



Waste Prediction Approach Using Hybrid Long Short-Term Memory with Support Vector Machine

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Abstract

As climate change increases the risk of extreme rainfall events, concerns over flood management have also increased. To recover quickly from flood damage and prevent further consequential damage, flood waste prediction is of utmost importance. Therefore, developing a rapid and accurate prediction of flood waste generation is important in order to reduce disaster. Several approaches of flood waste classification have been proposed by various researchers, however only a few focus on prediction of flood waste. In this study, a Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) approach is adapted to address these challenges. Two different raw datasets were obtained from the “Advancing Sustainable Materials Management: Facts and Figures 2015” source. The datasets were for 9 years (1960, 1970, 1980, 1990, 2000, 2005, 2010, 2014, 2015), and are labelled as the materials generated in the Municipal Waste Stream from 1960 to 2015 and the materials Recycled and Composted in Municipal Solid Waste from 1960 to 2015. The waste types were grouped as paper and paperboard (PP), glass (GI), metals (Mt), plastics (PI), rubber and leather (RL), textiles (Tt), wood (Wd), food (Fd), yard trimmings (YT) and miscellaneous inorganic wastes (IW).

Keywords Flood waste · Flood management · Long short-term memory · Prediction · Deep learning

Abbreviations

ANN	Artificial neural network
LSTM	Long short-term memory
LSTM-SVM	Long short-term memory-support vector machine
MAPE	Mean absolute percentage error
RMSE	Root mean square error
RNN	Recurrent neural network
SVM	Support vector machine

1 Introduction

Flooding is a natural disaster caused by heavy rainfall. Flooding creates debris and wastes which needed urgent attention [1]. During flood disaster, large amounts of wastes are generated hence the need for the prediction of flood waste generation thereby making a plan for appropriate treatment and action to be taken [2]. Flood waste can be classified into various types such as liquid, solid, hazardous, and recyclable. Flood waste prediction enables a government and agencies to estimate the wastes generated by flood in advance and make decisions and create relevant policies [3]. Flood waste can be caused by the following parameters, population, building type, lifestyle, flood protection value measures, area flooded, flood depth, flood duration, total amount of rainfall, duration between current and previous floods and country or urban [4].

Flood waste management can be used to reduce the damage and environmental pollution which is caused by delays in disaster recovery. Another challenge is the estimation of the precise quantity of waste to plan recovery strategies and policies [11]. Therefore, the need for a hybrid waste prediction model.

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Deep learning methods have received a growing interest in forecasting and have also been applied in various research areas such as speech recognition, stock prediction and so on. Long short-term memory (LSTM) is a type of recurrent neural network (RNN) that is able to learn long-term dependencies in sequence data. This makes it well-suited for tasks such as machine translation, text summarization, and speech recognition [5]. LSTM networks consist of memory blocks, or cells, that store information over time. Each cell has two states: the cell state and the hidden state. The cell state is the main chain of data flow, while the hidden state is used to control the memorizing process. The gates are used to control the flow of information into and out of the cells. These gates allow LSTM networks to learn when to forget information, when to update information, and when to keep information for long periods of time [6]. LSTM networks have been shown to be very effective at learning long-term dependencies. This makes them a powerful tool for a variety of tasks that require sequential processing.

Previous works have been developed on waste management and prediction, but most of these works uses machine learning. A few of the related works are listed respectively. Chen et al. [4] developed a framework to estimate the amount of waste generated by floods using an exponential model. The model used flood waste data ranging from five orders of magnitude and the result produced an acceptable correlation.

In 2010, [7] proposed a weekly solid waste generation in Mashhad, Iran using time series ANN approach. In this approach, ANNs with principal component analysis and Gamma test techniques was combined to improve the accuracy of their predictions. In [8] a neural network (NN) model was proposed to forecast municipal waste generation at a country level. Data from 26 European countries were used. From the results, it was shown that NNs can be applied successfully to forecast cases of datasets with missing data. Reference [9] compared the performance of time series ANN against three other machine learning methods to predict monthly waste generation in Logan City, Australia. The findings indicated that artificial intelligence models exhibit strong predictive capabilities and can be effectively utilized in developing models for forecasting municipal solid waste. By employing machine learning algorithms and training them with historical data on waste generation, monthly MSW generation can be accurately predicted. In a study by [10], an Artificial Neural Network (ANN) was employed as a surrogate model to forecast the solid waste collected from 2012 to 2016 at the Matuail landfill site in Dhaka South City Corporation (DSCC). The optimal ANN structure achieved a high learning ability, with a mean squared error (MSE) value of 9228 and an overall regression value of 0.98.

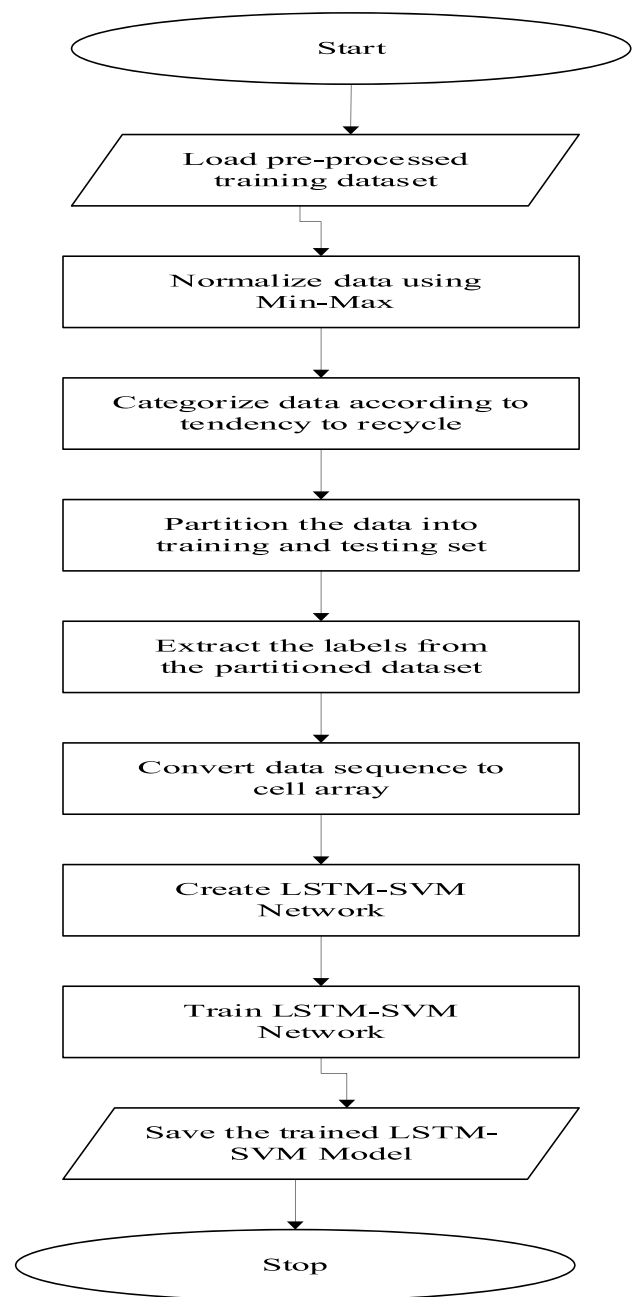


Fig. 1 Flowchart of the LSTM-SVM training of the waste prediction model

It was noted that most of the models highlighted in previous research are not well-suited for predicting waste after floods, due to the following challenges:

- i. Uncertainty of the flood event: Floods can vary greatly in their size, severity, and duration. This makes it difficult to predict the amount of waste that will be generated.

Table 1 LSTM-SVM training parameters for municipal waste prediction

Parameter	Specification
Network architecture	LSTM-SVM
Number of hidden units	200
Number of fully connected layers	1
Number of output layer (Regression output)	1
Optimizer	Adam (adaptive moment estimation)
Learning rate	0.005
Maximum epoch	250
PC used for simulation	64-bit OS, Core i5-5200U CPU @ 2.2 GHz, 4 GB RAM

- ii. Complexity of the waste stream: Flood waste can be highly heterogeneous, including a wide variety of materials, such as debris, household waste, and hazardous materials. This makes it difficult to develop a single model that can accurately predict the volume and composition of flood waste.
- iii. Accessibility of data: Data on flood waste is often limited and noisy. This can make it difficult to train and evaluate machine learning models for waste prediction.

