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DEEP LEARNING BASED A COMPREHENSIVE ANALYSIS FOR WASTE PREDICTION

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Abstract: *In its simplest definition, waste can be defined as any substance that is used, not needed and causes harm to the environment. Waste management covers control activities such as prevention of the formation of waste, reuse, separation according to its characteristics and type, storage, transportation, recycling and disposal. The main purpose of waste management is to leave a livable world to future generations, to create a sustainable environment, to protect natural resources, to save energy and costs, to reduce the rate of pollution and the amount of hazardous waste. In today's world where urbanization and industrialization rates are increasing, waste management is gaining importance. The aim of this study is to utilize waste data from Istanbul, Turkey's largest and fastest growing city, to estimate waste amount using a constructed Long Short-Term Memory (LSTM) based deep learning model. The developed LSTM-based model has been compared in practice with k-Nearest Neighbors (kNN), random forest (RF), Support Vector Machine (SVM), multi-layered perceptron (MLP) and Gated Recurrent Unit (GRU). As a result of the comparative and comprehensive analyzes, the experimental results showed that the developed LSTM-based deep learning method is more successful in the waste prediction problem than the other compared models.*

Key words: *waste management, deep learning, machine learning, Long Short-Term Memory*

1. Introduction

Municipal solid waste (MSW) is presently one of the most pressing concerns in urban planning. MSW creation has accelerated as a consequence of global urbanization, population increase, and massive material consumption. Along with processes such as urbanization and urban transformation, the amount of municipal rubbish generated is increasing. The volume of MSW, one of the most significant by-products of an civil lifestyle, is increasing even faster than the growth of urbanization as the globe rushes towards an urban future. Today, MSW generation has grown to

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almost 3 billion residential per day, resulting in 1.2 kg of waste per person/day (1.3 billion tonnes). By 2025, this number is expected to rise to 4.3 billion urban communities, producing 1.42 kg/capita/day of municipal solid and around 2.2 billion tons per year (Hoornweg & Perinaz, 2012). Due to the large quantity of generated waste, an increasing amount of MSW can cause severe damage to the environment and population health (Huang et al. 2020).

MSW management remains one of the best most tough problems for developing country governments to address to safeguard the environment and reduce public health risks. (Younes et al. 2016; Towa et al. 2020) and to maintain natural resources. To minimize the adverse effects of MSW, an accurate prediction of future waste volumes is a crucial issue. Efficient predicting of MSW generation is vital to the implementation of an optimum MSW management system as a primary tool for MSW management. Fu et al. (2015). Waste quantity predictions serve as the foundation for waste management process adoption, development, and optimization (Cubillos, 2020). Incorrect prediction of waste amounts can adversely affect process costs and cause systems to be inefficient. Another of the main challenges in using prediction models in waste management is the high variability and ambiguity of data wastage. The amount of waste produced can be affected by unpredictable factors such as people's behaviors, holidays, seasonal conditions. The volatile nature of waste data can cause problems in generating future forecasts. In addition, insufficient and incomplete data will reduce the accuracy of the predictions to be made.

In recent years, significant studies on waste prediction using statistical modelling techniques, including machine learning (ML), have been presented (Abbasi et al. 2013; Abbasi & Hanandeh, 2016; Johnson et al. 2017; Ghanbari et al. 2021). The application of deep learning models to prediction issues has risen to prominence as high-performance data processing and computer power have advanced. Deep learning is a kind of ML that uses numerous layers of artificial neural networks to learn nonlinear interactions. It differs from typical ML approaches in that it allows for the learning of nonlinear relationships (Le et al. 2019). Due to the approaches' ability to understand common uncertainty and learn from long-term patterns, deep learning methods have proved to be a valuable technique for waste prediction and modelling. The Deep Learning (DL) has recently become popular in municipal waste generation (Sakr et al. 2016; Adedeji & Wang, 2019; Akanbi et al. 2020). In particular, LSTM models have proved to be successful in waste prediction problem, the efficiency of the forecasts is strongly dependent on the volume of historical waste dataset utilized to train the methods (Cubillos, 2020). In this study, a waste management model, which reduces cost and environmental damage, has been developed by using deep learning. Waste prediction enables efficient management of waste storage, logistics and disposal processes. It directly affects the ecosystem from factors such as waste management, climate change and air pollution. Therefore, it is very important to make accurate waste predictions.

