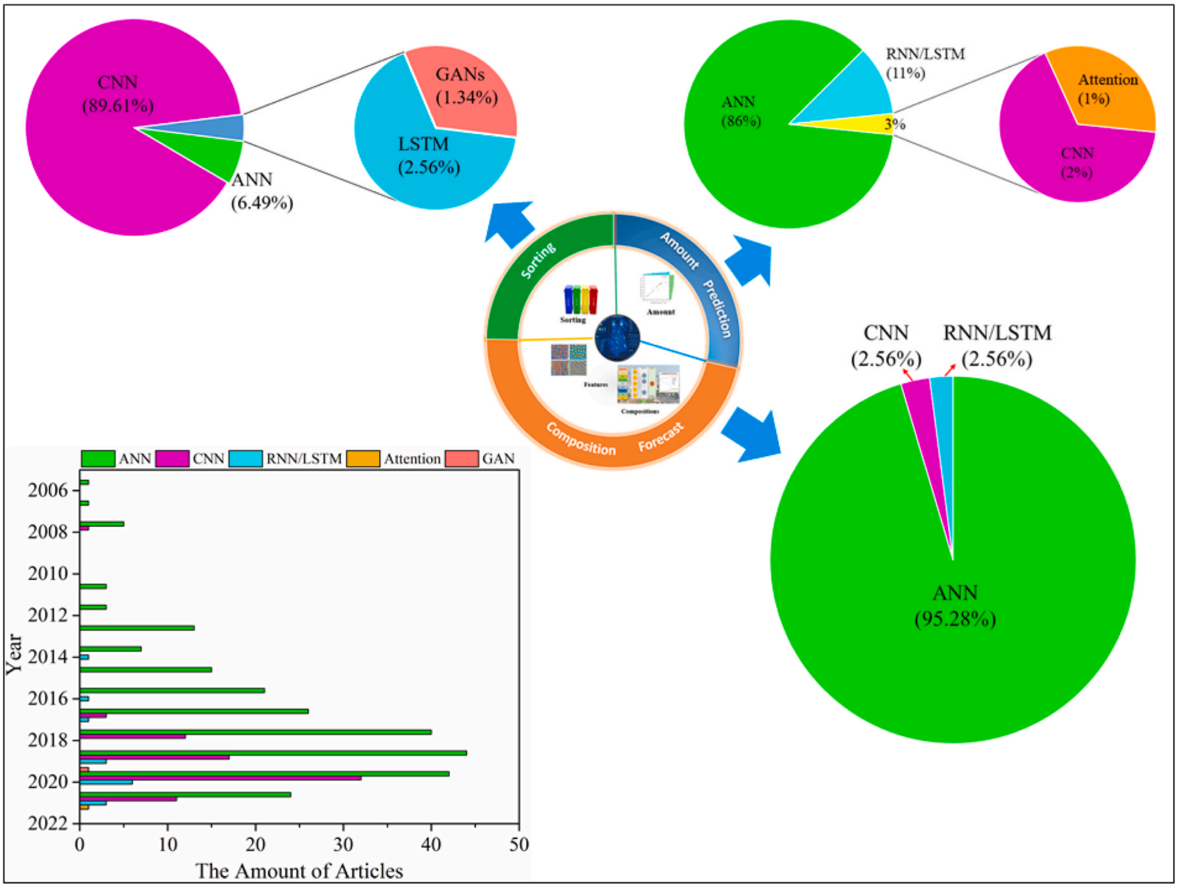

Fig. 4. Application of deep learning in MSW collection. ANN: artificial neural networks; CNN: convolutional neural network; RNN: recurrent neural network; LSTM: long short-term memory; GANs: generative adversarial networks.

other deep learning algorithms during the training process. Note that ANN, CNN, LSTM, attention, and GANs are considered as black boxes and that they constrain the model's transparency and explanations. In addition, the indexes for the evaluation of various deep learning-based models' performance are listed in Table S2 in Supplementary Materials.

3. Application of deep learning in the MSW collection

Fig. 4 demonstrates the publications that employed the deep learning approach in the collection of MSW. This section includes MSW amount prediction, the compositions of MSW forecasts, and MSW sorting. The previous studies on the ANN and CNN models show an upward trend, especially after 2015. Recently, the attention to deep learning algorithms, such as GANs and attention neural networks has significantly increased, as shown in the bar chart (Fig. 4).

Fig. 4 shows that the ANN model has been widely used in the prediction of the amount and compositions of MSW and that the studies that applied the CNN model in waste sorting account for 89.61%, followed by ANN (6.49%), LSTM (2.56%), and GANs (1.34%).

3.1. Amount and composition prediction of MSW

The significant increase in the living standards in cities and rapid urbanization lead to large quantities of MSW generation (Dutta and Jinsart, 2020). It is now very challenging to select and implement waste management strategies and pollution control technologies, since the generation of MSW is complex and non-linear process, involving multiply factors (Yang et al., 2021). Therefore, it is crucial to accurately predict the amount and compositions of MSW in megalopolis to provide policymaking references and take proper measures in advance. Deep learning algorithms can be ascribed to a large number of nonlinear functions, consisted of neural network structure, attributing to the excellent performance of deep learning on prediction. In other words, these multilayer nonlinear functions allow networks to learn the complicated and abstract features between variables and targets. Therefore, more and more works of literature reported that deep learning algorithms are taken to predict the amount and composition predictions of MSW, as showed in Table 2.

As summarized in Table 2, many researchers have applied the ANN model to predict the amount of MSW on different time scales, including weekly (Noori et al., 2009), seasonal (Azadi and Karimi-Jashni, 2016), and annual data (Oliveira et al., 2019). The coefficient of the ANN model determination ranges from 0.73 to 0.837, so it still has great room for improvement. Therefore, according to the data-driven characteristics of ANN models, some studies took some measures, such as more variates (Chhay et al., 2018) and enlarged time scales (Abbasi and Hanandeh, 2016), to improve the performance of ANN models, which achieved a higher R^2 (0.93–0.99), lower RMSE (0.002–450.84), MAE (0.001–228.53), and MAPE (0.07–0.0143).

Also, other deep learning algorithms have recently been considered in forecasting the amount of MSW. Niu et al. used the LSTM algorithm combined with data ranging from January 2018 to December 2019 to predict the MSW amount in Suzhou, China, and the model achieved a coefficient of determination (R^2) of 0.90 and an RMSE of 940 (Niu et al., 2021a). Lin et al. have proved that the use of CNN, LSTM, and attention algorithms to predict the amount of MSW is feasible and practical (Lin et al., 2021). The result indicated that the correlation efficiency between the predicted and actual values for the attention, CNN, and LSTM algorithm are 0.7806, 0.8641, and 0.8903, respectively. In addition, these three typical deep learning algorithms integration could enhance the

Table 2
Application of deep learning in prediction of MSW amount and composition.

