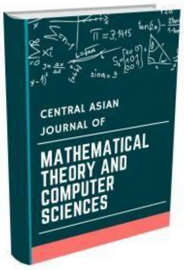

CENTRAL ASIAN JOURNAL OF
MATHEMATICAL THEORY AND
COMPUTER SCIENCES
https://cajmtcs.centralasianstudies.org/index.php/CAJMTCS
Volume: 06 Issue: 02 | April 2025 ISSN: 2660-5309

Article

Hybrid LSTM-DNN Model for Predicting Fuel Consumption in Open Pit Mining Trucks

Al Taee Wahhab Isam Hatif[*1], Dhahir Abdulhadi Abdullah[2], Alaa Nazeeh Mohmedhussen[3]

1. National University of Science and Technology MISIS
2. College of Science, Diyala University
3. MIREA- Russian Technological University

* Correspondence: Wahhab_isam@yahoo.com

Abstract: A dump truck's fuel efficiency is affected by a number of real-world factors, including driver conduct, road conditions, weather, and vehicle specifications. Additionally, potential engine malfunctions, regular wear and tear, and other factors can impact the vehicle'sperformance. By utilizing dynamic on-road data to predict fuel consumption per trip, the automotive industry can effectively reduce the cost and time associated with on-road testing. Furthermore, data modeling can provide valuable insights into identifying the underlying causes of fuel consumption by analyzing the input parameters. In this paper present, 1-proposes and evaluates new models for predicting fuel consumption of dump truck in open pit mining. These models combine the power of features derived from data locally collected by dump truck sensors and their analysis. 2- The structure Predicting fuel usage in open pit mining trucks using a hybrid LSTM-DNN model Double Long Short-Term Memory (LSTM) and double thick layers of Deep Neural Networks (DNN) form the foundation of the models' basic design, which consists of two separate components. 3- The proposed model performs better than existing models because to the addition of a new hybrid architecture, especially when it comes to accuracy measurement. The model's performance indicators, which include MAE, RMSE, MSE, and R2, show that it can produce highly accurate predictions.

Keywords: LSTM Algorithm, DNN, Dense, Predictive, Fuel Consumption

Citation: Hatif, A. W. I., Abdullah, D. A. Mohmedhussen, A. N, Hybrid LSTM-DNN Model for Predicting Fuel Consumption in Open Pit Mining Trucks. Central Asian Journal of Mathematical Theory and Computer Sciences 2025, 6(2), 200-212.

Received: 28th Feb 2025
Revised: 9th Mar 2025
Accepted: 16th Mar 2025
Published: 22th Mar 2025

1. Introduction

Fuel consumption (FC) in dump trucks is a noteworthy aspect of mining operations, comprising a significant portion of energy utilization [1]. Therefore, fuel expenses hold considerable prominence dump truck transportation companies. The cost of fuel is subject to substantial fluctuations, which can have a profound impact on the overall profitability of the business. Fuel expenses can constitute a substantial proportion of their operational costs. The quantity of fuel consumed by a dump truck is contingent upon various factors, including the distance covered, the load weight, and the terrain [2], [3]. A dump truck can get anywhere from 8 to 12 miles per gallon, in the average. In order to mitigate the impact of fuel expenses, numerous dump truck transportation companies employ strategies to enhance fuel efficiency. These strategies encompass the following:

1. Maintenance of their vehicles to ensure optimum performance,
2. The provision of training to drivers on fuel-efficient driving techniques,

3. Utilization of technology such as GPS systems to optimize routes,
4. The reduction of idle time.

Moreover, certain companies may also explore alternative fuel options, such as biodiesel or natural gas, in order to diminish their reliance on conventional diesel fuel. While the adoption of these alternatives may necessitate initial investment and infrastructure modifications, they have the potential to yield long-term cost savings and environmental advantages.

Counter measurements can be classified into three main categories:

1. Machine learning (ML): machine learning techniques include decision trees (DT), random forests (RF), and support vector machines (SVM), can be employed to construct models for detecting of predicting fuel consumption.

