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Gated Recurrent Unit for Landfill Area Estimation Based on Municipal Solid Waste Prediction

Tuba Batool[1] **Rozaida Ghazali**[1]* **Irfan Javid**[2] **Nureize Binti Arbaiy**[1]

[1]*Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia, Malaysia*
[2]*Department of Computer Science and Information Technology, University of Poonch, Rawalakot, AJK, Pakistan*
* Corresponding author's Email: hi210012@student.uthm.edu.my

Abstract: Solid waste management is an imperative aspect of a hygienic environment. Lack of attention towards solid waste management leads to environmental pollution which causes catastrophic health issues and reduces the quality of life. Therefore, it's required to develop environmentally safe and adequate protocols to manage solid waste for the fortification of human health and the environment. The study presents a master plan to facilitate the local municipal authorities in developing a better waste management framework. The main aim of the research is to predict municipal solid waste (MSW) collection by using the GRU model in Multan city, Pakistan. The GRU model has utilized a dataset collected through a weighbridge at Habiba Sial landfill site (HSLS) which is the most reliable source for the data. The dataset consists of monthly data for the past five years with a total of 180 records; 60 records for months 60 records for vehicle trip numbers and 60 for collected MSW. The number of months and monthly vehicle trip numbers have been used as the input data and monthly collected MSW has been used as output data. The window of time for collected data is June 2017 through June 2022. The dataset has been divided into 3 subparts where 70% of the data has been utilized for model training, 15% of the data has been used for model testing and 15% of the data has been utilized for validation purposes. The GRU model's performance has been evaluated by using the performance metrics; mean square error (MSE), and Regression values for training, testing, and validation data. According to the results, 2-5-2-1 topology with 5 hidden neurons gives the best results with the least value of MSE being 0.0388 and the maximum value of regression being 0.94. The study also proposed a master plan for waste management, considering options like landfilling, recycling, incineration, and composting. As the landfilling method is the most common practice to dispose of waste, therefore the study estimated the required landfill area based on the predicted solid waste generation rate and its collection rate by the year 2031 for Multan city, Pakistan. The master plan can be utilized alternatively, especially for the cities with the same type of demographics which may help the municipal authorities for the development of a better solid waste management framework.

Keywords: Municipal solid waste, Multan, Landfill area estimation, GRU, LSTM.

1. Introduction

1.1 Municipal solid waste management

Municipal solid waste (MSW) management is a globally solicitous concern as it exists worldwide. The growing population, economies, urbanization, and variation in lifestyle have majorly contributed to the augmentation of the MSW generation [1]. The world bank report has revealed that the yearly generation of municipal solid waste in the world is about 2.01 billion tonnes conservatively 33% of the inappropriate environmental management [2]. MSW is ramping up daily and is expected to surge to 70% by 2050 [3]. In developing economies, MSW management has become comparatively more serious apprehension about environmental degradation [4]. However, the problem lies because of insufficient attention to the solid waste management framework. The developing countries emphases on the technical perspectives for the collection and disposal of managing MSW rather than recycling or reusing it [5, 6]. Moreover, these developing economies have to face issues like a lack of financial resources, the expertise required to meet the challenges, waste collection equipment, workforces, employee training sessions, baseline study and required data [7]. The estimated cost consumption of solid waste management revenue for the collection of MSW is about 20-50% of municipal revenues, yet the collection is only about 50 to 70% [8, 9]. There are three common methods to deal with collected waste; open burning, recycling, and disposal at landfill sites [10]. Disposal at landfill sites is the most common method used for around 95% of collected solid waste [11].

1.2 Multan waste management and landfill disposal

Multan is area wise 3rd largest and 5th most colonized city in Pakistan [12] with 5.2 million inhabitants and generates a high volume of 1071 tons/day of MSW [13, 14, 15]. Solid waste has dramatically ramped up to 0.5 kg/capita/day and hence strives to deal with the collection of solid waste. Solid waste in Multan is managed by the Multan waste management company (MWMC). The total solid waste generated in Multan has a major portion of MSW which is 63% of the total generated waste. Other waste includes industrial waste (16.9%), commerce (3.8%), construction (7.9%), hospitals and clinics (1.3%), animal farms (3.9%), and other establishments (3.3%). The composition of MSW in Multan can be categorized as organic waste (52.6%), Inorganic waste (29.5%), and others (17.9%) [47]. MWMC is primarily responsible for collecting, transferring, and disposing of solid waste at landfill sites. Solid waste is collected in two different ways; door-to-door collection, and curb-side collection [13]. Sources used for waste collection are tractor trolleys, container lifters, tractor tanks, loaders, dump trucks, excavators, blades, and a variety of other utility and transport vehicles [14]. There are four different landfill sites for disposal: Habiba Sial landfill site (HSLFS), Shah Rukane Alaam, Multan Saddar, and Bowa Por [12, 13]. The further detailed composition of MSW is glass, and metal waste – 10%, rug, and textile waste- 2%, cardboard waste - 7%, vegetables, and food waste - 30%, Paper waste - 6%, Plastic, Rubber, and leather waste - 11%, wood and yard wastes - 16%, and some other waste (rock, cement, brick, and dirt, etc) -18% as shown in Table 1 [15]. MWMC has taken many remarkable initiatives to proliferate the quality of waste management in Multan. The most significant step is the development of an online system consisting of a dashboard known as the program monitoring unit (PMU) that contains records of all complaints which are addressed daily. It provides some additional features such as sanitation inspection and special monitoring unit (SMU). SMU is used to keep an eye on staff attendance, container monitoring, fleet tracking (TPL), and weigh bridge data monitoring [13]. With the help of the weighbridge, daily data about solid waste collection and the number of trips can easily be retrieved. Disposal of solid waste at landfill sites and insufficient relevant data are obstinate issues in developing countries [16]. It's quite unfortunate that municipal authorities could not properly utilize the available data retrieved through weighbridge for the progress of the solid waste management framework. Therefore, the available data should be utilized for the prediction of solid waste collection and landfill area estimation which can help the municipalities to enhance the quality of the solid waste management system and save the unnecessary area allotted for waste disposal.