The growing quantity of solid waste generated by municipalities, as well as its disposal, has been one of Turkey's substantial environmental issues, particularly in Istanbul (Turan et al. 2009). Istanbul has a population of over 15 million people, or roughly 19% of Turkey's overall population. Istanbul generates an average of 18,000 tons of domestic waste every day. MW is collected regularly from different locations of the city by the Istanbul Environmental Management Industry and Trade Cooperation (ISTAC) company. Nearly 22,000 tons of MW have been compiled annually with the most advanced technological tools and specific outfits. In this study, it is aimed to predict the amount of waste produced by using the waste data in Istanbul, Turkey's largest and most developed city. The dataset used consists of the daily waste amounts in Istanbul, recorded for approximately 6 years between January 1, 2016 and October 31, 2021. The developed LSTM-based model has been compared in practice with kNN, RF, SVM, MLP and GRU. Experimental results obtained according to MSE (Mean Squared Error), RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) metrics for each model have been compared. To our knowledge, no other study has used a deep learning model for predicting Istanbul's MSW generation.

The rest of the paper is presented as follows: The literature studies on waste prediction are covered in Section 2, which presents state-of-the-art methods for predicting and forecasting municipal waste. Data description and implementation of deep neural learning models are also presented in Section 3. Experimental results of the proposed LSTM model development and a comparison of metrics for several ML techniques are given in Section 4. Lastly, the discussion and conclusion are presented in sections 5.

2. Literature Review

A diverse variety of prediction studies on waste generation rates have been studied by many researchers. Many different methods, such as traditional models, regression analysis, time series analysis, and artificial intelligence are some of the approaches utilized for waste prediction (Lavee & Khatib, 2010; Abbasi et al. 2013). The capacity to efficiently learn both linear and non-linear connections among time series and good prediction ability are two of those approaches' key benefits over traditional time series methods. Recently, ML algorithms have been employed successfully to predict waste generation (Xu et al. 2021). To predict waste generation using SVM combined with partial least square (Abbasi et al. 2013), a gradient boosting model (Johnson et al. 2017), two hybrid models based on decision trees and neural network was applied to predict Canada - wide municipal waste generation SVM and RF (Kumar et al. 2018), a hybrid model based on SVM and recurrent neural network (Meza et al. 2019), Gaussian process regression (GPR) model tuned by Bayesian optimization (Ceylan, 2020), prediction model using four combination intelligent algorithms, namely SVM, an integrated artificial neural network (ANN), RF, and multivariate adaptive regression splines (MARS) models (Ghanbari et al. 2021), decision tree and RF approach (Joshi et al., 2021). Among numerous nonlinear methods, ANN is one of the effective non-linear models to predict MSW generation. ANN could produce high-accuracy nonlinear estimation thanks to its intelligent learning method and hierarchical design. It has been successfully used in MSW prediction (Kannangara et al. 2018; Coşkuner et al. 2021; Abbasi et al. 2013; Jahandideh et al. 2009; Nguyen et al. 2021; Wu et al. 2020).

Recently, the DL algorithms, a subset of ML algorithms, have recently shown huge success in a wide range of disciplines (Lecun et al. 2015; Kaya & Yıldırım, 2020). Deep learning allows models to construct hierarchical representations of incoming information with varying degrees of complexity. As a result, it can expose the complex structure of targeted information, enhancing pattern identification and classification capabilities (Lecun et al. 2015). One of the most important qualifications of deep learning architecture is that it can learn feature representations automatically, which saves time and effort. The rapid growth of deep learning can be attributed to improved chip processing capabilities, significant breakthroughs in ML algorithms, and the relatively low cost of computing hardware (Coşkun et al. 2017). Recently, DL approach has been widely used in waste generation at municipal level.