2: Deep Learning (DL): A subset of machine learning called "deep learning" is concerned with creating deep networks utilizing several kinds of layers, such as convolution, pooling, dropout, and fully connected layers (also called "dense" layers).. Deep learning-based predictive fuel consumption models can be produced using algorithms including convolutional neural networks (CNN), recurrent neural networks (RNN), autoencoders, restricted Boltzmann machines (RBM), deep belief networks, and deep neural networks.

3. Hybrid Techniques: A combination of different approaches is used to construct a more accurate and precise model. Deep learning algorithms have been effectively employed in various classification problems and used to forecast fuel consumption based on variables such as velocity, payload, loading duration, and travel duration and other [4].

The primary contributions of this paper can be categorized into three aspects.

First and foremost, this study proposes and evaluates new models for predicting fuel consumption of dump truck in open pit mining. These models combine the power of features derived from data collected by dump truck sensors and their subsequent analysis. By doing so, the proposed models are capable of extracting salient deep features by leveraging information from the selected features and integrating them. The architectural design of the models involves two distinct parts, Originally, Deep Neural Networks (DNN) with thick layers and Long Short-Term Memory (LSTM).

These two parts are subsequently connected at a specific point, resulting in the transformation of the model into a standard DNN model. The final node of this model is associated with fuel consumption. It is worth noting that the error value utilized during back propagation is identical for both the DNN - LSTM.based parts, ensuring that optimization is achieved in a harmonious manner. Through the utilization of this architecture, an improved model is created in comparison to models that separately employ and analyze data-based attributes obtained from dumper sensors.

The incorporation of a new hybrid architecture, which integrates two types of Double LSTM & Double Dense layers, leads to superior performance of the proposed models compared to other models proposed in the existing literature, particularly in terms of accuracy measurement.

To provide a better structure, the following sections are arranged as follows: The relevant work is presented in Section 2, the methodology is explained in Section 3, data collection and pre-processing are covered in Section 4, and the experimental results are covered in Section 5. Lastly, the paper is concluded in Section 6.

Literature Review

In 2015 Elnaz Siami-Irdemoosa, In this work, the artificial neurale network (ANN) technique is used to estimate the fuel consumption in mining dump trucks, In 2014 Lalit Kumar Sahoo the work focuses on benchmarking energy consumption and estimating minimum Specific Fuel Consumption (SFC) for dump trucks in mines and A generic amodel is presented tobenchmark energy consumption for dump trucks inmines. - The model estimates minimum specific fuel consumption and shows potential fuel savings [5].

In 2019 Thomas Bousonville the work about estimating atruck fuel consumption using machine learning techniques based on various external variables, Machine learning techniques can accurately predict truck fuel consumption. - Weather conditions data improves the fuel consumption forecast. In 2022 Dmytrychenko Mykola in has work does not provide a specific method for forecasting fuel consumption in dump trucks and Factors affecting fuel consumption during unloading of dump truck platform were identified, unloading rate is a key indicator for calculating fuel consumption. In 2020 Thomas Bousonville in has work the provided paper does not specifically mention forecasting fuel consumption in dump trucks. The work focuses on data-driven analysis and forecasting of medium and heavy truck fuel consumption in general, and the work provides adata-driven analysisand forecasting of medium andheavy truck fuel consumption, and emphasizes the need for transparency in determining the most fuel-efficient truck models [6]. The use of data to predict heavy truck fuel consumption in neural networks has been explored in several studies. One study proposed a Back Propagation (BP) neural network model based on heavy truck driving behavior data, which was improved using simulated annealing algorithm (SA), genetic algorithm (GA), and genetic annealing algorithm (GSA) [7]. Another study introduced aback propagation fuel aconsumption prediction model based onthe Cauchy MultiVerse optimizer (CMVO) for plateau conditions, which showed improved prediction accuracy compared to other algorithms [8]. Additionally, a framework was developed using machine learning algorithms and sensor data to estimate fuel consumption in construction trucks, demonstrating the viability of this approach in a real-world setting [9]. Finally, a deep learning approach was used to develop a generic modeling approach for vehicle engine-power estimation, resulting in more accurate fuel consumption estimation for heavy-duty trucks [10].

2. Materials and Methods

This asection elucidates the proposed hybrid deep a learning model employed inthis investigation.