Application	Model	Prediction content	Region	Input parameters	Dataset	Prediction Evaluation	References
MSW Amount	ANN	Forecasting the MSW generation in Tehran	Iran	Weekly time series of Waste generation in 2007	One year of MSW amount	R:0.837; AARE: 4.4%	Noori et al. (2009)
	ANN	Seasonal MSW generation rate in Fars province, Iran	Iran	Population; Frequency; Temperature; Altitude	The year of 2009–2010 data for 20 urban areas	R: 0.86; MAPE: 8%; MAE: 48.37%; NRMSE: 0.10; RMSE: 68.32	Azadi and Karimi-Jashni (2016)
	ANN	Estimate the annual amount (kg/inhabitant/year)	Portugal	Population; area; degree of urbanization; purchase power index; deprivation index and other 8 variables	42 municipalities in Portugal in 2015	R^2:0.73; Error: 10^{-7}–10^{-3}	Oliveira et al. (2019)
	ANN	MSW generation in Logan city	Australia	Waste generation from July 1996 to June 2014	Eighteen-year period from July 1996 to June 2014	R^2:0.99; MAE:0.001; RMSE:0.002; MAPE:3.39E-6;	Abbasi and Hanandeh (2016)
	ANN	Forecasting the MSW generation in China	China	8 socio-economic factors	The year of 2000–2016 data from China statistical yearbook	MAPE: 0.0143; RMSE: 450.84; MAE: 228.53; R^2: 0.931	Chhay et al. (2018)
	ANN	Predicting the MSW generation in Haryana, India	India	Time series about MSW amount	Data ranged from January 2010 to December 2014	MSE:0.0003714; RMSE: 0.01927; R: 0.8385	Singh and Satija (2016)
	LSTM	Predicting the MSW amount in Suzhou, China	China	Time series	730 data from Jan. 1, 2018 to Dec. 31, 2019	R^2: 0.90; RMSE: 940	Niu et al. (2021a)
	Attention	Predicting the amount of MSW in Shanghai	China	24 socioeconomic factors	Data ranged from 1990 to December 2018	R^2: 0.7806; MSE: 0.006 (train loss)	Lin et al. (2021)
	CNN	Predicting the amount of MSW in Shanghai	China	24 socioeconomic factors	Data ranged from 1990 to December 2018	R^2: 0.8641; MSE: 0.0086 (train loss)	
	LSTM	Predicting the amount of MSW in Shanghai	China	24 socioeconomic factors	Data ranged from 1990 to December 2018	R^2: 0.8993; MSE: 0.002 (valid loss)	
	LSTM + Attention	Predicting the amount of MSW in Shanghai	China	24 socioeconomic factors	Data ranged from 1990 to December 2018	R^2: 0.935	
	CNN + Attention	Predicting the amount of MSW in Shanghai	China	24 socioeconomic factors	Data ranged from 1990 to December 2018	R^2: 0.874	
	CNN + LSTM	Predicting the amount of MSW in Shanghai	China	24 socioeconomic factors	Data ranged from 1990 to December 2018	R^2: 0.0.944	
	CNN + LSTM + Attention	Predicting the amount of MSW in Shanghai	China	24 socioeconomic factors	Data ranged from 1990 to December 2018	R^2:0.953; MSE: 0.031 and 0.057 for train loss and valid loss, respectively	
MSW composition	ANN	Predicting the recyclables and garbage generation in Austin, USA	USA	The weekly amount of collected recyclables and garbage	Weekly collected recyclables (2008–2018) Weekly collected garbage (2004–2018)	Recyclables: MAPE: 10.92%~14.83%; Garbage: 11.76%~16.51%	Vu et al. (2019)
	ANN	Predicting the proportion of organic fraction, ash and stone, paper, plastic and rubber, textile, wood, metal, glass, metal, and others	China	Gas coverage rate in a residential area, economic development level, geographical location, city size, and year	Covered 292 cities in China	MSE:0.002–0.057; R^2:0.03–0.29; F:4.36–29.92	Ma et al. (2020)
	ANN	Forecasting the lower heating value (LHV) of municipal solid waste	–	The percentage of food, paper & cardboard, plastics, and wood	250 datasets of waste composition from 67 cities in 40 countries from 1970 to 2015	MAPE:19.38%	Wang et al. (2021)
	ANN	Predicted LHV	China	The amount of wood, paper, kitchen garbage, plastics, and textile	The actual composition of MSW from Beijing, Hongkong, and Shenzhen	RE: 20.5%	Xiao et al. (2009)

Where AARE: average absolute relative error; MAPE: mean absolute percentage error; MAE: mean absolute error; MSE: mean square error; NRMSE: normalized root mean square error; RMSE: root mean square error; R: correlation coefficient; R^2: coefficient of determination; RE: relative error; F: F-test.

performance of deep learning modules.

The composition of MSW is also one of the most fundamental parameters in waste management. Usually, the calorific content of MSW directly depends on the composition of MSW, which is often used to evaluate the energy-harvest potential of MSW incineration (Xiao et al., 2009). Table 2 reviews the studies that used the ANN model in the composition prediction of MSW in terms of macroscale and microscale.

Vu et al. employed the ANN model combined with a geographic information system (GIS) to predict recyclables and the generation of garbage generation in Austin, USA (Vu et al., 2019). Results indicated that the value from ANN resulted in mean absolute percentage errors ranging from 10.92% to 16.51%. Also, in the ANN model established by Ma et al. the gas coverage rate in a residential area and other four factors (economic development level, geographical location, city size, and year) were used as inputted variates (Ma et al., 2020). This model was used to predict the proportions of organic fraction, ash, stone, paper, plastic, rubber, textile, wood, metal, glass, metal, and other materials in China. The values of MSE, R^2, and F were found to be 0.002–0.057, 0.03–0.29, and 4.36–29.92, respectively. As for microscale MSW composition, studies were conducted using the amounts or percentages of various solid wastes to predict their lower heating values (LHV). However, only a few studies used deep learning algorithms to forecast the composition of MSW, and they showed the great potential of applying the deep learning approach in investigating the composition of MSW.

3.2. Sorting of MSW

The huge quantity of MSW generation calls for the proper classification, collection, and recycling of MSW to reduce the quantity of materials sent to landfilling and increase the number of recyclable materials. However, conventional waste classification mainly relies on manual selection, which has some limitations, such as low efficiency, and the potential risk of infection, especially during the COVID-19 pandemic (Iyer et al., 2021). With the development of computer hardware, deep learning has become a solution to many problems, including the identification (Sheng et al., 2020), detection (Nowakowski and Pamula, 2020), and sorting (Chu et al., 2018) of waste.

Training efficiency and accuracy, generalization, scalability, and robustness should be considered when selecting related algorithms to applied waste sorting machines. The training efficiency and accuracy of each algorithm for waste sorting would directly decide whether the algorithms can be selected or not. Generalization is the ability of the algorithm to adapt to fresh waste image samples. Due to the limitation of image samples, more powerful algorithms are expected to be found for wasting sorting. As for scalability, algorithms would be integrated with hardware, which revolved to the problem of scalability. In terms of robustness, the noise of the image sample would have a great harmful effect on the performance of the AI algorithms. Therefore, the factor of scalability also needs to be considered.

Due to the involved thousands of parameters that need to be tuned, it is hard to make quick decisions about the optimal structure of CNN for specific applications. Transfer learning, which is a specific branch of deep learning, aims to transfer knowledge to new systems or structures (Pan and Qiang, 2010). It can accelerate learning processes and enhance model accuracy by avoiding most of the re-initialization effort needed to designed self-organizing CNN structures (Hu et al., 2016) and by automatically deciding the structure size (Wang et al., 2019). Therefore, transfer learning has been applied to address waste sorting problems (Huang et al., 2020b; Vo et al., 2019). Also, many classic CNN structures have been proposed in the last decade (Girshick, 2015; Girshick et al., 2016; Melinte et al., 2020; Redmon and Farhadi, 2017; Szegedy et al., 2017).

Fig. 5 shows an overview of a CNN framework that can be used in waste sorting, where CaffeNet is taken as an example. First, by loading the pre-trained model like CaffeNet, the fully connected layers and output dimensions can be modified according to the actual demands. Second, several preprocessing techniques, such as horizontal flip, random crop, and normalization can be taken to prepare the training, validation, and test dataset. In addition, Table 3 shows the open sources of waste images sorting datasets. Third, the model performs the fine-tuned process to learn the characteristics of the waste types from the training set and uses the validation set to select the model with the best accuracy. Finally, this model is used to predict the final output of each input image in the test set (Vo et al., 2019).

Table 4 summarizes the previous studies that focused on employing deep learning approaches in the identification, detection, and classification of waste. Notably, most of the relevant researches used CNN or integrated it with other networks to identify or classify solid waste. Trashnet data released by Thung and Yang in 2016 is often used to evaluate waste classification models (Thung and Yang, 2016). For example, Toğaçar et al. (2020) used the CNN algorithm and Trashnet, which include organic class (13,966 images) and recyclable class (11, 111 images) to classify the solid waste as organic and recyclable categories. The result showed that the accuracy rate could reach 99.95%. In addition, by using the CNN algorithm to increase the number of training image data, and utilizing other models, such as SVM (Adedeji and Wang, 2019) and multilayer perception (Chu et al., 2018), the accuracy rate of waste classification can be improved (Huang et al., 2020b).