To address these challenges, this paper proposes a hybrid LSTM-SVM model for post-flood waste prediction. The proposed model combines the strengths of LSTM and SVM to achieve higher accuracy predictions, especially for complex and heterogeneous waste streams. The model is also relatively interpretable and robust to noise, which is important for disaster management applications.

Though LSTM-SVM has been used in previous research, this proposed LSTM-SVM model is an improvement over the previous LSTM-SVM methods in terms of accuracy, efficiency, and robustness. The model achieves higher classification accuracies of 98.34% and 96.27% during training on the MIT-BIH and PTB datasets, respectively, which shows an improvement of 1–2% over the previous state-of-the-art LSTM-SVM models.

The proposed LSTM-SVM model is also more efficient than the previous methods. The model uses a new training algorithm that can converge faster and with fewer parameters. This makes the model more scalable for large datasets.

This article contributions are mainly based on a recent invention of a deep learning approach for flood waste prediction. The work focuses on the waste prediction using LSTM-SVM. The waste was trained and tested using

LSTM-SVM. The significance of the proposed work is to improve the prediction accuracy of flood waste classification by fine-tuning and refining the model using deep learning model and to assists the governments and agencies to make informed decision and help in the proper planning of waste clean-up after floods.

The subsequent sections of this paper are organized as follows. Section 2 discusses research materials and methods. Section 3 presented the results obtained and discussion and Sect. 4 concludes the paper.

2 Materials and Methods

This section presents the dataset and method used in this research. A hybrid LSTM-SVM model was used to predict different waste types.

2.1 Study Area and Dataset

Two different raw datasets were obtained from the “Advancing Sustainable Materials Management: Facts and Figures 2015” source. The datasets were for 9 years (1960, 1970, 1980, 1990, 2000, 2005, 2010, 2014, 2015), and are labelled as materials generated in the Municipal Waste Stream from 1960 to 2015 and materials Recycled and Composted in Municipal Solid Waste from 1960 to 2015. The dataset of the materials generated in the Municipal Waste Stream consists of the amount of waste generated (in thousands of tons) per year, while the dataset of the materials Recycled and Composted in Solid Waste consists of the amount of municipal waste recycled (in thousands of tons) per year. In this study, the waste types were grouped as paper and paperboard (PP), glass (GI), metals (Mt), plastics (PI),

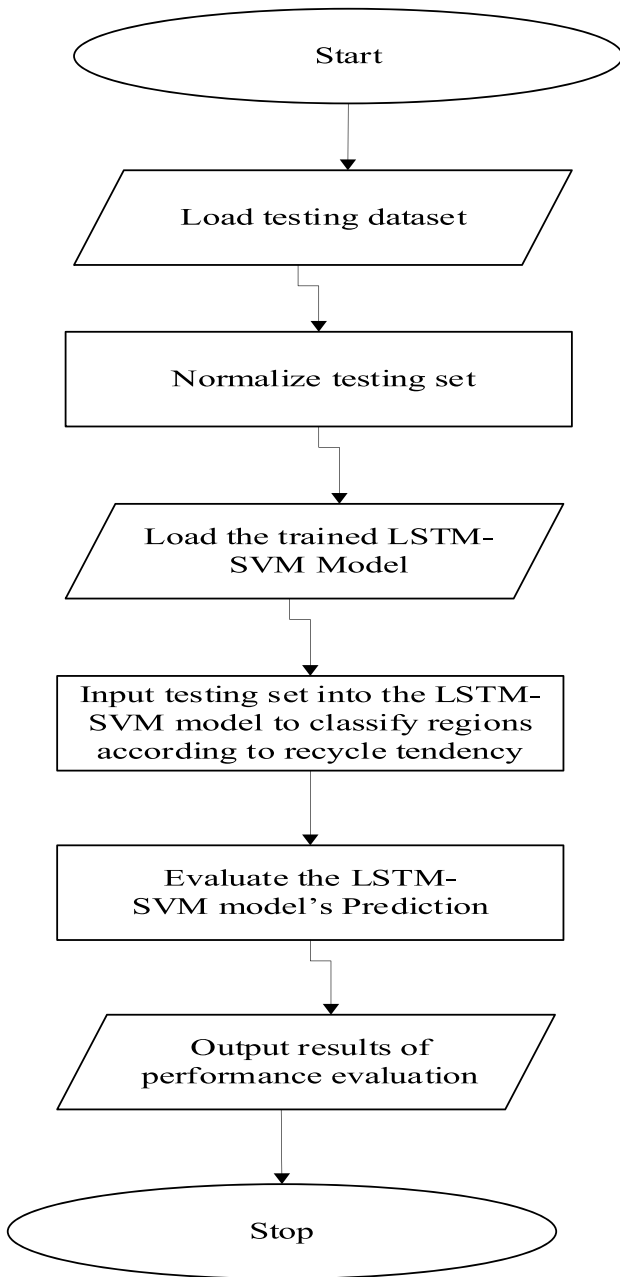


Fig. 2 Testing the LSTM-SVM model for predicting municipal waste

rubber and leather (RL), textiles (Tt), wood (Wd), food (Fd), yard trimmings (YT) and miscellaneous inorganic wastes (IW). It is worth noting that three different types of metal: Ferrous, Aluminium and Other Nonferrous were identified in the table, but were summed up simply as Metals (Mt).

2.2 Formulation of More Data Samples

To have a relatively large data samples for the deep learning process, the available yearly amount of a waste type was

used to generate more samples to in between the available years, and all the yearly values, both the available and formulated which gave a total of 56 years, were scaled by 365 to represent average daily amount. For example, the amount of PP waste for the year 1960 was 29,990; and dividing this by 365 gives 82.1644 as the average daily amount. Then, a predicted daily amount can be transformed into yearly amount by multiplying it by 365. Algorithm 1 illustrates the steps involved in generating the additional samples.

2.3 Developed LSTM-SVM Waste Prediction Model

Waste prediction model was developed for each waste type using the hybrid LSTM-SVM model. Figure 1 presents the flowchart for training the LSTM-SVM model. The first step was to load the generated waste data. Then the data was divided into training set and testing set. The training set and testing set were 90% and 10% of the total data, respectively. The training set consists of data for years 1960 to 2010 while the testing set consists of data for years 2011 to 2013. In the next step, the training was normalized to remove outliers. This was followed by the developing a LSTM-SVM model that was trained using the parameters contained in Table 1. Then, the normalized training data was used to train the developed LSTM-SVM model. The trained LSTM-SVM

Table 2 Materials recycled and composted in municipal solid waste from 1960 to 2015

Waste type	Sum (thousands of tons)	Rank	Remark
Paper and paperboard	257,630	1st	Recyclable
Glass	18,260	3rd	Recyclable
Metals	43,690	2nd	Recyclable
Plastics	12,486	4th	Recyclable
Rubber and leather	7340	7th	Recyclable
Textiles	10,840	6th	Recyclable
Wood	10,849	5th	Recyclable
Food	6392	8th	Non-recyclable
Miscellaneous inorganic wastes	27	9th	Non-recyclable

Table 3 Municipal solid waste by region

Country region	Regional waste throughputs (in tons per day per million persons)	Percentage
Northeast	420	32
South	380	29
Midwest	180	14
West	320	25

Table 4 Training data generated for amount of waste per type per region for the year 2015

	Northeast	South	Midwest	West
Paper and paperboard	14,502	13,143	6344.8	11,330
Glass	970	879	424.2	757
Metals	2634	2387	1152.2	2057
Plastics	1005	911	439.6	785
Rubber and leather	483	438	211.4	377
Textiles	784	711	343	612
Wood	851	771	372.4	665
Food	672	609	294	525
Miscellaneous inorganic wastes	1	1	0.4	1

Table 5 Waste generation prediction results by LSTM and LSTM-SVM model

Categories	LSTM		LSTM-SVM	
	RMSE	MAPE	RMSE	MAPE
Paper and paperboard	32.0644	0.7556	16.7616	0.4138
Glass	4.0163	0.5083	3.9556	0.4990
Metals	2.0153	0.1516	1.9033	0.1523
Plastics	4.7586	0.2272	3.1878	0.1565
Rubber and leather	1.2923	0.2549	1.0500	0.2185
Textiles	4.9129	4.9129	4.6036	0.5939
Wood	1.5347	0.1666	1.5974	0.1888
Food	4.3734	0.1862	9.0777	0.1862
Yard trimmings	2.6369	0.1029	2.5766	0.1275
Miscellaneous inorganic wastes	0.2779	0.1183	0.0697	0.0336
Average	5.78827	0.73845	4.47833	0.25701

model was saved as the prediction model for predicting future amount of waste.