Sakr et al. (2016) presented a combined convolution neural network (CNN) and SVM classification that categorized waste into 3 types: plastic, paper, and metal. They concluded that SVM had an accuracy of classification of 94.8 percent, while CNN only had an accuracy of 83 percent. SVM also demonstrated outstanding adaptability to various waste types. Adedeji and Wang (2019) suggested a new various waste classification system based on the 50-layer remaining net pre-train CNN model, which is a machine learning tool that is designed as an extractor, and SVM, which classifies waste into different groups/types such as glass, metal, paper, and plastic, among others.

Akanbi et al. (2020) employed multi-layer deep learning architecture to create a computational tool for estimating the amount of construction materials and building demolition waste. Cubillos (2020) implemented a multi-site LSTMNN to anticipate garbage generation rates from residences. According to their results, LSTM model can successfully developed the results by 85% on average when compared to classical ML methods such as ARIMA. Wang et al. (2021) proposed a CNN to categorize waste into nine different garbage categories such as kitchen, other, plastic, glass, paper or cardboard, metal, fabric, and other recyclable waste. Furthermore, data exchange between garbage containers and the waste management point has been taken from the Internet of Things (IoT) sensors embedded in garbage containers.

3. Data Analysis

Istanbul, which straddles the Bosporus strait and is in both Europe and Asia, has a population of over 15 million people, comprising nearly 19% of the total population, Istanbul is the most populated city in Europe and the fifteenth most crowded metropolis on the globe.

Istanbul is the most populated city in Europe, and the world's fifteenth-largest city. It is located on the Bosporus Strait, between the Black Sea and the Marmara Sea, in Turkey's northwest corner. Istanbul, Turkey is positioned at 41.015 latitude and 28.979 longitude. Istanbul, Turkey is in the urban place class of the Turkey country, with GPS coordinates of 41° 0' 54.493" N and 28° 58' 46.30" E.

An average of 18,000 tons of household waste is generated daily in Istanbul. Approximately 5 thousand tons of household waste have been transported by district municipalities and 13 thousand tons by Istanbul Environmental Management Industry and Trade Cooperation (ISTAÇ) transport fleet to Solid Waste Transfer Stations located on Istanbul Asian side and European sides. ISTAÇ operates with a total of 8 thousand tons' solid waste landfill on the European and Asian Sides of Istanbul, given in Fig. 1.

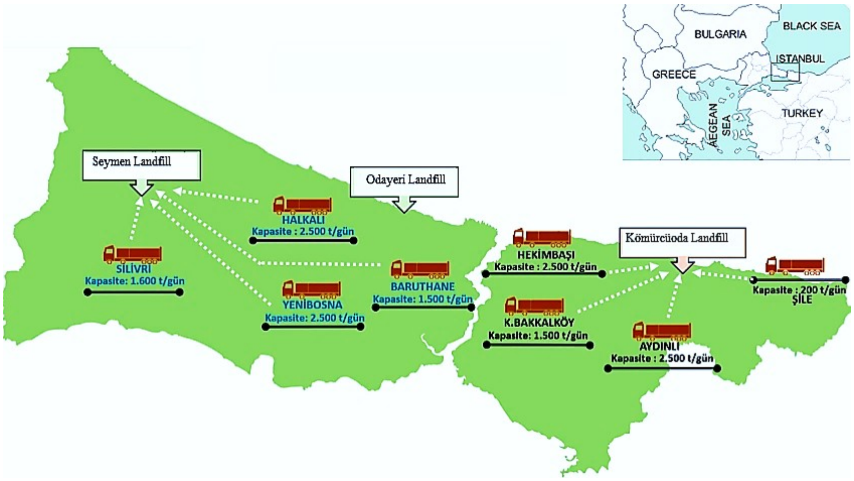

Figure 1. Istanbul waste network's structure

Due to the population growth in Istanbul, the amount of waste is constantly increasing due to the increase in residential areas. Municipal waste collected from houses and workplaces is collected and separated by district municipalities. Transfer stations have been put into operation due to the cost and time consuming of direct transportation of the waste collected by the district municipalities to the landfills. In this way, fuel savings are achieved by eliminating the commuting of small-capacity municipal waste collection vehicles to landfills over long distances, traffic density is reduced; and possible air pollution caused by exhaust emissions is prevented. Then, the waste is brought to the sanitary landfills by transport trucks from the transfer stations.