2.1 Introduces our hybrid deep learning LSTM-DNN Dense model.

In deep learning algorithms, specifically RNN-based methods, have been employed. Throughout the experiments, features were utilized for both machine learning methods and the DNN network. In cases where hybrid models amalgamate two disparate feature sets, The RNN-based model used to estimate fuel consumption features can be replaced with a CNN-based model [11], [12], [13], [14], [15]. However, it is worth noting that a CNN based model has substantial memory requirements and is incapable of capturing long-distance-dependent features [16]. On the other hand, LSTM and DNN-Dense layer have the capability to tackle more intricate pissues in contrast to typical machine learning algorithms, or shallow learning algorithms. Moreover, LSTM networks possess the ability to retain past information over extended periods of time, making them a common choice for time series forecasting due to their capacity to capture dependencies and sequential patterns within the data. Conversely, recurrent a neural networks (RNN) areunable to perform this task for prolonged durations. Because LSTMs have an internal state and are aware of the temporal structure in the inputs, they may model input series in parallel independently [17]. Consequently, our objective was to amalgamate the capabilities ofLSTM and DNN algorithms within asingle model and demonstrate how to effectively execute this integration.

3. Results and Discussion

The new hybrid architecture proposed within this investigation comprises a fusion of two distinct neural networks. Conversely, one cannot disentangle these two networks or execute independent training, thereby yielding a singular model. The reason for not separating these two networks is the prolongation of training and prediction durations that such a procedure would cause. Furthermore, considering the interconnectedness of the training process for both networks, a plethora of profound characteristics are revealed, resulting in an increase in accuracy [18], [19], [20], [21].

We adopted a RNN neural network consists of double LSTM layers and double Dense layers to be trained to predict the future sensors measurements for 5 timesteps. For training, we chose 100 timesteps for each patch (i.e., batch size = 100), while prediction will be for 5 future time steps. The training process lasted for 10 epochs. The reason behind adopting RNNs: Because they can identify patterns and sequential dependencies in data, LSTM (Long Short-Term Memory) networks and other recurrent neural networks (RNNs) are commonly used for time series forecasting. Using 2 LSTM layers followed by Dense layers in a forecasting model has these advantages.(Figure 1)

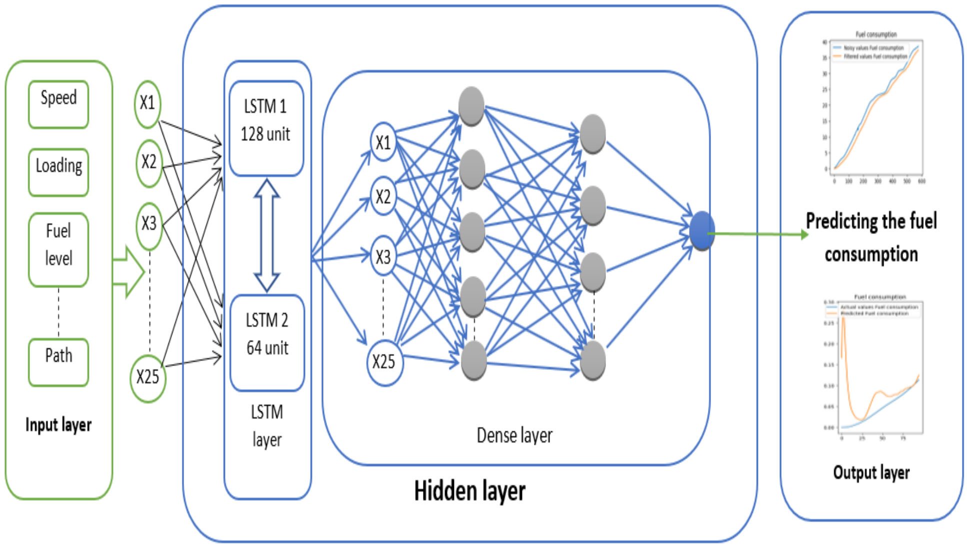

Figure 1. Architecture proposed LSTM-DNN model.

3.1 Deep learning algorithms

Deep learning algorithms, which have garnered significant attention in the past decade, belong to a subset of machine learning [22]. Notably, advancements in computational power and the expansion of data storage capabilities have significantly contributed to the practicality of deep learning methodologies. Consequently, deep learning amodels have demonstrated state-ofthe-art outcomes across various domains and large-scale datasets. Researchers have achieved remarkable outcomes inimage processing [23], efforts in machine translation and natural language processing. Moreover, deep learning a lgorithms have been applied to the predictive of yielding promising results.