Algorithm 1: Formulation of data samples

```

BEGIN
  Initialize an empty list data_samples to store the generated data samples

  FOR EACH waste type DO
    Load historical waste generation data for the nine years (1960 to 2015)

    FOR EACH year in the range DO
      Get the amount of waste for the current year as Lb
      Get the amount of waste for the next year as Ub

      IF Lb <= Ub THEN
        // Generate a random value greater than or equal to Lb but less than Ub
        RandomValue = RandomNumberBetween(Lb, Ub)
      ELSE
        // Generate a random value greater than or equal to Ub but less than Lb
        RandomValue = RandomNumberBetween(Ub, Lb)
      END IF

      // Add the generated value to the list of data samples
      AddTo(data_samples, RandomValue)
    END FOR
  END FOR

  Return data_samples
END

```

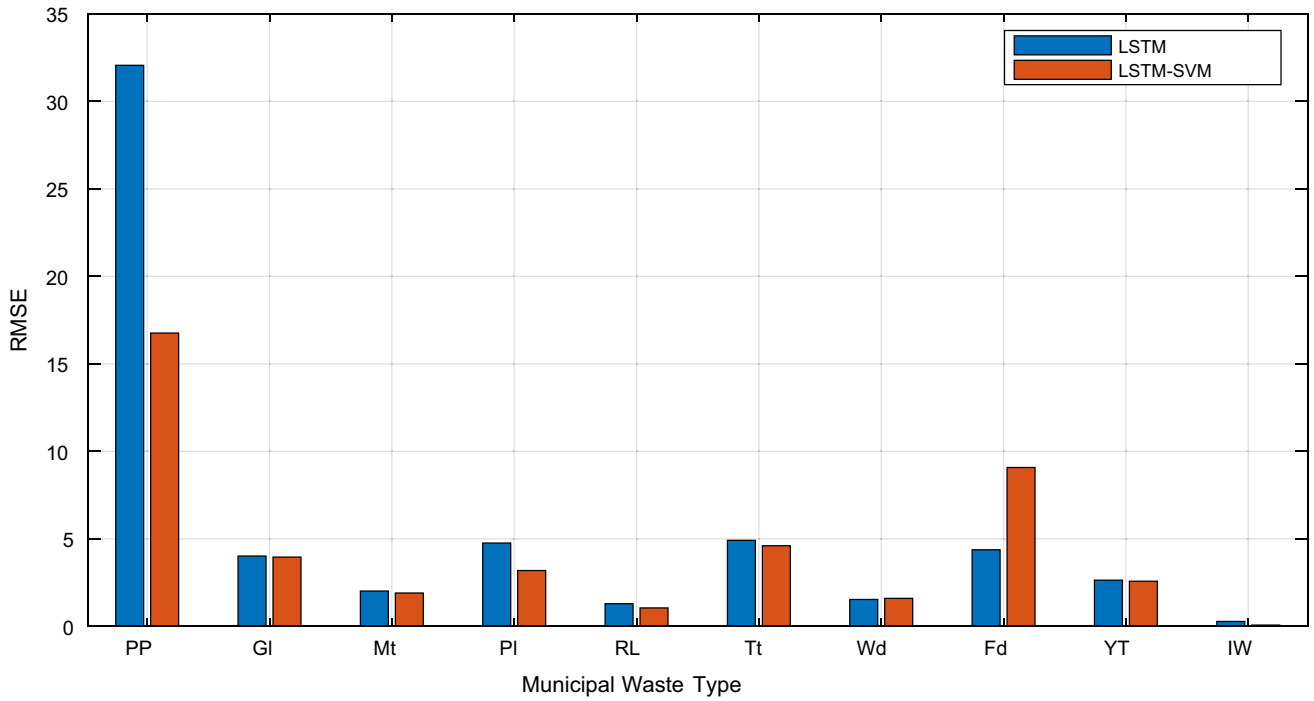


Fig. 3 Graph of the RMSE for LSTM-SVM and LSTM model

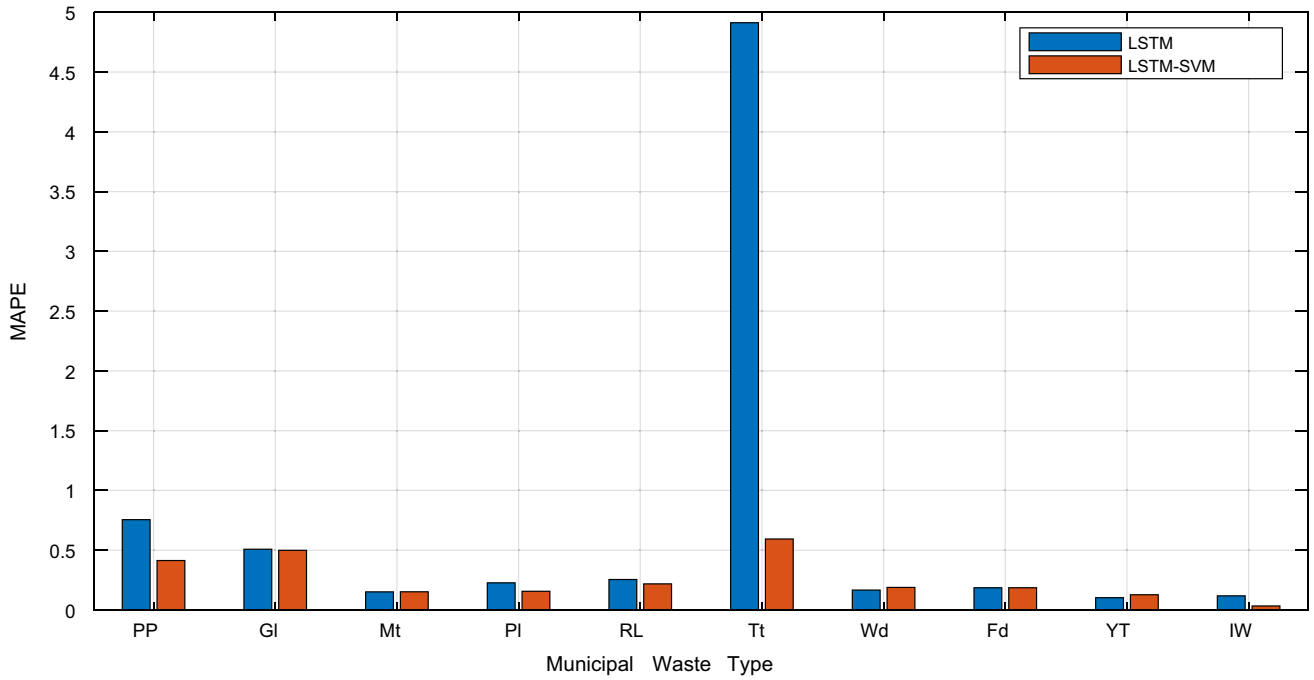


Fig. 4 Graph of the MAPE for LSTM-SVM and LSTM model

Table 6 Prediction of average generated waste by LSTM and LSTM-SVM model

Year	Actual	LSTM predicted	LSTM-SVM predicted
Paper and paperboard			
2011	193.4301	214.8736	195.0707
2012	194.9781	223.6536	200.1881
2013	191.7452	198.5603	177.7829
2014	187.9726	225.0939	191.2743
2015	186.4384	235.7748	203.0208