3.1. Dataset

In this study, an original statistical dataset consisting of daily waste amounts produced in Istanbul, recorded for approximately 6 years between Jan. 1, 2016 and Oct. 31, 2021, has been used. The dataset used consists of 2131 lines of waste data. The dataset contains the parameters of date and amount of waste produced. The first 10 rows of the dataset used are given in Figure 1. Fig. 2a shows the time distribution of the waste amounts in the dataset.

Date	Amount of waste (KG)
01.01.2016	12.563.850
02.01.2016	15.499.650
03.01.2016	15.587.150
04.01.2016	18.998.500
05.01.2016	20.989.950
06.01.2016	19.404.950
07.01.2016	18.931.400
08.01.2016	18.357.450
09.01.2016	18.926.000
10.01.2016	15.140.550

Fig. 2a

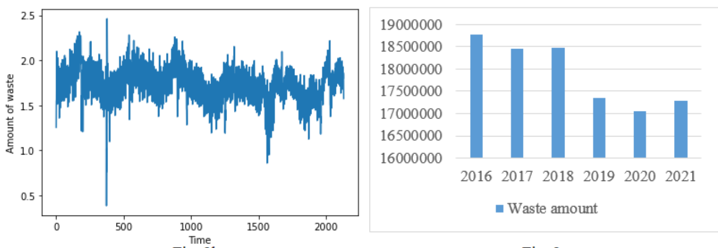

Fig. 2b Fig. 2c

Figure 2. Municipal waste amounts in the dataset

The distribution of the amount of waste produced over time is given in Fig.2b. In addition, Fig. 2c shows the average amount of municipal solid waste produced between 2016 and 2021.

3.1. Developed Deep Learning Based Waste Prediction Model

In this study, popular ML and deep learning models, that are widely used in the literature, such as kNN, RF, SVM, MLP, GRU and LSTM, are compared in practice. The dataset has been pre-processed before the models have been applied. Possible blank or incorrect fields in the dataset have been checked. After the data pre-processing step, training, validation, and test datasets have been selected. 80% of the dataset is split into training and 20% testing. 10% of the training data has been split for validation. Validation data has been used for the optimization of model parameters.

For predictions to be made on time series data using machine learning and deep learning, it is necessary to structure the time series data as a supervised learning problem. For y to represent output and x to represent inputs, time series data needs to be converted to input-output prefixes y=f (x) using a function f. In supervised learning problems, it is expected to be possible to predict future data using past observation data. In supervised learning problems, it is to predict the value at time t by using the observation data at t-3, t-2 and t-1 time steps. In this study, using a 3-dimensional sliding window structure, the observation data at t-3, t-2 and t-1 time steps are configured as inputs and the observation value at time t as an output. In this way, time series data is transformed into a supervised learning problem.

It is aimed to select the most suitable model parameters using validation data. Using the obtained parameters, the models have been created, and waste amounts have been predicted. The algorithm of the developed system is presented below:

Input: Input is the daily waste amounts.
Output: Output is the predicted waste amounts.
Start.
    Checking the missing and incorrect fields in the data (data pre-processing).
    Selecting training, validation and testing datasets and normalizing the data.
    Optimizing model parameters using validation data.
    Cross-validation using walk forward validation.
    Have the parameters with the lowest MSE value been selected? If yes go to step 7, if no go to step 4.
    Creation of the model.
    Making predictions using the created model.
    Calculation of MSE, RMSE and MAE scores according to the prediction results.
Finish.

Figure 3. The algorithm of the developed system

Deep learning models are artificial neural network models with complex architectures that aim to learn complex functions in high dimensions by making nonlinear transformations from input data to output data. LSTM is an advanced version of recurrent neural networks that stands out from other deep learning models.