The present study investigates the following deep learning-based algorithms:

Deep Neural Network (DNN): its classifiers often referred to as Dense layer classifiers [24], [25], consist of at least two hidden layers and exhibit a striking resemblance to the conventional multi-layer perceptron's. These classifiers are composed of a layered network structure, wherein each layer contains a specific number of neurons (also known as nodes). The node quantities and activation functions within the output layer are tailored to suit the classification problem at hand. Additionally, Dense layer possess hidden layers in conjunction with the input and output layers, enabling the extraction of intricate features. The dense employed in this investigation contains two hidden layers attributes, as depicted in Figure (2) Recurrent Neural Networks (RNN) are a class of deep learning algorithms that have been devised specifically for analyzing time-series data [26]. RNNs possess directional connections linking their internal nodes, which enable them to derive the subsequent time step by leveraging the information encoded in the preceding time step. As a consequence, RNNs are adept at handling sequential data. These networks find extensive application in diverse domains, including image processing and predictive tasks.

The Long Short-Term Memory (LSTM) model, which is a variant of the RNN algorithm [27], addresses the limitation of standard RNNs in establishing meaningful connections between data pieces with 10 or more-time steps. LSTM is capable of assessing the significance of information and, when necessary, retaining it for an extended duration. It can establish relationships even between data points that are separated by more than 1000-time steps, LSTM explain in section 3.3.

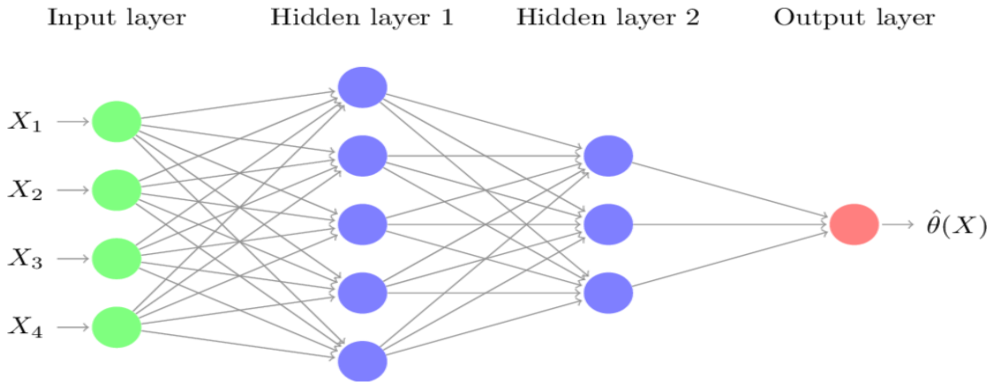

Figure 2. An example of DNN two Dense-layers.

3.2 Long Short-Term Memory (LSTM)

it's an architectural configuration of aRecurrent Neural Network (RNN). It finds application in several domains, as time series analysis, speech recognition, and natural language processing. In the specific context of open pit mining, LSTM presents the capability to analyze and predict various facets of the mining process. For instance, it can predict fuel consumption, project ore grades, forecast equipment failure, optimize production scheduling, and enhance safety measures. LSTM operates by leveraging memory cells that possess the ability to retain information for extended durations, thereby enabling the anetwork to discern and acquire knowledge from patterns in sequential data. Consequently, this renders LSTM particularly advantageous for scrutinizing time-dependent variables in open pit mining operations.

ft, it, ct, and Ot in Figure 3 indicate the input gate, output gate, forgetting gate, and output moment, respectively; the related weight coefficients, excitation function, and deviation amount are denoted by w, tanh, and b, respectively. Its input (xt) and output (ht−1) from the previous moment are coupled with the state unit (Ct−1) using the sigmoid function to determine the forgetting content; the forgetting gate determines how many state units (Ct−1) from the last moment are kept to the moment (Ct); When the input (xt) and output (ht−1) of the current moment are combined with the tanh function to create a new memory, the input gate controls how much of the input (xt) from the network is retained in the state unit (Ct). It can also prevent irrelevant information from entering the memory, Specifically, the Ct, or intermediate vector.