Table 1. MSW composition in Multan city

MSW categories	**Waste generation (%)**
glass, and metal waste	10%,
cardboard waste	7%,
rug, and textile waste	2%,
Paper waste	6%,
wood and yard wastes	16%,
vegetables, and food waste	30%,
Plastic, Rubber, and leather waste	11%,
other waste (rock, cement, brick, dirt, etc)	18%,

1.3 GRU application in solid waste prediction

Municipal solid waste is remarkably accelerating due to urbanization and economic factors that make MSW generation prediction an imperative concern in metropolitan sanitation [17]. Prediction of MSW with high accuracy can help to play a vital role in developing a strap framework for solid waste management that would lead to successful solid waste planning for its disposal at landfill sites [18]. The rapid growth of MSW has ramped up the emergence of the latest techniques for better management of MSW [19]. Underestimation of MSW generation prediction may lead to inadequate allocation of landfill areas for disposal which may cause pollution and health hazards [20]. Different municipalities have considered the MSW generation prediction as an important factor for metropolitan legislature and planning [21].

Different research works have been conducted for the prediction of solid waste using various models that could be classified either as regression models or time series models [22, 53, 54]. Studies conducted through regression models considered the relevance lies among solid waste generation and other demographics like population, literacy rate, employment status, etc. [23, 24]. Whereas studies conducted through time-series models considered the disparity of solid waste generation over time [25]. The accuracy of prediction based on regression models highly depends on the factors considered to predict waste generation [26]. Whereas the accuracy of predictions based on time series has specifically concentrated on the disparity of waste generation over time. Furthermore, a study was conducted to enhance the accuracy of MSW generation predictions that introduced time series analysis based on a layered model known as an artificial neural network (ANN) [27]. Time series ANN has been used to predict MSW generation rate in Iran and results revealed that model performance was acceptable [28]. Another study has been conducted for MSW prediction using the ANN model revealing that the results were appropriate to be used for better planning and management of solid waste [29]. Even though ANN has delivered high accuracy of predictions, it comes up with two major limitations; i) data provided to the model should be accurate and consecutive, even a trivial loss may generate inaccurate results; ii) the model should have access to the temporal effect window in waste generation, that means long term effects have to be ignored [17]. To overcome these drawbacks different deep learning models have been introduced [30], including the gated recurrent unit (GRU) which has extensively been used for time series analysis, such as, water quality prediction [31], and air pollutant concentration prediction [32]. GRU is the model with two gates (reset gate & update gate) and hence requires the least number of parameters for predicting with high accuracy. Furthermore, for time series data, GRU has shown promising performance in handling missing values [33]. A few researchers have used the GRU model for MSW prediction yet. A study has been conducted for solid waste generation prediction using Regularized Noise based gated recurrent unit (RNGRU) and results revealed that the RNGRU model has provided high accuracy of prediction with low error rates [34]. A detailed summary of GRU performance in solid waste prediction with different error matrices like mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and mean square error (MSE), has shown in Table 2.

Table 2. Summary of GRU model in prediction of solid waste

Model	MAE	RMSE	MAPE (%)	MSE
GRU [49]	111.6	127.9	11.9	-
GRA-GRU [49]	67.2	74.1	8.8	-
RN-GRU [48]	0.0147	0.0900		0.0010
GRU-auto-encoder (RNN) [50]	0.601	0.9875	-	-

1.4 Gap analysis of solid waste prediction studies

MSW management is a complex process that includes many diverse factors such as influencing factors exploration [35], the prediction accuracy of MSW generation, evaluations, transportation, and disposal of solid waste, etc. [36]. As MSW treatment depends on different influencing factors, researchers have primarily considered demographic, social, and economic dynamics to predict solid waste generation rate [37, 38]. Over time, deviation in the solid waste collection is considered the most influential factor to calculate the dumping proportion at different landfill sites [29]. A study conducted for waste generation using ANN included different economic and demographic factors such as total households, household residents, education, income per household, tourists' contribution towards waste generation, etc. The prediction was carried out by utilizing the data collected by a municipal authority which was a prime ratio of real generated waste [39]. Although the results of this study revealed accurate results for the prediction but didn't indicate the waste collection frequencies. A short-term study was conducted in Langkawi Island, Malaysia, for solid waste generation prediction on weekly basis using the ANN model, this study included different factors related to the solid waste collection e.g. the number of trucks, truck types, the total number of trips performed by trucks, fuel consumption, and human resources, etc. [40]. In this study, results showed high accuracy of the model but did not mention the seasonal variation which was an important aspect of the study. Additionally, research was conducted in Beijing for MSW generation prediction by using GRA-LSTM and calculating the landfill area based on that prediction. This study used 14 different factors which are divided into three major classes; social factors, economic factors, and demographic factors [36].