Some previous studies have focused on specific solid waste identification materials such as plastic, metal, and textile waste. Images from the WaDaba database were categorized, including polyethylene terephthalate (PET), high-density polyethylene (HDPE), polystyrene (PS), and polypropylene (PP) (Bobulski et al., 2021). The accuracy rate was found to be 74%, so there is still room to improve the performance of plastic sorting. CompostNet, a kind of CNN structure, was applied by Sheng et al. to categorize the food waste and the value of accuracy was just around 80% (Sheng et al., 2020). Liu et al. used the CNN algorithm to identify textiles based on the analysis of near-infrared spectroscopy and suggested that applying this approach can realize the automatic classification of several common textiles (Liu et al., 2019). However, more effects are still needed to improve the performance of the CNN algorithm with regard to the identification and sorting of waste.

4. Application of deep learning in MSW transportation

Fig. 6 and Table 5 show that only a few studies based on ANN and deep learning models focused on the transportation of MSW, and they mainly focused on route optimization, garbage classification systems, and waste detection of the equipment to reduce energy consumption.

In terms of transportation route optimization, a GIS integrated with an ANN model was applied to optimize the waste collection route according to the volumes of recyclables and garbage in various scenarios (Table 5). The results showed that compared with single and dual-compartment trucks, the dual-compartment trucks can save 10.3–16.0% in travel distance and slightly reduce emissions (Vu et al., 2019). Purkayastha et al. also used the ANN model to assess the allocation of garbage collection bins (Purkayastha et al., 2019). This study could help countries locating collecting bins and enhancing the collection efficiency of garbage.

The Internet of Things (IoT) technology was widely employed in waste classification. The MSW sorting system includes a waste classification algorithm, cloud, waste bin, and an information detective system (Fig. 6). To establish an automatic question answering system for waste classification, Jiang et al. applied the CNN and RNN model to train a waste image classification and natural language processing (NLP) (Jiang et al., 2020). The accuracy rate, precision rate, recall efficiency, and F1 were found to be 95%, 0.784–0.907, 0.791–0.898, and 0.787–902, respectively. A smart recycling bin with the help of the CNN algorithm was also invented by Baras et al. (2020), and it could make the accuracy rate reach 93.4%.

For the detection of MSW, it was combined with a road sweeper, which is a popular machine that helps preserve the cleanliness of cities

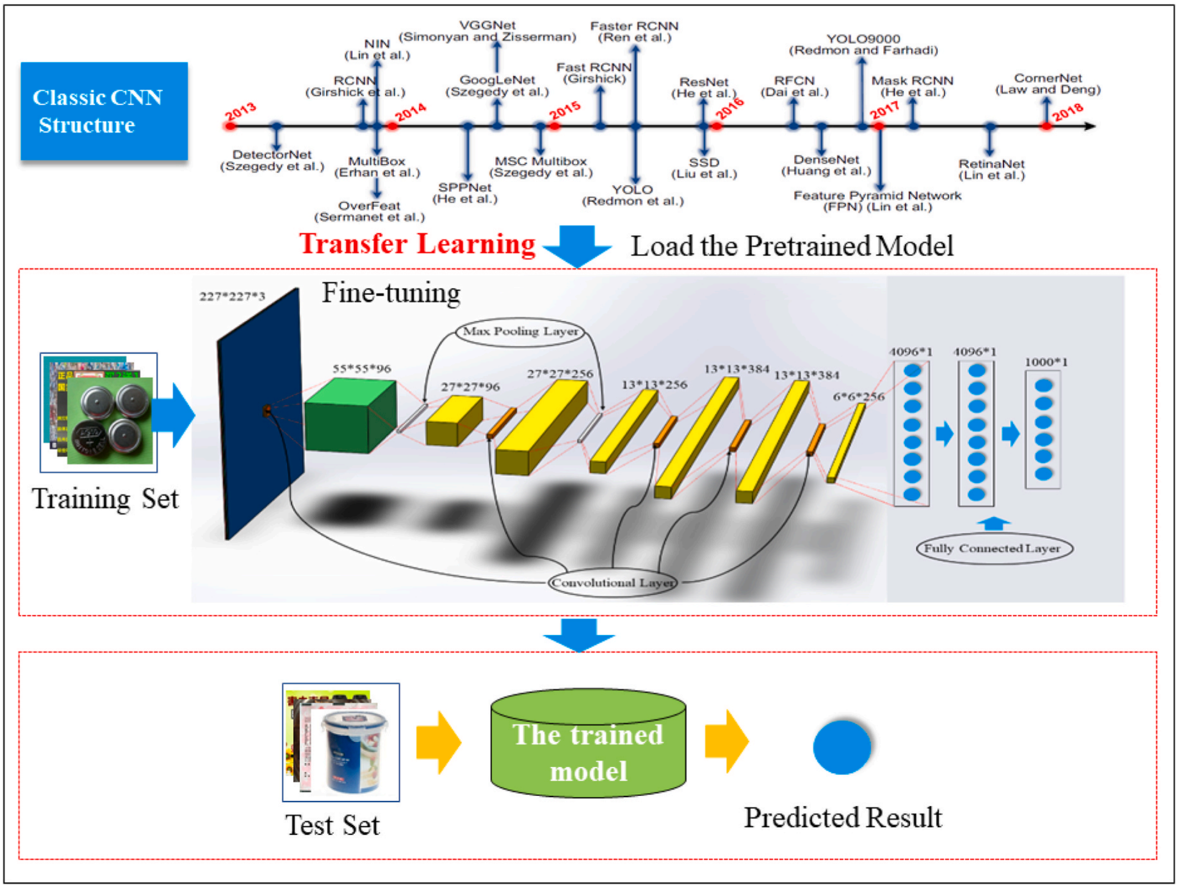

Fig. 5. Overview of the CNN framework for waste sorting: a case of CaffeNet.

Table 3
Open sources of datasets for waste image sorting or detection.

No.	Links	No. categories	No. subcategories	No. images
1	https://www.kaggle.com/techsash/waste-classification-data	2 (organic and recyclable)	–	25,077
2	https://aistudio.baidu.com/aistudio/datasetdetail/34554	4 (Hazardous; Organic; Recyclable; Residual)	114	>100,000
3	https://aistudio.baidu.com/aistudio/projectdetail/2147105?channelType=0&channel=0	4 (Hazardous; Organic; Recyclable; Residual)	40	>14,802
4	https://github.com/garythung/trashnet	6	–	2,572
5	http://tacodataset.org/stats	28	60	1,500
6	http://wadaba.pcz.pl/	7 (PET, HDPE, PVC, LDPE, PP, PS, and Other)	4	4,000
7	http://www.slipguru.unige.it/Data/glassense_vision/	7	136	2,000
8	https://openlittermap.com/	11	187	>100,000
9	https://www.imageannotation.ai/litter-dataset	24	3	14,000
10	https://github.com/datacluster-labs/Datacluster-Datasets	10	–	>9,000

Where PET: polyethylene terephthalate; HDPE: high-density polyethylene; PVC: polyvinyl chloride; LDPE: low-density polyethylene; PP: polypropylene; PS: polystyrene.

(Donati et al., 2020). The CNN algorithm was added to the road sweeper-operated system to save power energy. The experimental results showed that the waste identification system can save more than 80% of the electrical power currently absorbed by such cleaning systems and that it also can prolong the lifetime of the used brushes.

5. Application of deep learning in the final disposal of MSW

MSWM involved in collection (the prediction of MSW amount and composition, MSW sorting, and material recovery), transportation, and final disposal. Landfilling, thermochemical processes, composting, and anaerobic digestion are common ways for the treatment and disposal of MSW. This section systematically reviews the deep learning approaches employed in these processes. Fig. 7 shows the number of publications on the disposal and recovery of MSW using deep learning approaches. Many previous studies used the ANN model to investigate the problems related to the disposal of MSW. RNN/LSTM was applied to study the behavior of gases in the cases of landfilling and anaerobic digestion. Also, CNN and GANs were employed to identify the abstract features in the incineration and composting technologies, and the relevant details are discussed in the following section.

5.1. Sanitary landfills

The advantages of sanitary landfills, such as lower investment and easy operation, make them widely applied to the final treatment and disposal of MSW. Nevertheless, the leachate and gas generation from landfills cannot be neglected.