The main difference between RNN and LSTM is the retention time of information. LSTM is more advantageous than RNN because LSTM can process information in memory longer than RNN. LSTM cells retain cell states that have been read from and written to them. Based on the input and cell state values, the 4 gates regulate read, write and output to cell state. The developed LSTM based model is represented in Fig. 4.

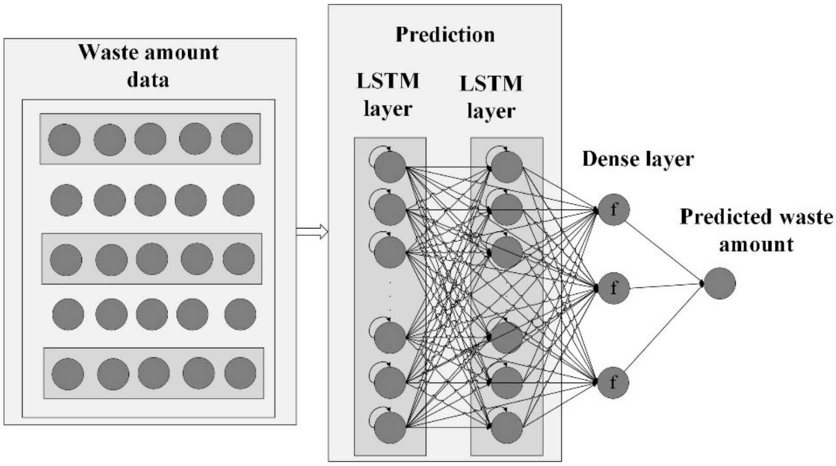

Figure 4. Developed LSTM-based deep learning model

LSTM stands out over other deep learning models because of its success in remembering long-term dependencies. In this study, the developed LSTM-based deep learning model is compared with kNN, RF, SVR, MLP and GRU in practice. The developed deep learning model takes daily waste data as input and produces the predicted amount of waste as output. The developed LSTM based prediction model consists of an input layer, two LSTM layers, a dense layer and an output layer. In this study, it is aimed to optimize the parameters of the developed model. The time series data converted into a supervised learning problem structure is presented as an input to the LSTM. With parameter analysis studies, it is aimed to reach the highest prediction accuracy with parameters such as the number of layers, the number of neurons, the number of epochs and the batch size. Adam has been used as the optimizer.

3.2. Experimental Results

In this study, a dataset consisting of daily waste amounts produced in Istanbul, recorded for approximately 6 years between January 1, 2016 and October 31, 2021, has been used. The dataset contains the parameters of date and amount of waste produced.

The developed LSTM-based deep learning model was compared against models such as kNN, RF, SVM, MLP, and GRU. MSE, RMSE and MAE values obtained for each model have been analyzed comparatively. The t_x is represents the actual value of the waste amount at time t. The $\overline{t_x}$is the predicted waste amount at time t. The error value is calculated by $t_x - \overline{t_x}$.

Scale-dependent metrics are effective when comparing different methods on the same dataset. Commonly used scale-dependent metrics are MAE and MSE metrics. The MAE metric is the mean of the errors as seen in Eq. (1).

$$MAE = \frac{1}{n}\sum_{x=1}^{n} |t_x - \overline{t_x}| \quad (1)$$

MAE is the difference between the predicted values and the actual values. It is the mean of the absolute value of each difference between the actual value and the predicted value for that sample across all samples of the dataset. MSE metric has been calculated by mean of the squares of errors as seen in Eq. (2), and the RMSE has been calculated by the square root of the mean of the squares of error as seen in Eq. (3).

$$MSE = \frac{1}{n}\sum_{x=1}^{n} (t_x - \overline{t_x})^2 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{x=1}^{n} (t_x - \overline{t_x})^2} \quad (3)$$

Walk forward validation has been used in the applied models to eliminate the overfitting problem and improve the generated models' quality. All applied models have been run 10 times, and the average of the obtained results has been taken. The dataset used consists of 2131 lines of waste data. 80% of this data is split for training and 20% for testing. After the training/test split, 1704 lines of data have been used in the training and 427 rows of data have been used in the testing. Table 1 and Fig. 5 show the average MSE, RMSE and MAE results obtained for each model.