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Results revealed the best performance of the GRA-LSTM model over other compared models but the study focuses on landfill area calculation for MSW generation and didn't consider the collected solid waste data which was the imperial factor for the utilization of landfill area. Another study was conducted in Australia for solid waste generation analysis and prediction using RNGRU. This study mainly considered waste in tonnes and some technical factors like moving average, relative strength index, etc. [34]. The results showed that RNGRU performed better than LSTM but this study also ignored the importance of seasonal variations. A massive study has been conducted by different researchers for solid waste prediction using different time series models like GRU, LSTM, and ANN [34, 36, 40,]. Different researchers have utilized different factors to enhance the accuracy of the model to achieve adequate prediction. However, many of these studies have not considered the waste collection frequencies. The estimation of MSW collection prediction with high accuracy can play a vital role in facilitating the municipal authorities to manage their resources in a better way.

1.5 Research contributions

The literature review has revealed that developing economies have many deficiencies in the framework of solid waste treatment because of underprivileged government infrastructure for waste management [41]. MSW management has become a major concern to take into account in domestic policies [42] as unmanaged waste results in environmental degradation and health hazards [4]. This concern leads to accurate solid waste generation prediction. Different studies have been conducted for the prediction of solid waste generation rate but prediction outcomes are not certain because of the vibrant nature of selected factors (social, economic, and demographic) [43]. Contrary to that, this study has utilized the waste collection frequencies collected through the weighbridge, which is a reliable data collection source and hence makes the prediction models capable of generating more accurate prediction results. This reliable data will help to produce an accurate MSW collection prediction that will be used to calculate the estimated landfill area required for disposal of waste. The accurate prediction of collected MSW will help the municipal authorities to build a sound framework for collected MSW management that may include proper planning and design for final disposal options. As the major final disposal option is dumping at landfill sites, adopted for roughly 95% of collected solid waste [11] so it leads to the accurate estimation of the required landfill area. The accuracy of landfill area estimation is based on the accuracy of collected waste prediction. The researchers have done little work on the estimation of the landfill area using weighbridge data [29]. This brings the necessity of immediate development of a prediction model with optimum results for MSW collection prediction and landfill area estimation based on reliable predictions.

This study majorly has two contributions; 1) MSW collection frequencies have been introduced as a reliable and useful factor for the development of sound framework for MSW management and GRU model has been used for MSW collection prediction based on data gathered through a weighbridge for Multan city of Pakistan. 2) Estimation of the actual required landfill area in Multan for collected MSW based on MSW collection prediction which will help the municipal authorities in decision making and resource management. The results will diminish the uncertainty of predictions based on the GRU model as collected data is more reliable and the number of influencing factors is very low.

2. Methodology

In this work, the data used for MSW collection prediction and landfill area estimation is time series data as collected data has been observed at different times. It can also be considered cross-sectional data as it has been collected at an identical point and we can name the data as assembled data (a grouping of cross-sectional and time series data) [44]. This data has been utilized for time series analysis to figure out the time series patterns and their suitability for training the GRU model to predict MSW collection rate. The workflow of this study has depicted in Fig. 1.

2.1 Study area

Multan is the 5th most inhabited city in Pakistan with a waste generation of 32130 tons/month [14]. municipal corporation Multan (MCM) has 68 union councils (UCs) which are administrated by the local government municipal authority of Multan named Multan waste management company (MWMC). There are four different landfill areas in Multan city Habiba Sial landfill site (HSLFS), Shah Rukane Alaam, Multan Saddar, and Bowa Por [12, 13]. The most popular landfill sites of these four are HSLFS and Shah Rukne Alam. These two sites are permanent whereas Multan Saddar and Bowa por are temporary sites. Shah Rukane Alaam landfill site is the second largest landfill site with an area of

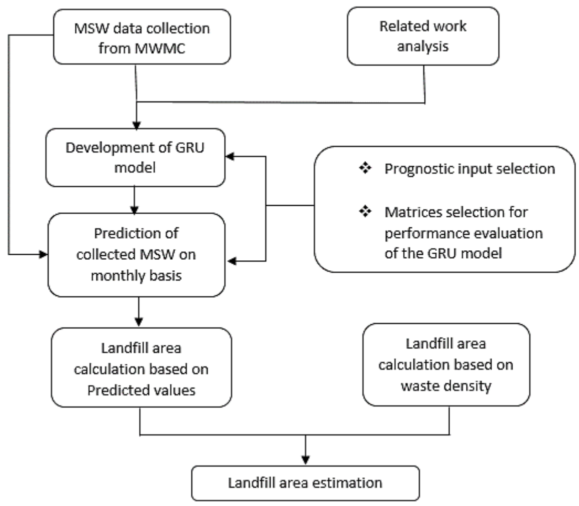

Figure. 1 Different phases of the conducted study

Table 3. Summarized dataset

Variables	Trip numbers	Collected MSW (tons)
Year	2017-2022	2017-2022
Months	60	60
Min	2,059	14,667
Max	4,096	28,670
Standard Deviation	409.1506743	2766.537842
Median	2,805	19,687
Average	2,879	20,267

304920 sq ft [14]. This site was receiving 30 to 40% of daily collected solid waste since 1995 but it was closed down in 2005 as the capacity was filled [45]. The largest landfill area in Multan city is the HSLFS landfill site that has been chosen for this study.