Table 7 Glass prediction of average generated waste by LSTM and LSTM-SVM model

Year	Actual	LSTM predicted	LSTM-SVM predicted
Glass			
2011	31.5425	32.9496	31.8920
2012	31.4959	32.1812	32.5650
2013	31.4575	26.4746	29.6695
2014	31.4521	24.3833	26.3625
2015	31.4247	29.5784	23.8732

Table 8 Metals prediction of average generated waste by LSTM and LSTM-SVM model

Year	Actual	LSTM predicted	LSTM-SVM predicted
Metals			
2011	63.8685	60.5765	57.3074
2012	63.5068	61.2432	57.9796
2013	64.0603	61.8695	58.8566
2014	64.7671	62.1030	59.2018
2015	65.7534	62.3597	59.5048

Table 9 Plastics prediction of average generated waste by LSTM and LSTM-SVM model

Year	Actual	LSTM predicted	LSTM-SVM predicted
Plastics			
2011	89.1589	85.7497	78.1037
2012	88.6822	85.8416	77.9747
2013	87.4575	86.1386	78.2287
2014	91.4795	86.3010	78.7807
2015	94.5205	86.4598	79.1702

Table 10 Rubber and leather prediction of average generated waste by LSTM and LSTM-SVM model

Year	Actual	LSTM predicted	LSTM-SVM predicted
Rubber and leather			
2011	21.3644	20.8735	19.6606
2012	22.1726	21.0501	19.7168
2013	22.1534	21.5226	19.7555
2014	22.4932	21.1315	19.7880
2015	23.2329	21.0888	19.8108

Table 11 Textiles prediction of average generated waste by LSTM and LSTM-SVM model

Year	Actual	LSTM predicted	LSTM-SVM predicted
Textiles			
2011	37.7918	36.7037	31.0967
2012	40.2904	34.4019	29.6147
2013	38.4959	35.1668	29.7849
2014	41.7534	36.7982	30.3320
2015	43.9178	36.9043	30.5630

Table 12 Wood prediction of average generated waste by LSTM and LSTM-SVM model

Year	Actual	LSTM predicted	LSTM-SVM predicted
Wood			
2011	44.0055	42.4880	39.2474
2012	44.0082	42.6226	39.4327
2013	43.3589	42.5984	39.3177
2014	44.1644	42.5911	39.3299
2015	44.6575	42.5360	39.2722

Table 13 Food prediction of average generated waste by LSTM and LSTM-SVM model

Year	Actual	LSTM predicted	LSTM-SVM predicted
Food			
2011	101.0849	98.8039	89.5011
2012	102.6110	99.7195	89.0419
2013	102.7863	100.4540	87.6057
2014	105.9452	101.0739	85.5195
2015	108.8493	101.5761	82.9971

Table 14 Yard Trimmings Prediction of average generated waste by LSTM and LSTM-SVM model

Year	Actual	LSTM predicted	LSTM-SVM predicted
Yard trimmings			
2011	91.7616	91.7111	87.7657
2012	93.2603	90.9044	87.7364
2013	91.9671	91.7511	87.8496
2014	94.5205	92.3873	88.0048
2015	95.1233	90.1620	88.0294

Table 15 Miscellaneous inorganic wastes prediction of average generated waste by LSTM and LSTM-SVM model

Year	Actual	LSTM predicted	LSTM-SVM predicted
Miscellaneous inorganic wastes			
2011	10.5945	10.5345	10.1134
2012	10.7918	10.5417	10.1552
2013	10.8384	10.5572	10.1944
2014	10.8767	10.5568	10.2023
2015	10.9315	10.5592	10.2981

Algorithm 2.1 was used to create synthetic data samples for waste generation based on historical records. An empty list that will be used to store the synthetic data was created and iteration was done through the different waste types. For each waste type, it retrieves historical waste generation data spanning nine years from 1960 to 2015. The algorithm then proceeds to iterate through each year within this time range.

For each year, the algorithm retrieves the amount of waste generated for the current year which is denoted as L_b , the lower bound and the following year (U_b), the upper bound. A synthetic data point between L_b and U_b was generated, ensuring the value falls within the range. If L_b is greater than U_b , the algorithm adapts by generating a random value between U_b and L_b to simulate waste generation.

The generated synthetic data point is added to the list for the corresponding year and waste type. This process continues for each year and each waste type, resulting in a comprehensive set of synthetic data samples that bridge the gaps and extend the historical waste generation data. The algorithm returns the list of synthetic data samples, which serves as an input to the waste prediction model.

From Table 1, the model is configured as an hybrid LSTM-SVM which combines Long Short-Term Memory

(LSTM) for sequential pattern learning and Support Vector Machine (SVM) for capturing non-linear relationships. It consists of an LSTM layer with 200 hidden units, facilitating the extraction and processing of temporal information. Additionally, there is a single fully connected layer for feature combination and a final output layer with a single node, indicating its application to regression tasks. The training process employs the Adam optimizer with an adaptive learning rate of 0.005, and the model undergoes a maximum of 250 training epochs to learn and adapt its parameters to the provided data.

The features are extracted using the mean, standard deviation, and minimum and maximum values of each variable in the historical data, frequency of different values in each variable and the trend of each variable over time.

2.4 Testing of the LSTM-SVM Model for Municipal Waste Prediction

Figure 2 presents the procedure for testing the trained LSTM-SVM model for predicting future number of municipal wastes. The testing dataset is first normalized and then passed as input to the developed LSTM-SVM model to predict the number of municipal wastes for subsequent years. This was used to predict for the years 2014 and 2015. It is noteworthy that prediction model developed for Metals wastes type can only be used to predict future amount of Metal wastes.

2.5 Pre-processing of Data for the Prediction of Areas with Recyclable Tendency

To be able to detect areas that will have higher or lower tendencies to recycle, the data available from Materials Recycled and Composted in Municipal Solid Waste from 1960 to 2015 were utilized. The following steps were taken to generate the training dataset:

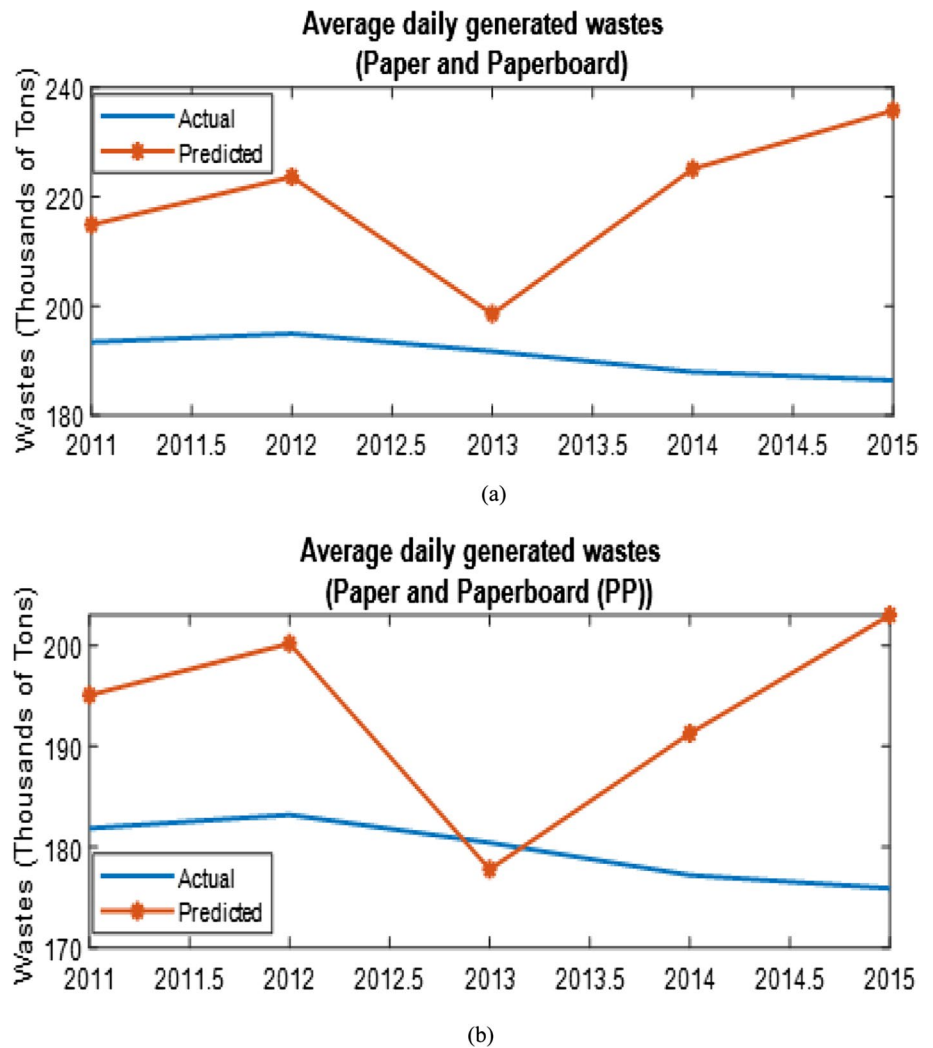
Step 1: The amounts of waste (in thousands of tons) from 1960 to 2015 were summed up for each waste type as contained in Table 2.