Table 4
Application of deep learning in MSW sorting, recognition, and detection.

Model	Content	Input Parameters	Dataset	Prediction Evaluation	References
CNN + Multilayer Perceptions	Identifying recyclable waste (40 items) and other wastes (10 items)	Labelled images	5,000 images	Accuracy: 90%	Chu et al. (2018)
CNN	Classification of organic and recyclable waste	Labelled images	25,077 waste images (13,966 organic class; 11,111 recyclable class)	Accuracy: 99.95%	(Toğaçar et al., 2020)
CNN	Sorting plastic, paper, and metal	Labelled plastic, paper, and metal images	6,000 images	Accuracy: 83%	Sakr et al. (2016)
CNN	Identifying recyclable materials	Labelled images	2,527 images (594 paper; 501 glass; 137 trash; 410 metal; 482 plastic; 403 cardboard)	Accuracy: 94%	Aral et al. (2018)
R–CNN	Real-time waste identification	Labelled images	2,527 images (594 paper; 501 glass; 137 trash; 410 metal; 482 plastic; 403 cardboard)	Accuracy: 95.97%	Melinte et al. (2020)
CNN (VGG19, DenseNet169, NASNetLarge)	Classifying garbage in the waste image dataset	Labelled images	One is a single waste image dataset with a total of 2,527 images, and another dataset is manually collected with a total of 5,000 images.	Accuracy: 96.5%	Huang et al. (2020b)
ResNet-50 (CNN)+ SVM	Waste material classification system	Labelled images	1,989 images including glass, paper, plastic, and metal	Accuracy: 87%	Adedeji and Wang (2019)
DNN-TC	Automatically classifying trash	Labelled images	One is a single waste image dataset with a total of 2,527 images, and another dataset is manually collected with a total of 5,904 images contained organic, inorganic, and medical wastes.	Accuracy: 94%	Vo et al. (2019)
CNN + PCA	Plastic waste classification system	PET, HDPE, PP, PS	PET class: 33,000 images HDPE class: 36,000 images PS class: 37,440 images PP class: 3,380 images	Accuracy: 74%	Bobulski et al. (2021)
CNN (CompostNet)	Classifying for meal waste	Labelled images	5,278 images	Accuracy: 77.3%	Sheng et al. (2020)
CNN	Textiles waste classification	NIR spectroscopy from 780 to 2,526 nm	263 spectrum samples	Recall rate: 0.95; Precision rate: 0.96	Liu et al. (2019)
CNN (AlexNet)	Recycled clothing classification system	Internet of Things	3,300 clothing data	Precision: 53.33–74.20%	Noh (2021)

Where PET: polyethylene terephthalate; HDPE: high-density polyethylene; PP: polypropylene; PS: polystyrene; NIR: near infrared.

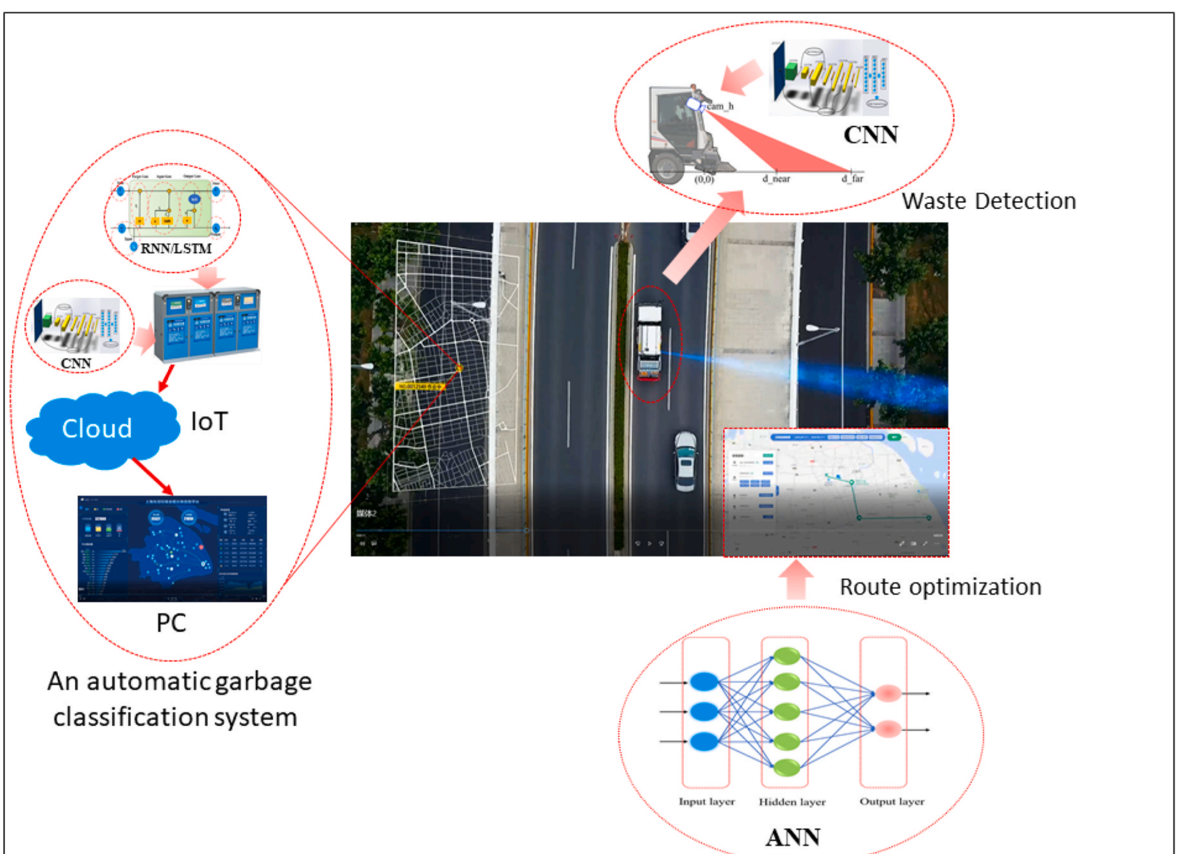

Fig. 6. Overview of deep learning application in MSW transportation.

Table 5
Application of deep learning in MSW transportation.

Application	Model	content	Input parameters	Dataset	Result	References
Optimized route	GIS-ANN-VRP	Waste collection route optimization	The volume of recyclables and garbage in different scenarios	Weekly collected recyclables (2008–2018) Weekly collected garbage (2004–2018)	10.3–16.0% travel distance saved	Vu et al. (2019)
	ANN	Assessment of collection bin allocation	Population density, street width, and other 5 variates	1,000	MAE: 0.1092–0.1445 RMSE: 0.1787–0.2826 R^2: 0.9892–0.9982	Purkayastha et al. (2019)
Equipment	CNN	Automatic question answering system to waste classification	Question about waste classification	9,272 items	Accuracy rate: 95% Precision: 0.784–0.907 Recall: 0.791–0.898 F: 0.787–902	Jiang et al. (2020)
	U-Net (CNN)	An energy-saving road sweeper	Image	400 image pairs	Save more than 80% electrical power	Donati et al. (2020)
	CNN	Smart recycling bin	Entry Area-camera module-identification Unit-electromechanically controlled seal-waste storage-cloud	2,527 images	Accuracy rate: 93.4%	Baras et al. (2020)
	ResNet-34 (CNN)	An automatic garbage classification system	Hard hardware + classification algorithm	4,168 images	Accuracy rate: 99% Reaction time: 0.95s	Kang et al. (2020)

Where MAE: mean absolute error; RMSE: root mean square error; R^2: coefficient of determination; F: F-test.