Habiba Sial landfill site (HSLFS) was constructed through a project of the government of Punjab sponsored by the asian development bank (ADB) and was approved in 2005 [46]. The total area of this site is 566280 sq ft with a storage capacity of 217,935 cubic meters [45]. There is no current capacity for this landfill site as it has been filled [14]. It is owned by the MWMC which has installed the Weighbridge at this site to keep a record of daily dumped solid waste [12].

2.2 Data sources

Data for this study has been collected from Multan Waste Management Company (MWMC), for every month of the last five years (June 2017 – June 2022). The dataset includes, total generated solid waste, collected solid waste, vehicle trip numbers for waste collection, and waste transferred at the landfill site. According to the MWMC, 100% of the collected solid waste has been transferred at the landfill site to dispose waste. The collected solid waste data has been maintained by the MWMC through the installed computerized weighbridge. Therefore, this study uses reliable data that has been used in its raw form. A brief statistic of the dataset is given in Table 3.

2.3 Model development

2.3.1. Data preparation and prognostic input selection

According to the data gathered through Multan waste management company (MWMC), the collected MSW is about 60 to 70 % of the total gene rated MSW in Multan. This collection variation is influenced by many factors which include the total MSW generation in the city, season, and available resources. Solid waste generation depends on different factors like GDP, consumption expenditure, green space area, transport vehicles, population, education, employment status, etc. [36]. All these factors are indirectly responsible for solid waste collection variation. MWMC has to confront different factors that affect the collection of solid waste over time such as the number of waste containers (currently 170), temperature and rainfall, number of workers in MWMC, the performance of MWMC fleets, repair, and maintenance costs, the workload on staff, temporary landfill site constructions, etc. These factors have a direct influence on solid waste collection. As all these factors are primarily responsible for waste collection variations so, this study focuses on the MSW collection frequencies over time for the prediction of MSW collection and evaluation of the GRU performance.

The dataset consists of a total of 180 records; 60 records for months 60 records for vehicle trip numbers and 60 for collected MSW. The number of months (60 records) and monthly vehicle trip numbers (60 records) for the past five years have been used as the input data and monthly collected MSW (60 records) has been used as output data. The window of time for collected data is June 2017 through June 2022. The first 120 values have been used for the development of the GRU model and 60 values have been used to evaluate the performance of the GRU model toward the prediction of MSW collection that is further used for landfill area estimation which has been summarized in Table 3 which clearly shows the collection variations over time. Maximum values for MSW collection are perceived in the autumn season, Average values are observed in the winter season and the least collection values have been observed for the

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summer season. The model is developed to predict the MSW collection rate at the Habiba Sial landfill site (HSLFS). The accurate analysis of monthly MSW collection is a complex process as it depends on many diverse factors (as discussed earlier) also there is some quantity of other waste such as industrial or construction waste like cement, bricks, etc. Logically, collected MSW is about 82%, and the rest of the waste (18%) is industrial or construction waste, we consider that waste as 'other' and we converge the total MSW collection to 100% by adding 'other'. But the GRU model doesn't define it and considers the MSW quantity as 100%.

The degree of freedom used for the study is as two input parameters and one output parameter. The input parameters are the number of months and monthly vehicle trip numbers and the output parameter contains the quantity of MSW collection at HSLS. Data has been divided into 3 subparts where 70% of data has been utilized to train the model, 15% of data has been used for model testing and 15% of the data has been utilized for validation purposes.

In forthcoming research work, the prediction models may also be learned for the boundary conditions to achieve prediction results with more accuracy and precision.

2.3.2. Gated recurrent unit and experimental setup

In the GRU model, the reset gate is responsible to determine the least important data coming from the previous state and ignore that data for the next state whereas the update gate is responsible to maintain the most vital data from the previous state to the next state. The equations used by the GRU model to process the information are as follows:

$$G_r = \text{sigma}\,(A_r\, x_t + W_r\, h_{t-1}) \quad (1)$$

$$\tilde{h}_t = \tanh\,(A_h\, x_t + W_h(r_t \times h_{t-1})) \quad (2)$$

$$G_z = \text{sigma}\,(A_z\, x_t + W_z\, h_{t-1}) \quad (3)$$

$$O_t = (1 - z_t)\, h_{t-1} + z_t\, \tilde{h}_t \quad (4)$$

where G_r is the reset gate vector, G_z is the update gate vector, $\tilde{h}_t$ represents the candidate activation vector, O_t is the output vector, sigma and tanh are the activation functions, and A and W are the associated weights. Moreover, short-term dependencies are learned by the reset gate whereas the update gate is responsible for long-term dependencies as shown in Fig. 2.

In this study, the input layer has 2 variables X_1 and X^2 where X_1 represents the number of months and X_2 represents the monthly vehicle trip numbers, 2 hidden layers have been utilized with 5 hidden neurons and the output layer contains the amount of MSW collection at HSLS as shown in Fig. 3.