Step 2: The waste types were ranked according to the volume recyclable and composted.

Step 3: The country was divided into four regions namely Northeast, South, Midwest, and West. And the estimated municipal waste throughputs (in tons per day per million persons) were obtained from the available record and were expressed in percentage as contained in Table 3.

Step 4: The percentage of waste for each region in Table 3 was used to generate the amount of waste type per

Fig. 5 Actual and predicted graph result for paper and paperboard for **a** LSTM and **b** LSTM-SVM



year (1960 to 2015) for each region as contained in Table 4 for 1960.

2.6 Developing the Prediction Model for Regions with Recyclable Tendency

The dataset generated as described in Sect. 2.5 was used to train the LSTM network for predicting areas with recyclable tendency. The parameters used for creating and training an LSTM regression network are contained in Table 5. Target class is the rank of tendency to recyclable based on the amount of recyclable waste (thousands of tons) by region of the country. There are four (4) regions namely Northeast, South, Midwest and West. The categorization is as follows:

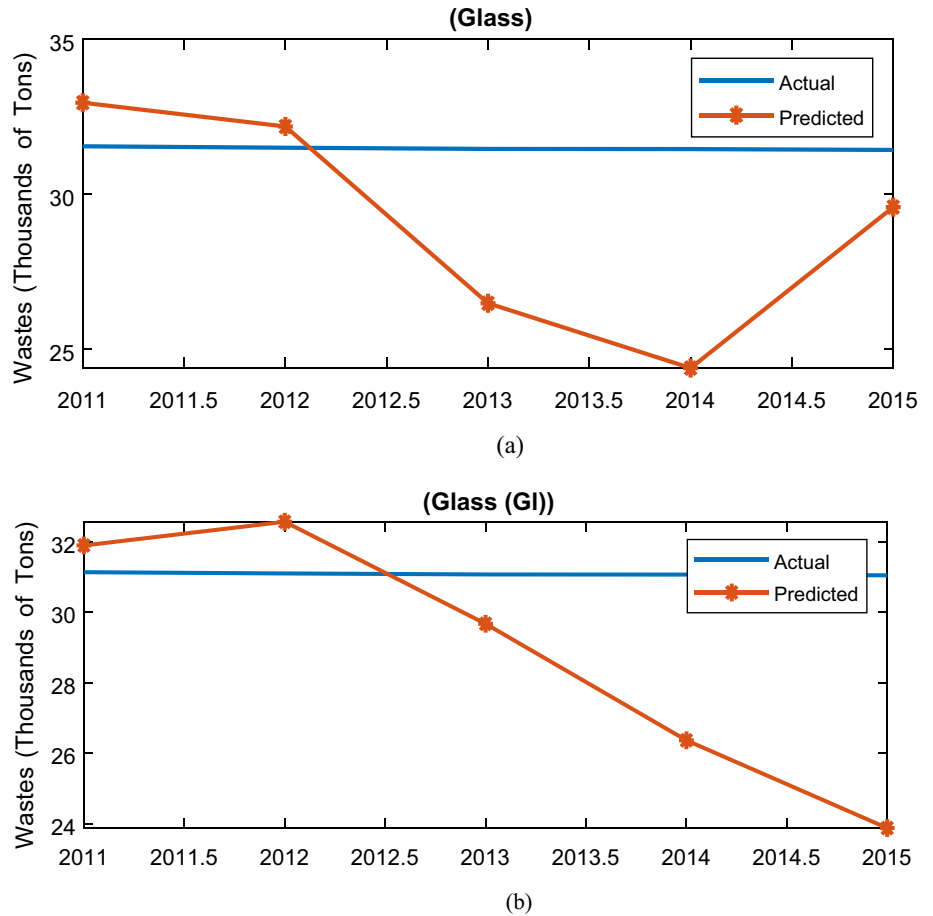
- Category 1: 1st region with tendency to recycle.
- Category 2: 2nd region with tendency to recycle.
- Category 3: 3rd region with tendency to recycle.
- Category 4: 4th region with tendency to recycle.

2.7 Performance Evaluation

The most commonly used performance evaluation metrics for waste prediction are Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The equations of these metrics are shown below:

$$\text{Root Mean Square Error (RMSE)} : \sqrt{\frac{\sum_{i=1}^N (y_i - x_i)^2}{N}}$$

Fig. 6 Actual and predicted graph result for glass for **a** LSTM and **b** LSTM-SVM



$$\text{Mean Absolute Percentage Error (MAPE)} : \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - x_i}{y_i} \right|$$

where y_i is the actual value for the period i . x_i is the forecasted value for the period i . N is the number of observations.

3 Results and Discussion

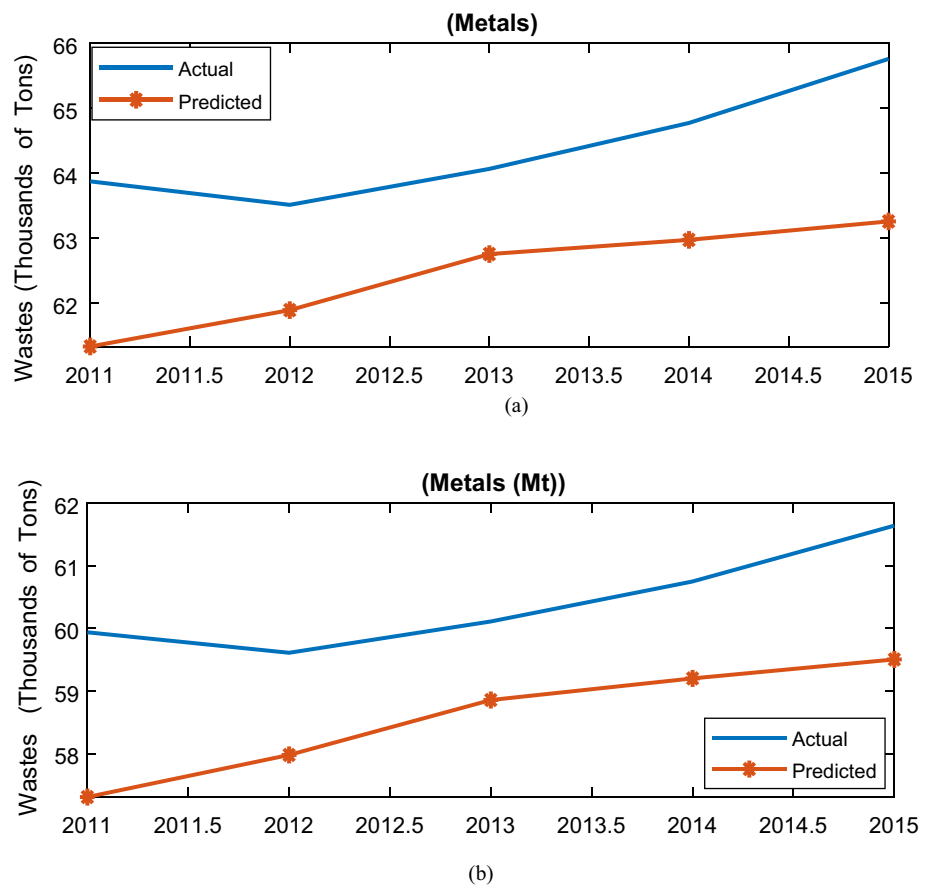
The results obtained from the LSTM and LSTM-SVM were presented and discussed in the section. The two models were compared to determine the best using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

3.1 Waste Generation Prediction

The waste prediction system was tested separately on each of the waste categories using the LSTM-SVM model. The metrics used in comparing the results are RMSE, and MAPE. Table 5 shows the RMSE and MAPE results for the waste categories for LSTM-SVM and LSTM model respectively.