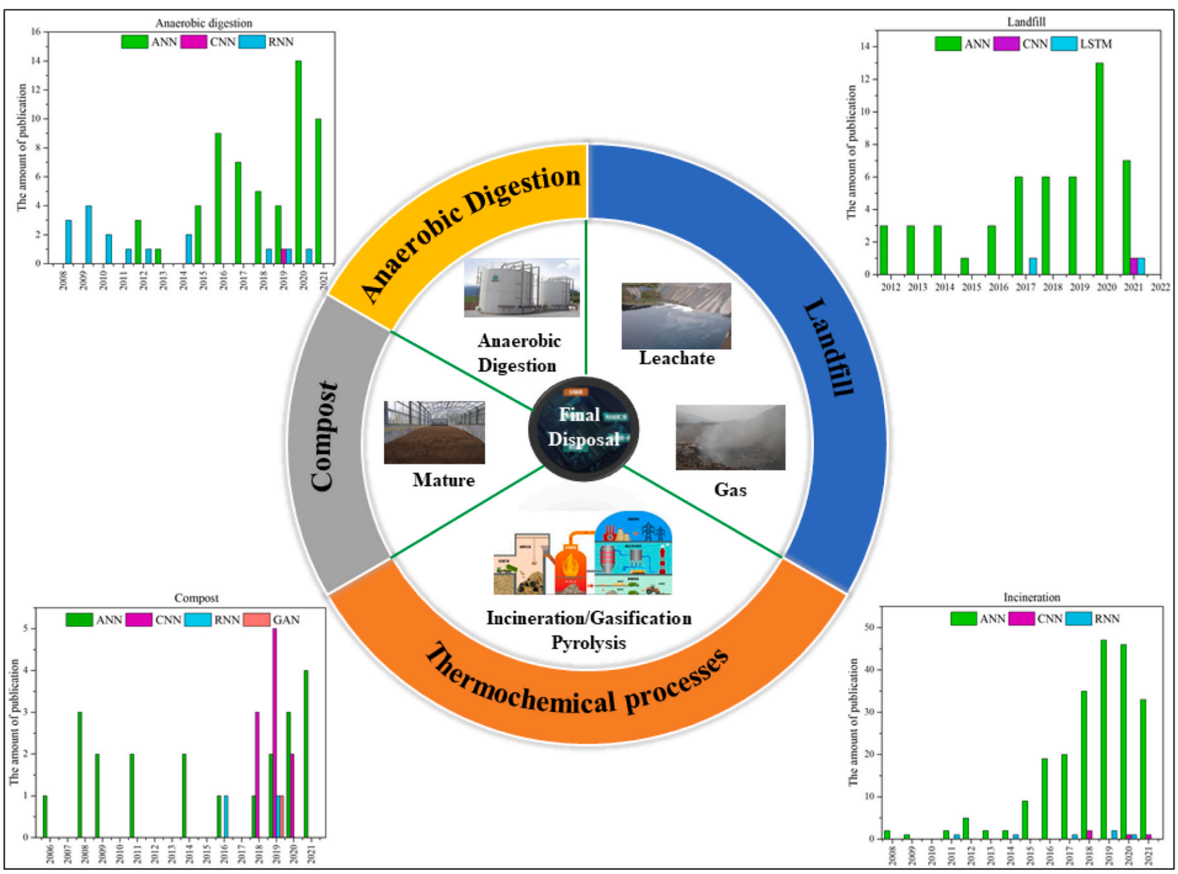

Fig. 7. Deep learning application in the disposal and recovery of MSW. ANN: artificial neural network; CNN: convolutional neural network; RNN: recurrent neural network; LSTM: long short-term memory; GANs: generative adversarial networks.

5.1.1. *Leachate*

Table 6 reviews the deep learning approaches applied in landfilling from the perspectives of leachate, the behavior of landfill gas, and others pollutants. In terms of leachate, previous studies mainly focused on simulating the behavior of leachate (Azadi et al., 2016, 2018) and the removal of pollutants.

It is a popular method to use experiments and the ANN model to investigate the treatment of landfill leachate. The values of R^2 and RMSE between experimental and the predicted values were found to be 0.941–0.984 and 1.45–2.52, respectively. Also, Azadi et al. used a similar method to optimize the treatment of landfill leachate (Azadi et al., 2018). It was considered that using the ANN model to predict the characteristics of landfill leachate, such as the COD load (Azadi et al., 2016) and penetration (Bagheri et al., 2017). In addition, the RNN

Table 6
Application of deep learning in sanitary landfilling.

Application	Model	Content	Input Parameters	Dataset	Prediction Evaluation	References
Leachate	ANN-GA	Optimizing the treatment of landfills leachate	pH, tungsten content, calcination temperature, and exposure time	The number of datasets:150	R: 0.98–0.99 MAPE: 0.04 NRMSE: 0.03–0.05	Azadi et al. (2018)
	ANN	Predicting leachate COD load	Number of days after waste deposition; rainfall; bottom CCL thickness; top cover thickness; top CCL thickness	63 datasets	R: 0.98–0.99 MAPE: 23.21–58.24 NRMSE: 0.02–0.04 RMSE: 39.03–94.03	Azadi et al. (2016)
	ANN-Fuzzy-Logic	Predicting leachate penetration	Hardness, turbidity, the concentration of Fe, Pb, Cr, and other 9 elements	Leachate concentrations at the depth of 20 m from 2005 to 2015	R^2: 0.9998	Bagheri et al. (2017)
	RNN	Lead removal from sludge leachate	Dosage, contact time, and temperature	The training data is 120	R^2: 0.9687	Çoruh et al. (2017)
Gas behavior	ANN	Methane content	Landfills gas extraction rate and landfills leachate	130 set of data points	R: 0.7112–0.7898 MAPE: 2.1075–3.1862	Behera et al. (2014)
	ANN	Prognosticating methane emissions	CO_2, O_2, and temperature	7 different points of the area during July 2002–April 2003	R: 0.81 RMSE: 1095 MAE:7.98	Ozcan et al. (2006)
	CNN	Detecting methane emissions	Labelled leak images	1M labelled videos of methane leak images	Detection accuracy reached 99%	Wang et al. (2020)
	ANN-GA	Simulating gas generation and transport	CH_4, CO_2, O_2, and static pressures	1100 data points	R^2: 0.924–0.941	Li et al. (2011)
Others	ANN	Landfills area estimation	Trip numbers and monthly	5 years of solid waste landfills data	R^2: 0.849–0.915	Hoque and Rahman (2020)
	ANN	Predicting landfills surface temperature	Ambient air temperature, humidity, wind velocity, evaporation, waste amount, and emitted methane	54 landsat satellite images time series covered: 1985–1992 and 2000–2016	R: 0.884	Hani and Nawras (2019)
	ANN	MSW compression ratio	Dry unit weight, dry weight water content, and organic materials	64 oedometer tests	R: 0.90–0.904 MAE: 0.0235–0.048 RMSE: 0.0515–0.0602	Mokhtari et al. (2015)
	ANN	Predicting compressive strength and tensile splitting strength	Water, cement, rice husk ash, and other 12 factors	66 runs	R^2: 0.9811–0.9902 MAE: 0.481–0.055; AE: 0.019–0.123; MAPE: 2.088–2.905 RMSE: 0.072–0.648	Getahun et al. (2018)
	ANN-Monte-Carlo-simulation	Computing seismic fragility analysis of geo-structures	The unit weight, friction angle, cohesion, and other 3 factors	2800 set of data points	R^2: 0.994–0.999	Lagaros et al. (2009)

Where AE: average error: ANN-GA: artificial neural network based genetic algorithm; ANN-Fuzzy-Logic: artificial neural network based fuzzy logic algorithm MAPE: mean absolute percentage error; MAE: mean absolute error; MSE: mean square error; NRMSE: normalized root mean square error; RMSE: root mean square error; R: correlation coefficient; R^2: coefficient of determination; RE: relative error.

algorithm was applied to forecast the removal of pollutants, such as the heavy metals in leachate (Çoruh et al., 2017). The R^2 between the predicted and actual values was found to be 0.9687, and it was found that RNN has an excellent performance in lead removal.

5.1.2. Landfill gas behavior and others

From an environmental and safe perspective, the methane and odors in landfills need to be treated. Some previous studies (Behera et al., 2014) employed the ANN model, data about the extraction rate of landfill gas, and the amount of landfill leachate to forecast the content of methane (Table 6). Ozcan et al. predicted the behavior of methane emission, and the values of R, RMSE, and MAE were found to be 0.81, 1095, and 7.98, respectively (Ozcan et al., 2006). In addition, the risk of methane leak was identified by the pre-trained CNN model, which could detect the phenomenon of methane leak, and the detection accuracy could reach 99% (Wang et al., 2020).