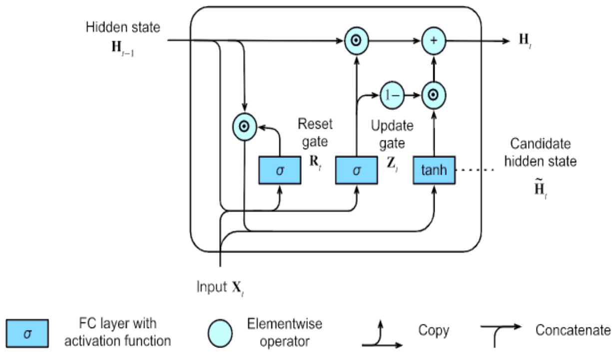

Figure. 2 GRU Architecture [51]

Furthermore, the input variables have been trained for 100 epochs for the altered number of hidden neurons within two hidden layers, and each training iteration uses random weights between 0 and 1. Adam has been used as an optimizer. Dropout was set to 0.3 within the layers to avoid the overfitting problem. Early stopping has also been used during the training process i.e no alteration in loss validation within 15 epochs will stop the training. Moreover, weight matrices are stored when the loss of the current epoch is less than the loss of the previous epoch and the output node shows the waste quantity. Python has been used to develop the GRU model. The competency of the model has been evaluated through error matrices as shown in Fig. 4.

2.3.3. Model performance evaluation

In this study, the performance of the GRU model for MSWC prediction has been evaluated by using two matrices; mean square error (MSE), and regression values for training, testing, and validation data.

$$\text{MSE} =.\frac{\sum_{i=1}^{T}(\mathrm{Wi}-\mathrm{Zi}\,)2}{T} \quad (5)$$

where W_i = Real value at the i^{th} point.
Z_i = Predicted value at the i^{th} point.
T = Total number of observations

MSE has been calculated by squaring the variance that lies between the actual and predicted values and dividing the result by the total number of observations. It computes the average squared error between the actual and predicted values. The smaller the value of MSE, the higher the performance of the model.

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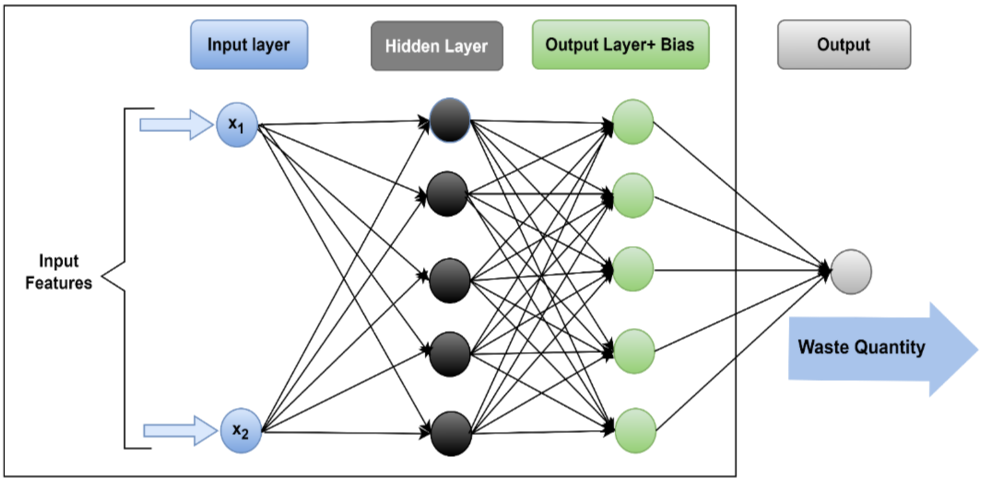

Figure. 3 Internal architecture of GRU model for MSW collection prediction

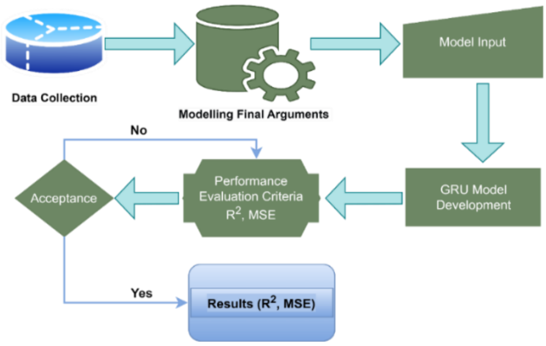

Figure. 4 GRU model development and proficiency evaluating matrices

One of the most powerful statistical approaches to explore the association between the actual value and the predicted value is regression analysis. The higher the value of R, the higher the performance of the model.

$$R^2 = 1 - \frac{RSS}{TSS} = 1 - \frac{\sum_{i=1}^{T}(Wi - Zi)2}{\sum_{i=1}^{T}(\overline{Wi} - Zi)2} \tag{6}$$

where R^2 represents the coefficient of determination, RSS represents the squared sum of residuals and TSS represents the total sum of squares.

2.4 Landfill area calculation

In the current study, the landfill area has been calculated by using the GRU model results for MSW collection prediction. A general mathematical formula has been used for the estimation of the required landfill area that has been utilized in some research papers [29, 36].

$$AL = M \times WL \times R \times 1.5 / (Wbd \times H) \tag{7}$$

Where AL = area of the landfill site
M = collected MSW
WL = Window of life for landfill site
R = the total number of residents (population).
Wbd = Bulk density of MSW
H = Landfill height

The major factor for landfill area calculation is the height of the landfill site which usually varies from 3 m to 30 m [29]. In this study, the height of the Habiba Sayal landfill site (HSLS) which is 22 m [14], has been considered to perform the calculations.