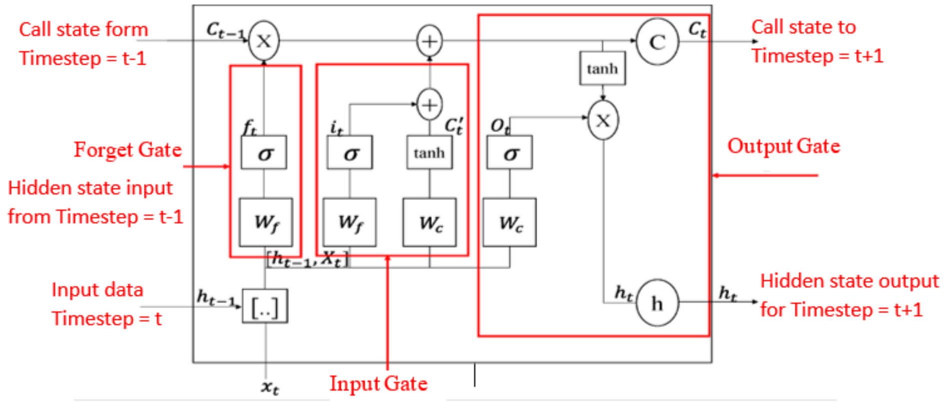

Figure 3. Illustrated the internal structure of LSTM's unit.

This regulates the addition of fresh data in conjunction with the sigmoid function's output (it); the output gate regulates (Ct) the amount of the state unit's output to the LSTM model's current output (ht) value. The operation amechanism is shown inEquations (1) – (6).

Retention of forgotten gate control information:

$$f_t = \sigma \;\; w_f \cdot [h_{t-1}, x_t] + b_f \quad (1)$$

Storage ofupdated information:

$$i_t = \sigma(w_t \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$C' = \tanh(w_c \cdot [h_{t-1}, x_t] + b_c) \quad (3)$$

Aggregate ainput information andupdate information:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot C'_t \quad (4)$$

Detarmine the output infourmation:

$$O_t = \delta(w_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

Output infourmation activation:

$$_t = O_t \cdot \tanh(C_t) \quad (6)$$

3.3 Data Collection and Pre-Processing

Data collection method: such as path, speed, route, dump truck status, and load dump track and other data, by using sensors located in the dump truck, through which data on fuel consumption can be collected and proven to be reliable. The data is read from the sensors when the dump truck is moving, especially while loading raw materials (there is the maximum load for the engine and torque). During road testing. For every journey, the sensors produce data in a CSV file second by second. We have 3112 rows and 40 characteristics, including engine speed (rpm), speed (km/h), and fuel rate (l/h). (Figure 4)

	len	Speed	Latitude	Longitude	Instant weight	Longitudinal inclination	Lateral slope	Height	Fuel level, liters	Fuel level, percent
0	10	5	54.159399	87.121072	221.0	2.0	4.00	287.0	NaN	NaN
1	13	11	54.159434	87.121223	221.0	1.0	3.00	288.0	NaN	NaN
2	15	8	54.159445	87.121263	221.0	3.0	3.00	288.0	NaN	NaN
3	18	9	54.159449	87.121298	223.0	5.0	3.00	288.0	NaN	NaN
4	21	8	54.159459	87.121334	224.0	2.0	3.00	289.0	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...
3107	2218	5	54.152425	87.120592	217.0	-3.0	5.00	363.0	NaN	NaN
3108	2219	4	54.152436	87.120615	219.0	-2.0	2.00	363.0	NaN	NaN
3109	2221	4	54.152442	87.120635	221.0	-1.0	2.00	363.0	NaN	NaN
3110	2222	4	54.152448	87.120657	224.0	-1.0	2.00	362.0	NaN	NaN
3111	2223	3	54.152458	87.120678	225.0	-2.5	1.05	362.0	NaN	NaN

3112 rows × 40 columns

Figure 4. Data read from dump truck sensors in csv file.