Moreover, the application of ANN in the estimation of landfill areas (Hoque and Rahman, 2020), forecasting of the surface temperature of landfilling (Hani and Nawras, 2019), prediction of compression ratio (Mokhtari et al., 2015), prognostication of compressive strength (Getahun et al., 2018), and computation of the seismic fragility analysis of geo-structures were discussed (Lagaros et al., 2009). Nevertheless, only a few studies reported the application of other deep learning models in landfilling disposal. It is suggested that there is great potential for employing deep learning in addressing the problems that exist in landfilling.

5.2. Thermochemical process

5.2.1. Incineration

Table 7 lists the deep learning model applied in MSW incineration. The emission of dioxin, which is hazardous for human health (Berg et al., 1999), needs to be considered during the process of MSW incineration. An ANN model integrated with a principal component analysis (PCA) was proposed by Bunsan et al. and it was applied to predict the concentration of dioxin emission by using data of waste loading, activated carbon injection frequency, and other 21 factors based on 4-year monitoring data of an incinerator in Taiwan (Bunsan et al., 2013). The conditions of the combustion regimes have a direct influence on the formation of dioxin. Tokarev et al. (2018) and Groβkopf et al. (2021)

Table 7
Application of deep learning in MSW incineration.

Application	Model	Content	Input Parameters	Dataset	Prediction Evaluation	References
Incineration	ANN-PCA	Predicting dioxin emission	Waste loading, activated carbon injection frequency, and other 21 factors	4-year monitoring data of an incinerator in Taiwan	R^2: 0.998	Bunsan et al. (2013)
	CNN	Monitoring combustion regimes	Label data	10,000 images	Average accuracy: 97.9%	Tokarev et al. (2018)
	CNN	Burner flame segmentation	Label images	3,000 images	Intersection over union metric $\geq$ 0.7	Groβkopf et al. (2021)
	GANs	Measuring the burden surface of the furnace	3D burden surface images	7,510 images	Accuracy: 0.90 RMSE: 0.099	Huang et al. (2020a)
	LSTM	Predicting the performance of the boiler	Feedwater pressure, feedwater temperature, conveyor speed, and incinerator temperature	215 data point	MAPE: 1.14–4.21	Shaha et al. (2020)
	ANN	Evaluating the heating values of burning MSW online	The feeding rate of MSW and coal, average bed temperature, the change rate of bed temperature, and other 7 factors	2,200 samples	Training time: 4.85s Precision rate: 73.5%	You et al. (2017)
	ANN	Predicting Cr adsorption efficiency	pH, initial concentration, contact time, dosage	32 samples	R^2: 0.878–0.999 MSE: 0.0002–0.0093	Asl et al. (2013)
	ANN-GA	Forecasting particle size distribution	Residence time, initial particle size distribution (d_0, n_0), IBA mass fraction Mass fraction of either small glass beads (0.2–0.6 mm) or large glass beads (1.7–2 mm)	281 samples	R^2: 0.9867–0.9938 RMSE: 0.0277–0.0355	Farizhandi et al. (2016)

Where ANN: artificial neural network; ANN-GA: artificial neural network based genetic algorithm; ANN-PCA: artificial neural network based principal component analysis algorithm; CNN: convolutional neural network; GANs: generative adversarial networks; LSTM: long short-term memory; MSE: mean square error; RMSE: root mean square error; R^2: coefficient of determination.

Table 8
Application of deep learning in MSW recovery in terms of gasification and pyrolysis.

Application	Model	Content	Input Parameters	Dataset	Prediction Evaluation	References
Gasification	ANN	Predicted LHV	The amount of wood, paper, kitchen garbage, plastics, and textile	The actual composition of MSW from Beijing, HK, and Shenzhen	Relative error: 20.5%	Xiao et al. (2009)
	ANN	LHV of gasification products	C, H, N, S, O, MC, ash, ER, Tg	57 datasets	R^2: 89.94–99.25% MSE: 0.00077–0.00496	Pandey et al. (2016)
	RNN/LSTM	Detecting anomalies in a thermal furnace	Temperature, the concentration of oxygen and carbon dioxide	9 collective anomalies time series	–	Sergey and Butakov (2018)
	GRU-auto-encoder (RNN)	Detecting abnormal operating conditions of steam drums in a gasification plant	Steam drum feedwater flow, out steam flow, and other 15 factors	10,080 samples	Accuracy rate: 0.935–0.9875 MAE: 0.136–0.601	Ma and Li (2020)
	ANN-heterogeneous pruning ensemble	Predicting liquid ammonia yield	Outlet gas temperature of ammonia cooler and other 10 factors	5,394 samples	MRE: below 2.5%	Dai et al. (2020)
	LSTM	Forecasting air concentration	Gas flow, airflow, secondary airflow, and other 2 factors	40,000 samples	MSE: 0.00041–0.08812	Ke et al. (2017)
Pyrolysis	1D-CNN	Calculating pyrolysis kinetic	The data about thermos-gravimetric analyses	600 pairs of relevant data (E, A)	Accuracy: over 97.6%	Kuang and Xu (2018)
	CNN	Computing pyrolysis kinetic modeling	The data about the kinetic model	2,500 input-output pairs	AE: less than 3%	Hua et al. (2018)
	Res50-UNet (CNN)	Pyrolysis reactor monitoring	The RGB-colored infrared images	5,000 photos	Accuracy rate: 0.929	Zhu et al. (2019)
	ANN	Effluent prediction in steam cracking modeling	Temperature, pressure, the product ratio of ethylene to ethane, propylene to ethylene, methane to propylene	272 detailed industrial naphtha composition	MSE: 0.05–2.40	Plehiers et al. (2019)
	ANN	Predicting the biochar yield	Pyrolysis temperature, heating rate, holding time, moisture content, and sample mass	33 experimental data	APRE: 0.1395 AAPRE: 3.8615 RMSE: 0.4638 R^2:0.9056	Cao et al. (2016)
	RNN/LSTM	Investigating pyrolysis behavior	Flow rate, pressure, temperature	12,000 samples	MSE: 0.008 $\pm$ 0.0013 R^2: 0.939 $\pm$ 0.012	Zhang et al. (2019)

Where AAPRE: average absolute percent relative error; AE: average error; ANN: artificial neural network; ANN-heterogeneous pruning ensemble; APRE: average percent relative error; CNN: convolutional neural network; GRU-auto-encoder: gate recurrent unit based auto-encoder; MAPE: mean absolute percentage error; MAE: mean absolute error; MSE: mean square error; MRE: mean relative error; Res50-UNet: Res50 based UNet structure; RMSE: root mean square error; R^2: coefficient of determination; 1D-CNN: 1 dimension-convolutional neural network.

applied the CNN algorithm with label images to monitor combustion regimes, and they could effectively reflect the burner state. In addition, Huang et al. proposed the GANs structure to measure the burden surface of a furnace with 7,510 3-dimension burden surface images, and results showed that the values of accuracy and RMSE was found to be 0.90 and 0.099 (Huang et al., 2020a), respectively.