3. Results and analysis

This study has been conducted by utilizing various networks with multiple hidden neurons to find out an optimum neuron number with the best results as shown in Table 4. The study has used monthly collected MSW data at the landfill site for the period of July 2017 through July 2022.

3.1 Model performance based on regression values

The performance of the GRU model has been evaluated by using the performance metrics mean square error (MSE), and regression values for training, testing, and validation data for collected MSW for the past 5 years. The best values have been observed for 5 neurons where the value of MSE is 0.0388 and the value of R is 0.94 as shown in table 4. For 5 neurons, the value of regression for training data is 0.96 (closer to 1), for testing data is 0.92 (closer to 1), and for validation data is 0.94 as shown in Fig. 5.

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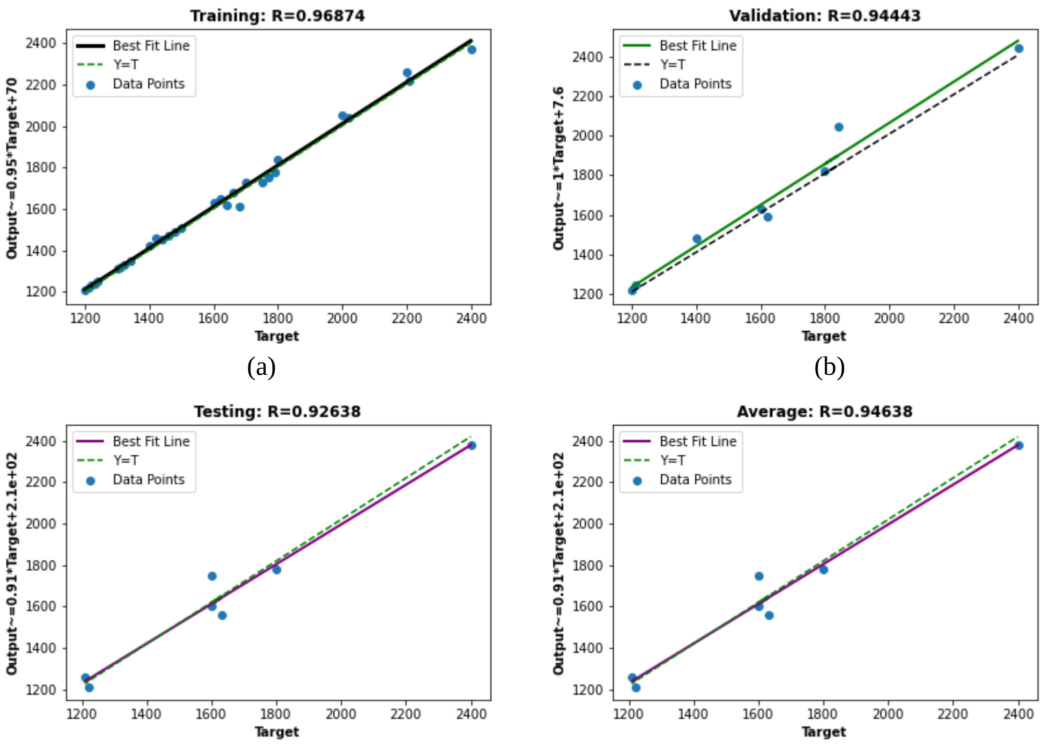
Table 4. Training, testing, and validation of the GRU model

GRU model structure	MSE	Best epoch	No. of hidden neurons	Regression (R)				Equation
				Training Data	Testing Data	Validation	Average	
2-2-2-1	0.0410	8	2	0.817	0.83	0.72	0.81	0.77*target+3.9e^{+03}
2-3-2-1	0.0405	10	3	0.7268	0.72	0.86	0.78	0.65*target+5.2e^{+02}
2-4-2-1	0.0389	3	4	0.7862	0.81	0.68	0.77	0.89*target+2.8e^{+02}
2-5-2-1	**0.0388**	**24**	**5**	**0.9687**	**0.92**	**0.94**	**0.94**	**0.86*target+1.9e^{+02}**
2-6-2-1	0.0415	4	6	0.8902	0.92	0.89	0.92	0.83*target+2.8e^{+02}
2-7-2-1	0.0399	2	7	0.805	0.81	0.78	0.79	0.67*target+4.9e^{+02}
2-8-2-1	0.0413	11	8	-0.0688	-0.79	-0.62	-0.25	0.39*target+3.1e^{+03}
2-9-2-1	0.0396	6	9	0.1424	0.18	-0.64	0.10	0.021*target+8.9e^{+2}
2-10-2-1	0.0400	7	10	0.8771	0.92	0.89	0.91	0.93*target+2.5e^{+03}
2-11-2-1	0.1392	1	11	0.9432	0.81	0.96	0.92	0.95*target+74
2-12-2-1	0.1003	79	19	0.394	0.003	0.56	0.33	0.78*target+4.8e^{+02}
2-13-2-1	0.0710	6	13	0.9787	0.56	0.86	0.82	0.74*target+2.5e^{+03}
2-14-2-1	0.0854	5	14	0.8962	0.86	0.79	0.86	0.82*target+3.6e^{+02}
2-15-2-1	0.1637	12	15	0.7363	0.61	0.77	0.72	0.57*target+7.6e^{+02}
2-16-2-1	0.0609	3	16	0.8132	0.83	0.79	0.83	0.76*target+3.8e^{+02}
2-17-2-1	0.0526	24	17	0.9528	0.68	0.60	0.76	0.79*target+4.1e^{+02}
2-18-2-1	0.0390	37	18	0.8133	0.67	0.74	0.73	2.1*target+3.8 e^{+02}
2-19-2-1	0.0469	1	19	0.9137	0.62	0.92	0.83	0.91*target+2.3 e^{+02}
2-20-2-1	0.1188	9	20	0.9621	0.72	0.94	0.89	0.93*target+2.7 e^{+02}