It was observed from Table 5 that LSTM-SVM produced the least average RMSE of 4.47833 when compared with LSTM that produces an average RMSE of 5.78827. The average MAPE is 0.73845 for LSTM and 0.25701 for LSTM-SVM. Paper and paperboard category have the highest RMSE of 16.7616 and the lowest was for the Miscellaneous inorganic wastes' category at 0.0697 while MAPE has the highest of 0.5939 in textiles and the lowest of 0.0336 was in the miscellaneous inorganic wastes for the LSTM-SVM model. For LSTM model, paper and paperboard produced the highest RMSE of 32.0644 while the lowest was

Fig. 7 Actual and predicted graph result for metals for **a** LSTM and **b** LSTM-SVM



0.2779 for miscellaneous inorganic wastes. The highest MAPE was from the textiles' category with 4.9129 while yard trimmings have a MAPE of 0.1029 which is the lowest for LSTM model.

Comparing the two models, it was observed that the LSTM-SVM model produced the lowest average RMSE and MAPE which shows that the LSTM-SVM model outperforms the LSTM model. The corresponding graph showing the RMSE and MAPE for both LSTM-SVM and LSTM model was shown in Figs. 3 and 4 respectively.

3.2 Average Waste Prediction

Average waste prediction in thousands of tons was also done using LSTM-SVM and LSTM model from year 2011 to 2015 for each of the wastes' categories. The years 2011 to 2013 was used to train the model while Years 2014 and 2015 was used to predict the waste generated. Tables 6, 7, 8, 9, 10, 11, 12, 13, 14 and 15 show the prediction for each category

for both LSTM and LSTM-SVM. The corresponding graphs were shown in Figs. 5, 6, 7, 8, 9, 10, 11, 12, 13 and 14.

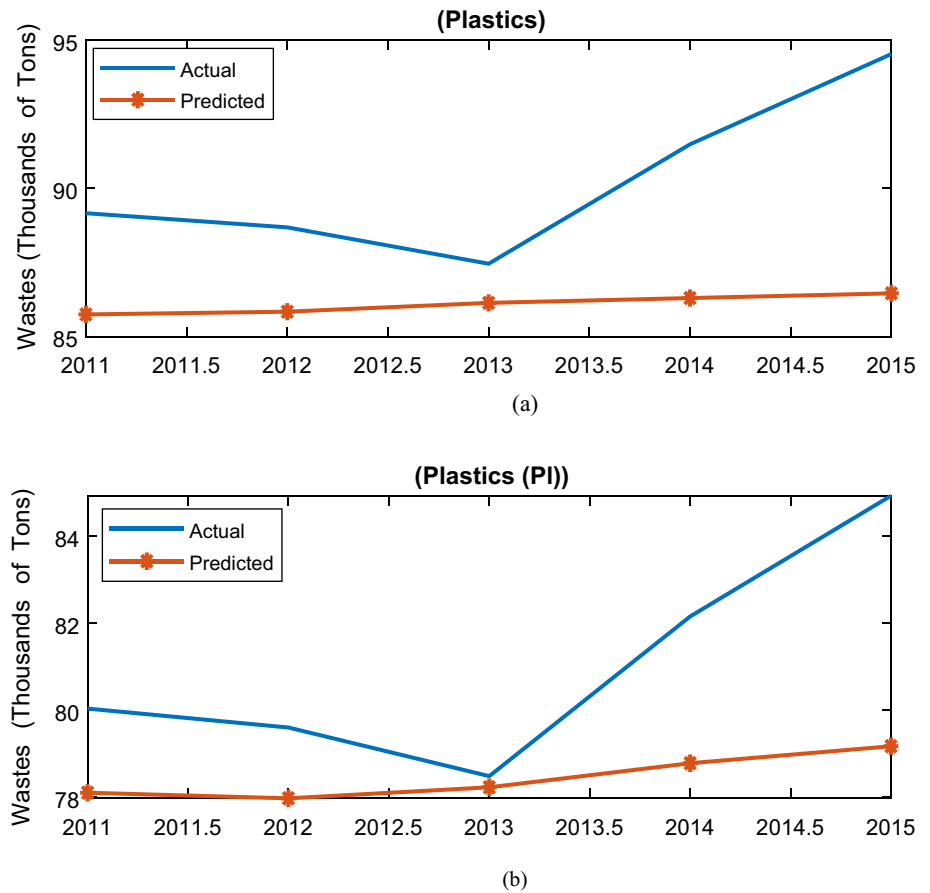
From Table 6, it was observed that LSTM-SVM produced the best results as the predicted results were similar to the actual results when compared with the LSTM model which shows that the LSTM-SVM model is better than LSTM model.

From Table 7, it was observed that the predicted value of LSTM-SVM model was high for year 2012, 2013 and 2014 when compared to LSTM. The corresponding graph is shown in Fig. 6.

From Table 8, it was observed that the predicted value of LSTM-SVM model was lower for all the years when compared to LSTM. The corresponding graph is shown in Fig. 7.

Considering Table 9, the predicted value of LSTM-SVM model was lower than the predicted value of LSTM. The corresponding graph is shown in Fig. 8.

Fig. 8 Actual and predicted graph result for plastics for **a** LSTM and **b** LSTM-SVM



The predicted value of LSTM-SVM model was lower than the predicted value of LSTM from Table 10, and the corresponding graph is shown in Fig. 9.

Considering Table 11 for the prediction of textiles, LSTM-SVM also performed better than its corresponding LSTM as the results are lower when compared to LSTM. Figure 10 shows the corresponding graph.

From Table 12, wood waste prediction for LSTM-SVM was lower than that of LSTM indicating that the LSTM-SVM model outperforms the LSTM model. The corresponding graph is shown in Fig. 11.

From Table 13, it was observed that the yearly prediction from 2011 to 2015 for LSTM-SVM is lower than that of LSTM for food waste indicating that LSTM-SVM model performed better. Figure 12 shows the graphical representation.

Table 14 indicates that the LSTM-SVM model outperformed the LSTM as the yearly prediction output is lower

than that of the LSTM model for yard trimmings. Figure 13 shows the graph indicating the output for yard trimmings.

Table 15 indicates the predicted results for miscellaneous inorganic waste for LSTM-SVM and LSTM models. From the table, the results of LSTM-SVM were lesser than that of LSTM indicating a better performance. Figure 14 shows the corresponding graph for both models.

4 Conclusion

An accurate prediction of the waste generation rate is very important for waste management and future planning and to detect areas that have higher or lower tendencies to recycle. There has been recent research on waste prediction using machine learning but these models still need further improvement. This research applied a hybrid LSTM-SVM model to predict solid waste. The waste was classified into

Fig. 9 Actual and predicted graph result for rubber and leather for **a** LSTM and **b** LSTM-SVM