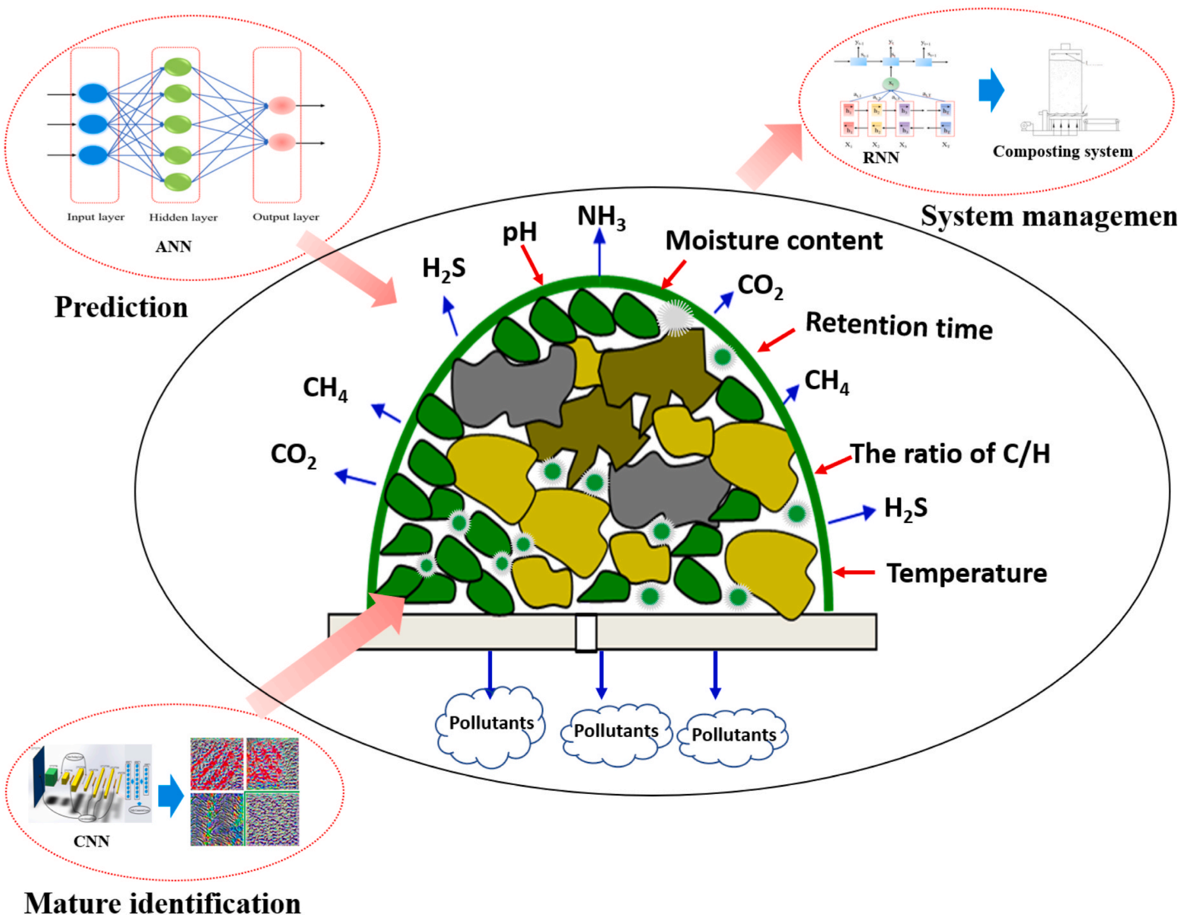

Fig. 8. Overview of deep learning application in composting.

In addition, the LSTM algorithm was also employed in predicting the performance of boilers (Shaha et al., 2020). In terms of the calorific content of MSW, You et al. evaluated of heat values of burning MSW online by using the ANN model, and they considered parameters such as the feeding rate of MSW/coal and other 8 factors (feeding rate of coal, average bed temperature, change rate of bed temperature, furnace outlet gas temperature, steam temperature, steam pressure, primary air flow, and secondary air flow) (You et al., 2017). An ANN model was also used to analyze fly ash indicators, such as heavy metals (Asl et al., 2013) and the distribution of particle size (Farizhandi et al., 2016).

5.2.2. Gasification and pyrolysis

Deep learning applied in gasification and pyrolysis are listed in Table 8. For MSW gasification, as shown in Table 8, the previous studies mainly focused on the prediction of the low LHV (Pandey et al., 2016; Xiao et al., 2009), detection of anomalies in the process of gasification (Ma and Li, 2020; Sergey and Butakov, 2018), and forecasting the products (Dai et al., 2020; Ke et al., 2017).

Deep learning algorithms are the data-driven model that has been considered as effective methods for modeling chemical processes (Peng et al., 2017; Yan et al., 2014). Also, they play a crucial role in quality monitoring and production safety, including MSW gasification and pyrolysis disposal (Table 8). Kuang and Xu (2018) and Hua et al. used one dimensional and two dimensional CNN models to calculate the kinetic parameters of pyrolysis, respectively. The CNN algorithm was also applied to monitor the conditions of the reactor, and the accuracy rate could reach 92.9% (Hua et al., 2018). Zhang et al. used the LSTM, which can remember the time series or sequence problems, to investigate the pyrolysis behavior with 12,000 samples concerning flowrate, pressure, and temperature, and the MSE and R^2 were 0.008 ± 0.0013 and 0.939 ± 0.012, respectively (Zhang et al., 2019).

5.3. Composting and anaerobic digestion of MSW

5.3.1. Composting

Fig. 8 overviews the deep learning method applied to composting. As known to all, the maturity of composting is a critical criterion for measuring the quality of composting products. Compared with the traditional biochemical test method, the deep learning method, which is time-saving and easy to use, can predict or identify the maturity of composting. Xue et al. proposed the application of CNN structures with nearly 30,000 images to different composting materials to realize the fast evaluation of the maturity of composting (Xue et al., 2019). Also, Kujawa et al. used a CNN to identify the maturity of composting and the classified error ranged from 0.51% to 17.77% (Table 9) (Kujawa et al., 2019, 2020). The microbial enzymatic activity is crucial to MSW degradation. Chakraborty et al. applied an ANN model with 98 datasets of visible near-infrared diffuse reflectance spectroscopy to rapidly estimate the composting enzymatic activity, and the R^2 and RMSE were found to be 0.91 and 0.07–3.79, respectively (Chakraborty et al., 2014). The parameters, which impact the enzymatic activity of microorganisms, were also discussed. An ANN model with 5,382 daily tuples concerning the composting days, pH, composting temperature, moisture content, food waste, mature compost, sawdust, and soil was applied to predict the influential operational composting by Lin et al. (2016). It pointed out that the R^2 between the predicted and actual values ranges from 0.892 to 0.974.

In addition, gases like CH_4, CO_2, NH_3 and H_2S, are a serious concern in composting processes. The pollutants produced from compost also

Table 9
Application of deep learning in composting and anaerobic treatment of MSW.

Application	Model	Content	Input Parameters	Dataset	Prediction Evaluation	References
Composting	CNN	Classification of compost maturity	Images illuminated with visible light, ultraviolet light, and mixed visible and ultraviolet light	1,312	Classification error: 0.51%~17.77%	Kujawa et al. (2020)
	CNN	Identifying co-substrate composted with sewage sludge	Label images	2,340 images (963 × 648 pixels)	Classification error: 4.1%–11.0%	Kujawa et al. (2019)
	CNN	Predicting compost maturity	Label images	31,863	Accuracy rate:0.995–0.997	Xue et al. (2019)
	RNN	Improving management of windrow composting systems	Precipitation, air temperature, pond volume, material volume, TSS, BOD, NO_3	Time series data from nine years (2001–2009)	R^2: 0.98–0.99 RMSE: 0.07–3.79	Bhattacharjee and Tollner (2016)
	ANN	Rapidly estimating compost enzymatic activity	The reflectance spectra	98 datasets	R^2:0.91 RMSE:13.38	Chakraborty et al. (2014)
	ANN	Catechol determination in compost bioremediation	The time profile of the amperometry signal	39 compost extract samples	RMSE: 8.600–10.70	Tang et al. (2008)
	ANN	Predicting compost parameters	pH, temperature, and other 6 factors	5,382 daily tuples	R^2:0.892–0.974	Lin et al. (2016)
Anaerobic Digestion	ANN-PCA	Evaluating methane yield	pH, MC, total volatile, volatile fatty acids, total COD, and volume of biogas produced	23 days detected data	R^2:0.732	Nair et al. (2016)
	ANN	Prognosticating biogas production rate	Reactor fill ratio, influent-effluent pH, influent-effluent alkalinity, organic loading rates, effluent COD, effluent TSS, effluent SS, VSS	60 experimental data	R^2:0.985 RMSE:217.4 MAE:156	Tufaner and Demirci (2020)
	ANN	Optimizing lipase enzyme production	pH, temperature, agitation speed, time	–	R^2: 0.9918–0.9949	Selvakumar and Sivashanmugam (2017)
	Deep Belief Network	Measuring the concentration of volatile fatty acids (VFA)	pH, CH_4, CO_2, and other 5 factors	1,000 datasets	RMSE:733.23–762.48	Chakraborty et al. (2014)
	LSTM	Predicting biogas production	Physical and chemical parameters (a total of 83 parameters)	On-line measurements during 366 days of continuous operation	RMSE:1.7%	McCormick and Villa (2019)
	1-D CNN	Predicting biogas production	Physical and chemical parameters (a total of 83 parameters)	On-line measurements during 366 days of continuous operation	RMSE:2.6%	
	LSTM-1-D-CNN	Predicting biogas production	Physical and chemical parameters (a total of 83 parameters)	On-line measurements during 366 days of continuous operation	RMSE:19.0%	

Where MAE: mean absolute error; R: correlation coefficient; R^2: coefficient of determination; RMSE: root mean square error.

cannot be neglected, and the ANN model was employed to determine the concentration of catechol in compost bioremediation (Tang et al., 2008). Finally, a data-driven model like RNN was used to improve the management of windrow composting systems (Bhattacharjee and Tollner, 2016).