Data Imputing / Attribution: Removing features that have a considerable proportion of missing values, exceeding 40%, were taken into account for various reasons. These reasons encompass data quality, reliability, and data integrity. Features with a notable proportion of missing values may possess inadequate data integrity or quality, potentially compromising the reliability of said features. Moreover, the presence of substantial proportions of missing data could potentially introduce bias or distortion, leading to inaccurate conclusions or models. (figure 5)

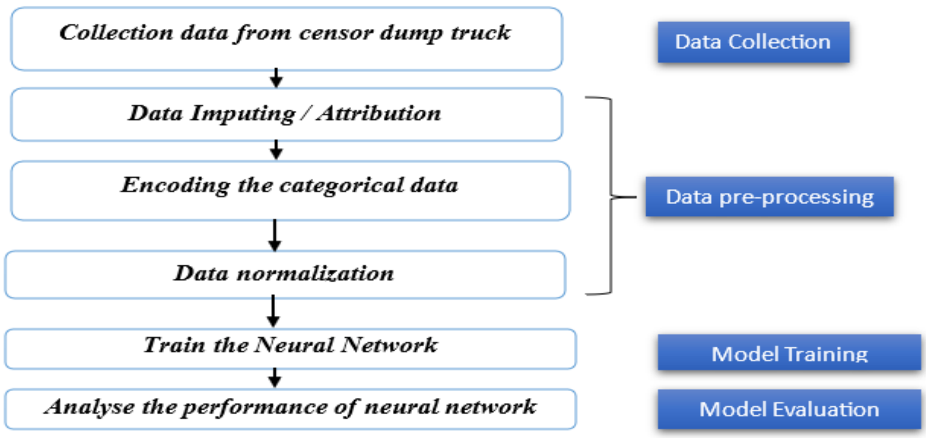

Figure 5. Workflow for predict future values modelling.

Encoding the categorical data: When pre-processing categorical data, one-hot encoding is a technique that transforms categorical variables into a format that machine learning algorithms may employ to enhance model performance. It converts categorical data into a binary format that machine learning algorithms can comprehend and utilize with ease..

Data normalization: The pre-processing step in machine learning, known as feature scaling, is of utmost importance as it entails the transformation of dataset features to a standardized scale without compromising the inherent differences in value ranges. This process is implemented to ensure thatall featurese are brought to acomparable scale or range, thereby presenting multiple advantages of them:

Facilitates Convergence: Normalizing data facilitates the rapid convergence of aoptimizations algorithmse, (such asgradient descent), by preventing the occurrence of substantial weight updates that may impede the efficiency of the learning process.

Prevents Dominance of Certain Features: If normalization is not performed, there is a possibility that features with larger scales will exert a stronger influence on the model, resulting in biased predictions. The act of normalizing guarantees that all features contribute equitably to the learning procedure.

After preprocessing the data and removing the columns which have above 40% leak and imputing the missing data for columns that have missing records, we have to filter the signals (data) to make the records smooth and more reliable for training the RNN model. Here we filter the data using EMA filter (Exponential Moving Average) which has a parameter span that determines how much samples to take for exponentially averaging the values to fill in the missing data with. we illustrate our results for each feature (sensor record data).

The Exponential Moving Average (EMA): The filter is an Infinite-Impulse Response (IIR) low-pass, discrete filter. By exponentially discounting earlier data, it gives more weight to recent data, and exhibits similar behavior to the discrete first-order low-pass RC filter. In contrast to a finite impulse response (FIR) filter, most EMA filters are not windowed and rely on all previous inputs to determine the next value. However, there are exceptions to this rule, and it is possible to construct a windowed exponential moving average filter with exponentially weighted coefficients. It is simple to find the difference equation for an exponential moving average filter.

$$y[n] = \alpha x[n] + (1 - \alpha) y[n - 1]$$

The current output in this equation is denoted by $y[n]$, the prior output by $y[n - 1]$, and the current input by $x[n]$. The variable α is a number between 0 and 1. If $\alpha = 1$, there is no filtering and the output is just equal to the input. 'Exponential' is the name given to the filter since the weighting factor of the prior inputs drops exponentially[28].

After processing the data, the (EMA) filter was applied to the real data available to us through the dump truck sensors. We obtained the results Filter data.

Feature Engineering: To enhance the modeling process, it is necessary that the collected data accurately reflects the underlying reality. The original dataset often includes various forms of interference, such as incomplete or erroneous values, superfluous information, or anomalous readings stemming from sensor malfunction or the unavailability of recording. By means of feature engineering, the raw data is subjected to a transformation that captures the essence of the interplay between different features within the predictive model, thereby resulting in an overall improvement in performance, see Table 1.