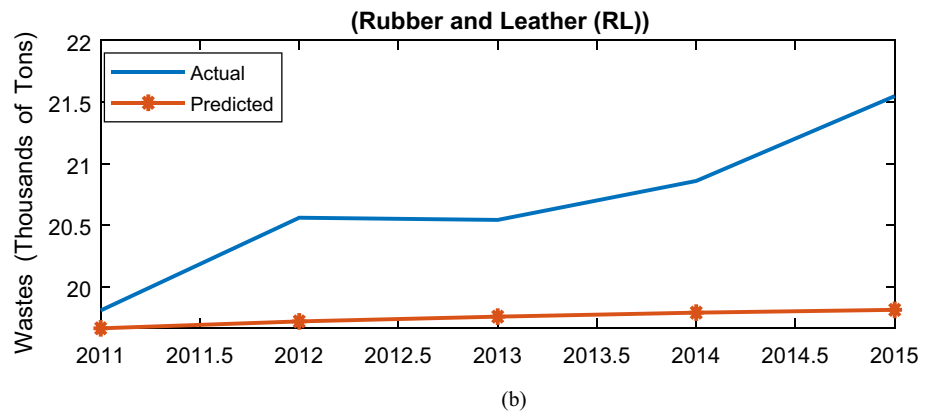
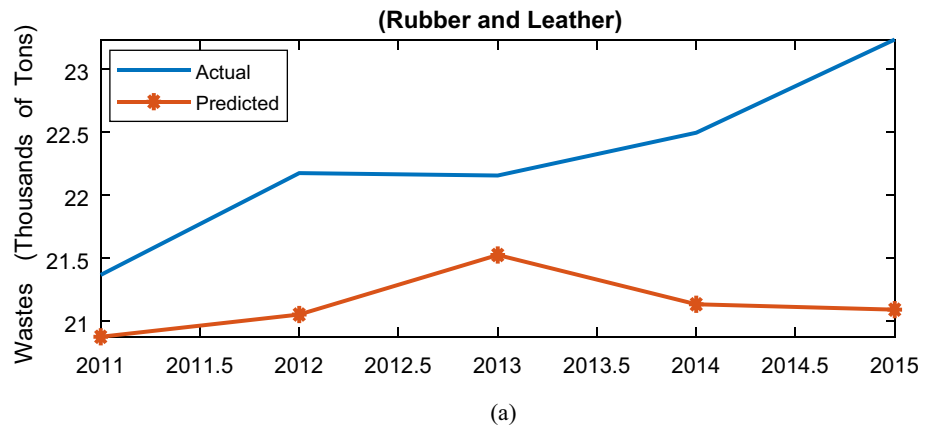


Fig. 10 Actual and predicted graph result for textiles for **a** LSTM and **b** LSTM-SVM

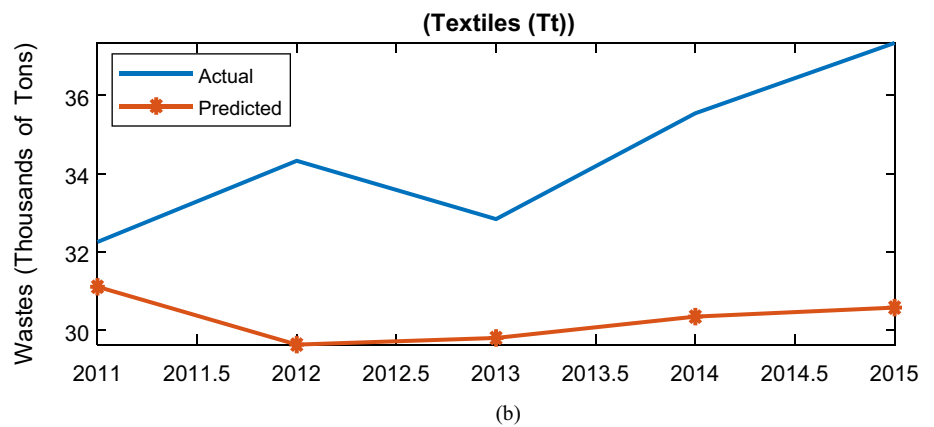
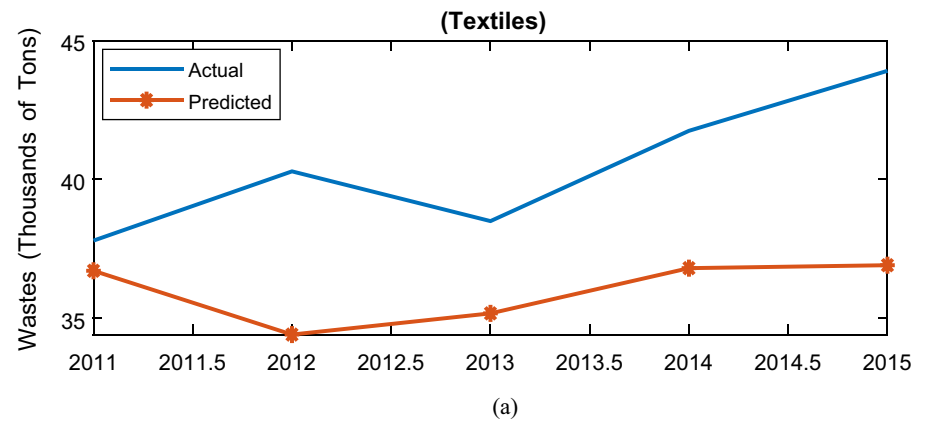


Fig. 11 Actual and predicted graph result for wood for **a** LSTM and **b** LSTM-SVM

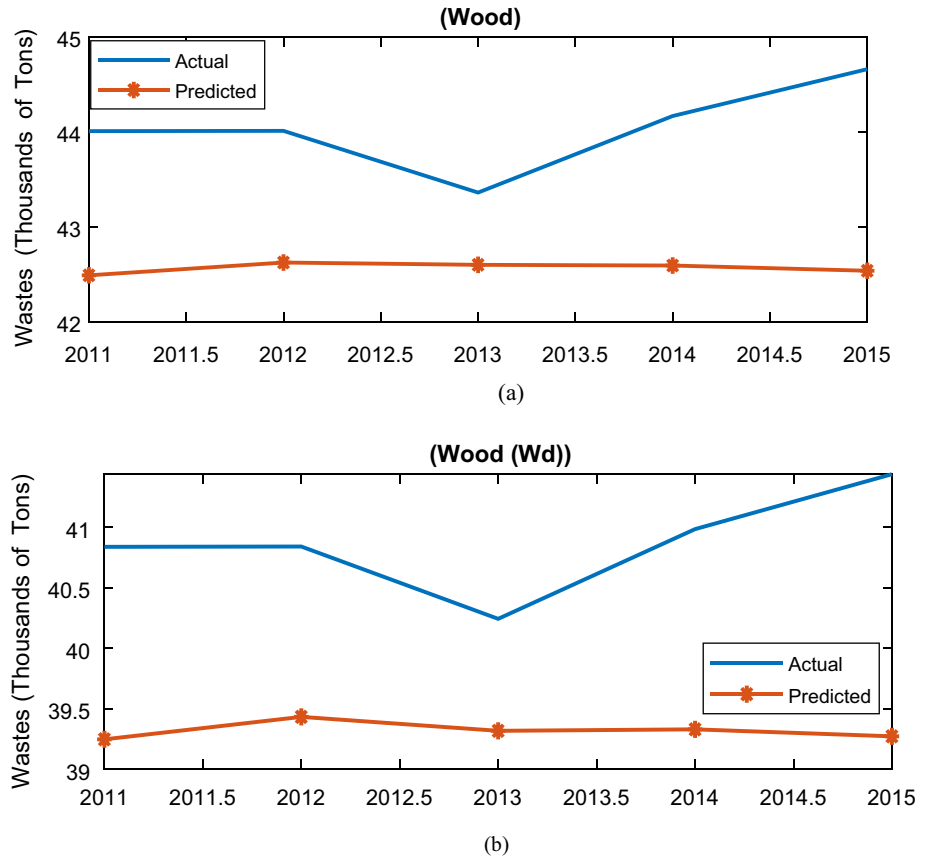


Fig. 12 Actual and predicted graph result for food for **a** LSTM and **b** LSTM-SVM