5.3.2. Anaerobic digestion

Anaerobic digestion is a kind of microbial conversion method that occurs in aqueous environments. Some benefits of anaerobic digestion make it more attractive than other available technologies (Appels et al., 2011), for example, (i) it allows waste with high moisture levels without any pretreatment (Ward et al., 2008); (ii) the valorization of the biogas generated during the process of anaerobic digestion is energy efficient and environmentally friendly (Smet et al., 1999); (iii) the slurry can be utilized in agriculture as a fertilizer and organic amendment (Tambone et al., 2009). Fig. 9 and Table 9 overview the deep learning models applied to anaerobic digestion. These models mainly focused on predicting the production of biogas, methane, and lipase enzymes, as well as the measurement of the concentration of volatile fatty acid (VFA).

Biogas, which consists of 65% CH_4, 35% CO_2, and other trace gases, such as H_2S, H_2, and N_2, was prognosticated by data-driven models like ANN (Tufaner and Demirci, 2020), LSTM, 1D-CNN, and LSTM-1D-CNN (McCormick and Villa, 2019). This model showed an excellent performance in the prediction of biogas production generation. Deep learning has great potential in addressing the challenges of anaerobic digestion. Chakraborty et al. proposed a deep belief network (DBN) model for measuring the concentration of VFA in real-time online (Chakraborty et al., 2014). DBN is one deep neural network and it can predict the VFA concentration by forming more abstract high-level representations of the combination of the low-level features from the datasets. It pointed out that this model is more precise than conventional methods.

6. Challenges and future perspectives

Deep learning has a potential to substantially increase the efficiency throughout the whole life cycle of MSWM. As what have been presented before, cases included but not limited to more accurate prediction of waste quantity and composition and intelligent sorting and identification of MSW. During transportation, MSW can become traceable and anti-tampered with the aid of deep learning. It is also increasing applied in waste treatment to optimize process parameters and detect abnormal operation conditions.

Nevertheless, application of deep learning in MSWM stays in its infancy and requires great efforts for further development. First, deep learning is basically a data-driven approach and needs extensive information to achieve state-of-the-art performance. In additional to conventional engineering parameters, “big data” from macro-to meso- and micro-level, from producers to users, and from collection, transportation, to treatment and recycling processes are to be gathered and integrated. It may handle data of numerical, textual, media, and other types. Numerical data, for example, socioeconomic statistic and physicochemical properties are used for treatment plant development and

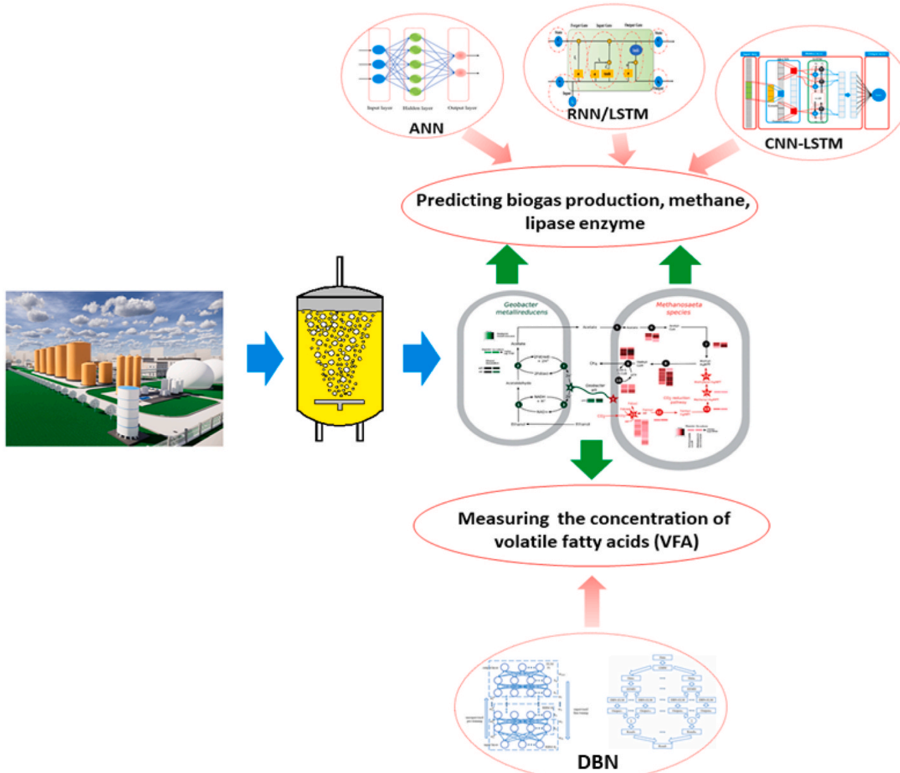

Fig. 9. Overview of deep learning application in anaerobic digestion (DBN: deep brief network).

process optimization. Images and videos are required in waste sorting, semantic segmentation, and anomaly detection. To obtain and transfer these data, investment should be devoted not only to environmental industrial equipment, but to new IT infrastructure including wireless sensor networks and IoT devices.

Moreover, there remains a knowledge gap between waste management and data science. Waste management developed a large number of environmental science and engineering models which follow physical laws and simulate processes of mass balance, energy balance, mechanics, and chemical and biological reactions. These models are to be incorporated with data processing and analytics of machine learning, so that data science can truly serve waste management.

It is worth noting that although a "black box" model is often labelled onto deep learning, an integration of actual engineering processes based on natural physical and chemical properties into the intelligent modeling can be accomplished. A good example is using visualization technologies, such as class activation mapping (CAM), and gradient-weighted class activation mapping (Grad-CAM) to clarify the mechanism of CNN during the training process of MSW sorting (Selvaraju et al., 2019). These approaches can make the "black box" become more transparent and interpretable.

7. Conclusions

This paper provides a comprehensive review of deep learning and its application in MSWM. Overviews of ANN, CNN, RNN/LSTM, Attention, and GANs and their algorithms as well as a comparison of them, are discussed. The application of deep learning was reviewed in terms of collection, transportation, and final disposals and recovery. Regarding to the collection of MSW, the ANN model was widely used in the prediction of the amount and compositions of MSW, and the studies that applied the CNN model to waste sorting account for 89.61%, followed by ANN (6.49%), LSTM (2.56%), and GANs (1.34%). Although the CNN model achieved good performance in MSW sorting, more efforts still need to be made to improve the performance of the CNN algorithm concerning specific waste identification and sorting in terms of efficiency and scalability. Regarding the transportation of MSW, the performed studies mainly focused on route optimization, garbage classification systems, and waste detection for the equipment. However, the related studies to MSW transportation are still rather less, so there is great potential to using deep learning algorithms in solving the MSW transportation issues from the perspectives of energy economy and pollutants reduction. As for the final treatment and recovery processes, deep learning was used in the fields of sanitary landfills, incineration, gasification, pyrolysis, compost production, and anaerobic digestion. While the limitation of MSW data are becoming the biggest challenge for the performance of deep learning, there is potential for employing the IoT technology in obtaining and gathering the related valuable data, even in the processes of collection, transportation, final disposal and recovery.

Declaration of competing interest

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.

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Appendix A. Supplementary data

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