Table 1. Experimental results for each model according to the MSE, RMSE and MAE

Model	MSE	RMSE	MAE
kNN	1756420233222.19	1325300.05	978735.43
RF	1756605384968.68	1325369.90	978556.77
SVM	1722543245603.30	1312456.95	972004.19
MLP	1700317575744.18	1303962.26	932025.24
GRU	1672888061407.19	1293401.74	930672.17
LSTM	1670468166123.95	1292465.92	930325.64

The experimental results show that the average MSE values of kNN, RF, SVM, MLP, GRU and LSTM are 1756420233222.19, 1756605384968.68, 1722543245603.30, 1700317575744.18, 1672888061407.19, 1670468166123.95, respectively. The average RMSE values of kNN, RF, SVM, MLP, GRU and LSTM are 1325300.05, 1325369.90, 1312456.95, 1303962.26, 1293401.74, 1292465.92, respectively. The average MAE values of kNN, RF, SVM, MLP, GRU and LSTM are 978735.43, 978556.77, 972004.19, 932025.24, 930672.17, 930325.64, respectively.

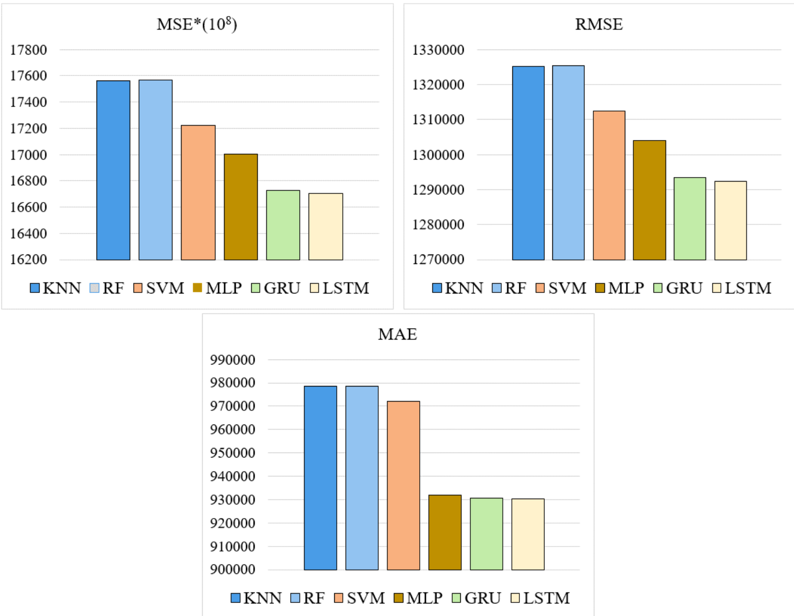

Figure 5. Comparative experimental results according to MSE, RMSE and MAE

Experimental results showed that LSTM is more successful in waste prediction than kNN, RF, SVM, MLP and GRU. The LSTM's superior performance over other models is due to its architecture, which incorporates unique units in addition to the regular units found in the GRU. Fig. 6 shows the prediction results of LSTM on the test data.

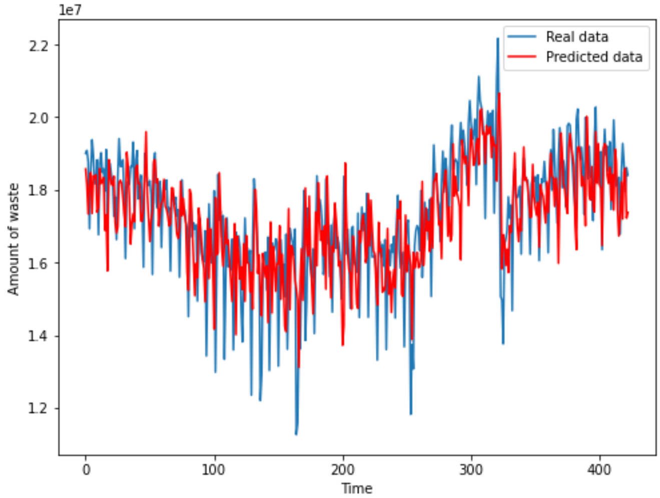

Figure 6. *Prediction* results of LSTM

As seen in Fig. 6, the data marked in blue shows the test data, and the data marked in red shows the prediction values. The test dataset consists of 427 rows of data, that is, the amount of waste produced for 427 days. On the real data, the developed LSTM based prediction model shows a successful pattern.