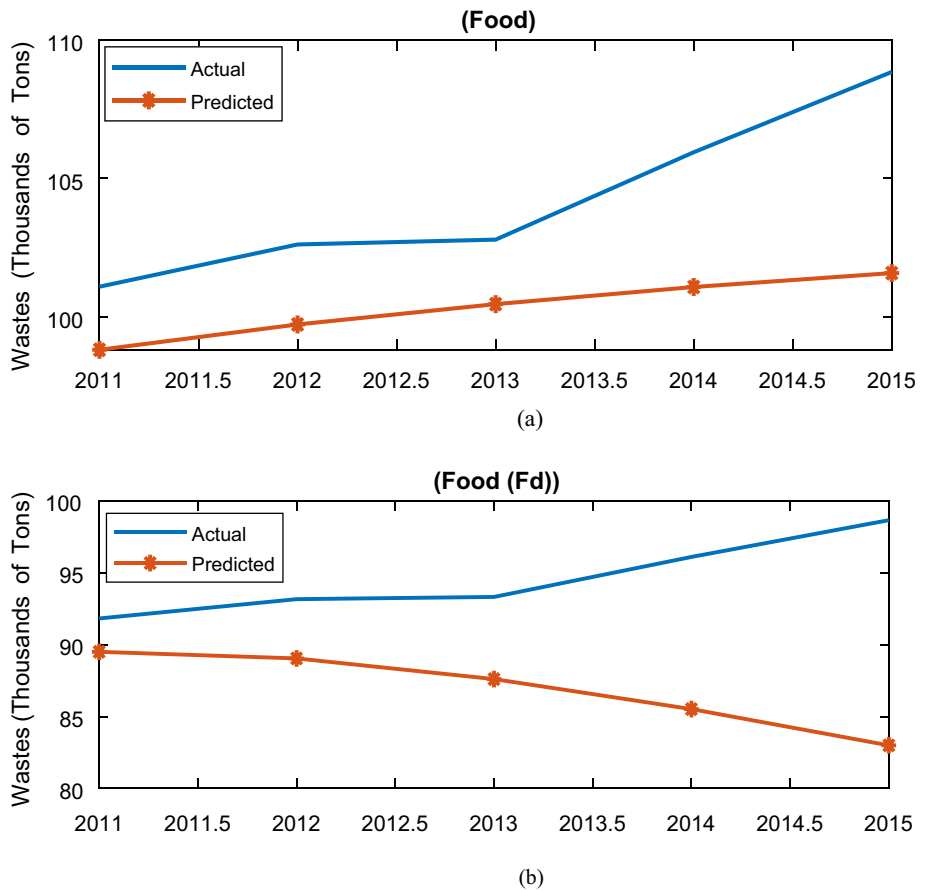


Fig. 13 Actual and predicted graph result for yard trimmings for **a** LSTM and **b** LSTM-SVM

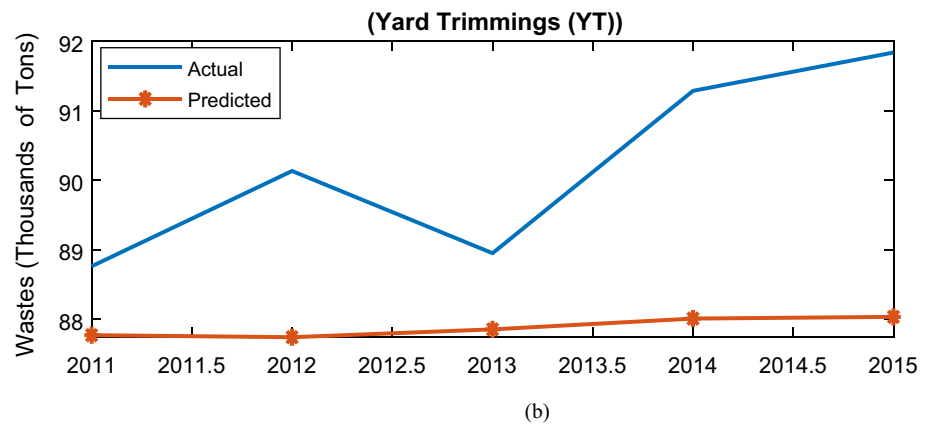
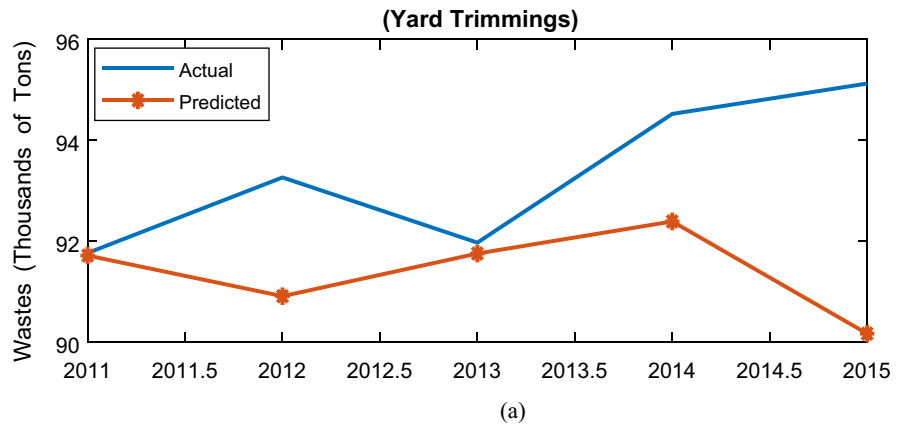
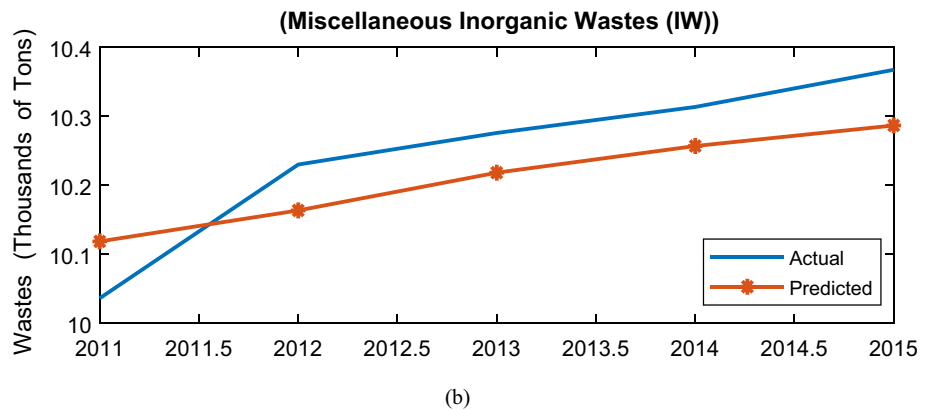
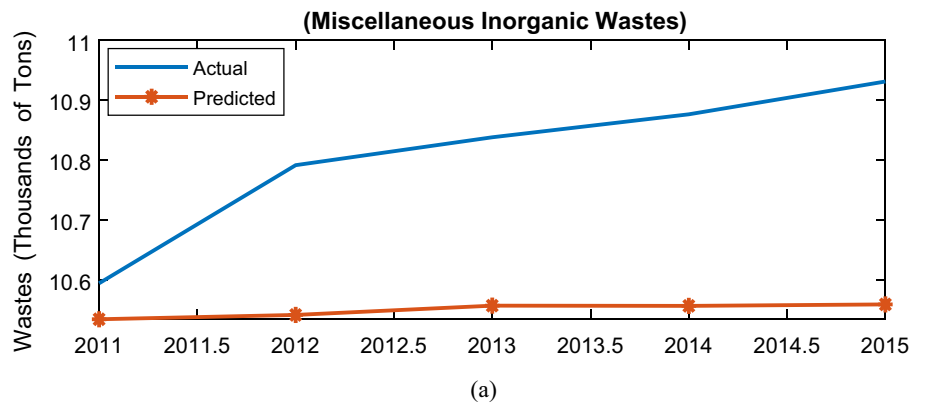


Fig. 14 Actual and predicted graph result for yard miscellaneous inorganic wastes for **a** LSTM and **b** LSTM-SVM



ten categories and the performance of the developed LSTM-SVM model was compared with the LSTM model for all the categories using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). The results showed that hybrid LSTM-SVM outperformed that of LSTM as the LSTM-SVM produced the least MAPE and RMSE. The developed model can be used for better implementation of waste management system.

Author contributions FF conceived and designed the study, developed the hybrid LSTM-SVM model, implemented, and evaluated the model and wrote the paper. IA collected and preprocessed the data, assisted in the development and evaluation of the model, and contributed to the writing of the paper. RMN provided technical expertise on LSTM and SVM models, assisted in the implementation and evaluation of the model and contributed to the writing of the paper. All authors have read and approved the final manuscript.

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Data Availability <https://stats.oecd.org/Index.aspx?DataSetCode=MUNW>.

Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

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