(a) (b)

(c) (d)

Figure. 5 Performance evaluation of GRU model for MSW collection prediction for Multan city

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3.2 Prediction of MSW collection by GRU

The best performance of the GRU model has been evaluated by testing the different numbers of neurons for selected input variables. According to the results, a 2-5-2-1 topology with 5 hidden neurons gives the best results where 2 is representing the number of inputs, 5 is representing the number of hidden neurons, the next 2 is representing the number of hidden layers and 1 is representing the output node. The GRU model has used input data (MSW) at an instance of time t denoted by Mt to make the future prediction. The mathematical equation for the prediction of time series data can be represented as:

$$S_{(t)} = P(S_{t-1}, S_{t-2}, S_{t-3}, \ldots\ldots\ S_{t-n}) \tag{8}$$

In this Eq. 8, the output of the equation is the future predicted value for MSW at time t which is calculated by using the function P for the historical n number of values of the MSW like $S_{t-1,}$ S_{t-2} S_{t-3},...., S_{t-n} where n is 120. The predicted values are compared with the actual values of the data collected through the weighbridge for HSLFS, Multan to come up with the evaluation results of the GRU model. MSW collection has been predicted by the GRU model for HSLS every month for the past 5 years as shown in Fig. 6 and the accuracy results for the GRU model have been shown in Fig. 5.

3.3 Estimation of required landfill area

The study has been conducted to forecast the obligatory landfill area for the forecasted waste generation rate and waste collection rate of Multan city by the year 2031 [52] as shown in Fig. 7. As there is no capacity left for waste dumping at the Habiba Sial landfill site, MWMC is utilizing temporary sites for waste disposal [14]. MWMC has to create a new framework for MSW management. This study presents the master plan to facilitate the MWMC for waste management in Multan city. The plan has been proposed based on forecasted MSW generation and collection by the year 2031 [52]. The predicted MSW generation for Multan city is approximately 2500 tons/day and the collected MSW has been approximated to 1900 tons/day as shown in Fig. 6. The master plan has considered other options like recycling, incineration, and composting besides landfilling. Although, the plan considered other options that may be utilized by the MWMC for waste management, a major portion of waste still has to be dumped at the landfill site. Estimation of the landfill area will facilitate the municipal authority of Multan city to generate a sustainable plan for MSW management. For the estimation of landfill area, the major requirement is the density of collected MSW. The average solid waste composition, collected weight (tons/day), and density has been shown in Table 5 which has been utilized by the study for landfill area estimation for Multan city. In the study, the average density of solid waste at HSLS is approximately 107.0923981 kg/m3.

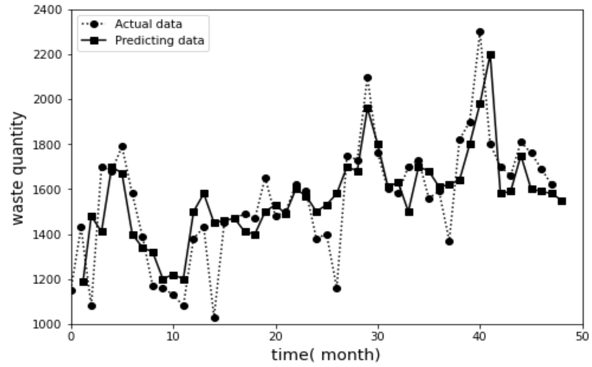

Figure. 6 GRU prediction on MSW collection on monthly basis for Multan city.

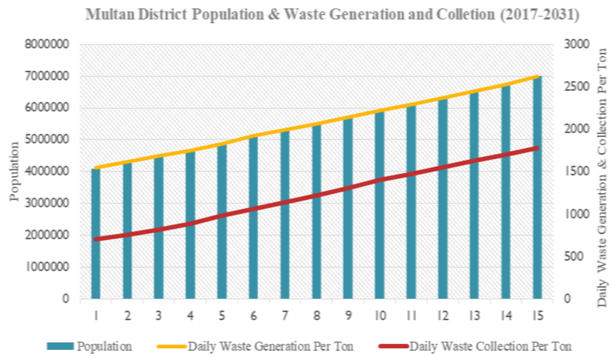

Figure. 7 Multan solid waste generation and collection by the year 2031 [52]