It is seen that SVM is more successful in waste prediction than kNN and RF. SVM requires less computation than kNN and is easier to interpret but can only describe a limited set of models. Also, kNN can find very complex patterns, but its output is more difficult to interpret. Both algorithms work better on categorical data. kNN is resistant to noisy training data and is effective in the case of a large number of training samples. RF works with a mixture of numerical and categorical features. RF is advantageous when features are of various scales. As a result, RF can utilize the data as is. SVM maximizes the distance between different points and calculates the distance between points. In the classification problem, RF gives the probability of belonging to the class, while SVM gives the points closest to the boundary between classes. Since the features in the data are numerical, SVM performed better than RF and kNN.

SVM generally has higher prediction accuracy than MLP. SVM is usually better at prediction as there are advanced computations such as translating n-dimensional space using kernel functions. Neural network models require scaling of features. The numerical features in the dataset used in this study caused MLP to perform better than kNN, RF and SVM.

As presented in Fig. 2c, the average amount of waste between 2016-2021 is 17894680.5. In Table 2, a comparative analysis of the MAE values, which express the average error values obtained from the applied models, according to the average waste amount values is presented.

Table 2. Failure rates of applied models according to average waste amount and MAE values

Model	MAE	Failure rates (%)
kNN	978735.43	5.46
RF	978556.77	5.46
SVM	972004.19	5.43
MLP	932025.24	5.20
GRU	930672.17	5.20
LSTM	930325.64	5.19

Table 1 shows the failure rates according to the average waste amount and MAE values for the models applied. Equation 4 has been used to calculate the failure rate.

$$\text{Failure rate} = \frac{\text{MAE*100}}{\text{Mean waste amount}} \tag{4}$$

As seen in Table 1, the average waste amount and the failure value calculated according to the MAE values of the models have been calculated as 5.46 % for kNN, 5.46 % for RF, 5.43 % for SVM, 5.20 % for MLP, 5.20 % for GRU and 5.19 % for LSTM.

4. Conclusions

The waste amount prediction problem is an important research area for waste management and recycling. Excessive population growth, combined with technological improvements and industrialization, are placing increasing pressure on the environment all around the world. While the development of production and marketing activities required a more intensive use of natural resources, the wastes created as a result of this trend have reached levels that endanger the environment and human health.

The goal of this research is to establish an LSTM-based trash prediction model employing daily waste data. Using data from Istanbul's daily garbage, the constructed result was validated against kNN, RF, MLP, and GRU. The dataset used consists of the daily waste amounts produced in Istanbul, recorded for approximately 6 years between January 1, 2016 and October 31, 2021.

The experimental results show that LSTM, GRU and MLP models have very successful results. Following these models, SVM, RF and kNN have been successful, respectively. The most successful results have been obtained with LSTM, and the most unsuccessful results have been obtained with kNN. The failure rate of LSTM is 5.19% while the failure rate of kNN is 5.46%.

As a result of the comparative and comprehensive analyses, it has been seen that the LSTM-based deep learning model is applicable to the waste prediction problem.

In the literature, there are studies in which machine learning and deep learning methods are used in waste management. However, there is no successfully implemented study to predict the amount of waste produced. In this study, the waste data of Istanbul, one of the largest industrial and tourist cities in the world, has been used for the first time in the literature. Experimental results showed that the deep learning-based prediction model can be successfully applied in industrial areas such as waste management. In future studies, more successful prediction results can be obtained by developing hybrid deep learning models.

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