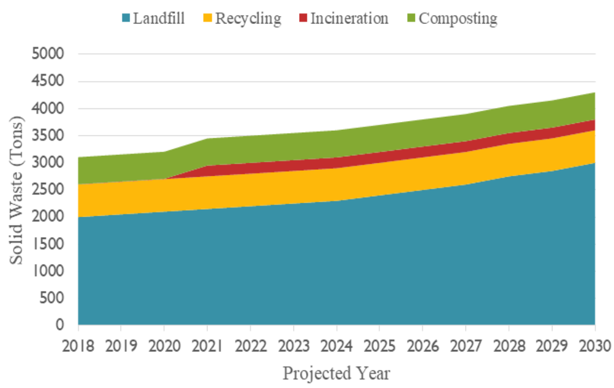

Figure. 8 Proposed master plan for MSW management in Multan city based on solid waste collection prediction based on the GRU model

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Table 5. MSW composition at landfill site Multan

MSW categories	Waste generation (%)	Weight (kgs/day)	Volume (m^3)	Average waste Density (kg/ m^3)	Compacted Volume (m^3)	Compacted Density (kg/ m^3)
vegetables, and food waste	31.03%	1593140	1487755	33.22801	371938.75	132.91204
rock, cement, brick, dirt, etc	27.92%	1433930	1338644	29.90737	334661	119.62948
Leaves, Grass, straws, etc	20.22%	1038240	969462.1	21.6545	242365.525	86.618
rug, and textile waste	7.52%	386380	360551.6	8.058701	90137.9	32.234804
Plastic, Rubber	5.69%	291970	272811	6.089598	68202.75	24.358392
Paper	2.73%	140020	130891.8	2.920386	32722.95	11.681544
Animal waste	2.56%	131210	122741	2.736637	30685.25	10.946548
Wood	1.25%	64310	59932.14	1.341309	14983.035	5.365236
Glass	0.75%	38300	35959.29	0.79882	8989.8225	3.19528
Metal	0.32%	16600	15342.62	0.346225	3835.655	1.3849
Unclassified	0.01%	520	479.457	0.010846	119.86425	0.043384
Total	**100%**	**5134620**	**4794569.967**	**107.0923981**	**1198642.492**	**428.3695924**

4. Discussion

4.1 GRU performance for MSW collection prediction

The accuracy of the GRU model for the prediction of MSW collection has been shown in Fig. 5 which depicts an acceptable performance of the model. 70% of the data has been utilized to train the model, 15% has been used for validation and 15% has been used for testing. The value of regression (R) for the training data is 0.96, for validation is 0.94, and for testing is 0.92 with the average value of R=0.94. Fig. 7 shows the splendid performance of the GRU model where predicted values are quite closer to the available data.

4.2 Calculation of landfill area and master plan

To come up with the master plan, the MSW collection for Multan city has been considered as input for the study. The master plan has considered options like recycling, incineration, composting, and landfilling. Although, the plan considered other options that may be utilized by the MWMC for waste management, a major portion of waste still has to be dumped at the landfill site which has been calculated by using Eq. 7. The graphical representation of the master plan has been shown in Fig. 8. Estimation of the landfill area will facilitate the municipal authority of Multan city to generate a sustainable plan for MSW management.

According to the GRU predictions, the amount of MSW that has to be dumped at the landfill site is about 1330 tons/day by the year 2031 which is about 70% of the total collected MSW. Therefore, the estimated landfill area with the capacity of handling this amount of MSW is about 4080814.83 m2 According to the plan, the rest of the 30% of the collected MSW has to be managed through other techniques like recycling, incineration, and composting. Recycling can be opted for about 10% – 15% of the collected MSW, incineration can opt for 5% - 8% of the collected waste, and composting can opt for 10% - 15% of the total collected MSW as shown in Fig. 9. Utilizing these options can save about 30 % of the landfill area.

5. Conclusion

The study has overviewed different strategies utilized for solid waste prediction by using deep learning models. The core objective of the study is to predict the MSW collection with the most reliable data by using the GRU model and to estimate the landfill area for better waste management. The study has utilized only two input variables (months and MSW generation) for the prediction of MSW collection. The dataset has been collected for Multan

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city, through a weigh bridge which makes the data more reliable. Data has been divided into 3 subparts where 70% of the data has been utilized to train the model, 15% of the data has been utilized for model testing and 15% of the data has been utilized for validation purposes. The performance of the model has been evaluated with the help of regression (R) values and mean square error (MSE). The prediction results depict the acceptable performance of the GRU model with best values for 2-5-2-1 topology with 5 hidden neurons with the least value of MSE being 0.0388 and the maximum value of regression being 0.94. The study has also estimated the required landfill area based on solid waste generation and collection prediction by the year 2031 which is 4080814.83 m2 and proposed a master plan by considering some other options like recycling, incineration, and composting besides landfilling for better waste management in Multan city. In future research, some other factors like the number of fleets, number of workers, and number of trips for waste collection may also be utilized as input variables to enhance the model performance.

Conflicts of interest

The authors of this research paper declare that they have no conflicts of interest related to the research presented in this manuscript.

Author contributions

Each author contributed to this research in different ways. The specific contributions are as follows: "Conceptualization, methodology, data analysis literature review, and data collection by Tuba Batool; software, validation, formal analysis by Tuba Batool, Irfan Javid and Nureize Binti Arbaiy; writing—original draft preparation by Tuba Batool; visualization, supervision, project administration, and funding acquisition by Dr. Rozaida Ghazali.

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