Table 1. A collection of characteristics for modeling fuel consumption.

NO.	Features	Description
1	Path	The route it follows dump truck while moving from one location to another.
2	Speed	Speed of dump truck atthe current instance (km/h)
3	Engine speed	Speed of aengine (rpm)
4	Load capacity	Dump truck with a payload capacity of tons
5	Current engine load	Load onthe engine (%)
6	Longitudinal inclination	The longitudinal direction for the vertical alignment of the road.
7	Lateral slope	
8	Dump truck model	Dump truck identifier
9	ICE.Fuel consumption	How much fuel you consume per unit of trip
10	Fuel consumption	Actual fuel reading in the tank
11	Right rear cylinder pressure	Basis for gaining a measure of how the various components move around for dump truck
12	Pressure left rear cylinder	Basis for gaining a measure of how the various components move around for dump truck
13	Dump truck	Type of dump truck
14	Dump truck status_Loaded moves forward	Dump truck forward movement
15	Dump truck status_Loaded moves backward	Dump truck movement backwards
16	Dump truck status_Loaded stands	Loaded dump truck condition
17	Estimated engine torque output (percentage of reference)	Torque of engine (%)
18	X-axis acceleration	Acceleration can occur along an X axis
19	Y-axis acceleration	Acceleration can occur along an Y axis
20	Z-axis acceleration	Acceleration can occur along an Z axis
21	Latitude	Values that describe the route's path in the response
22	Slope	The average incline or the road that the dump truck is operating on.
23	Instant weight	The weight of the dump truck varies when loaded and unloaded
24	Longitude	
25	len	

Experience results compared to performance measures.

The coefficient of determination (R2/accuracy), mean squared error (MSE)/loss, mean absolute error (MAE), and root mean square error (RMSE) are used to assess how well the suggested model predicts fuel consumption. Below is an explanation of the laws for each of them. The fuel consumption of contemporary dump trucks is modeled in this study utilizing sensor data collected on various highways, driving situations, and outside variables. 25 features such as path, dumper loadThe model uses several inputs, such as engine load (%), engine speed (rpm), vehicle speed (km/h), etc. For training, we chose 100 time steps for each patch (i.e., batch size = 100), while prediction will be for 5 future time steps. The training process lasted for 10 epochs; The training process continued for 10 eras. Both training and validation data's mean absolute error (MAE) and mean square error (MSE) are displayed in the loss plots in Figure (5).The minimums disparity between the generalization agap observed in the training data andthe validationa datas loss plots is

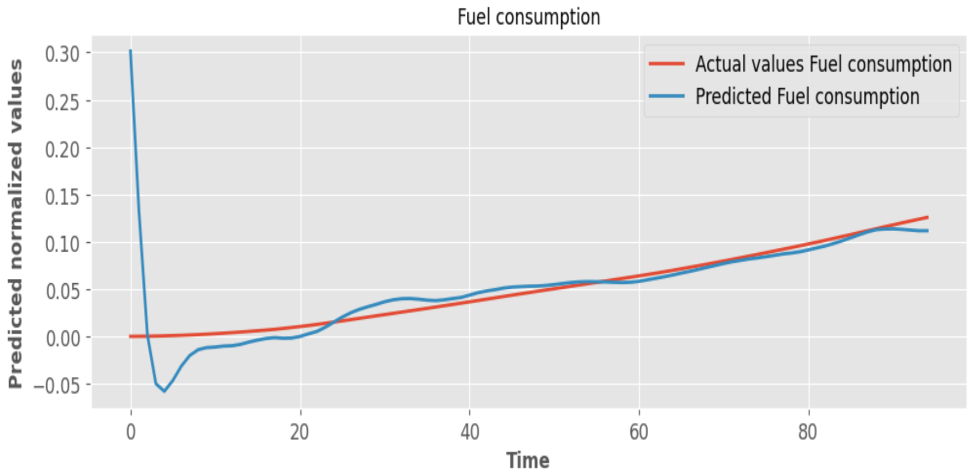

Figure 6. Fuel Consumption.

indicative of a well-suited model. The generalizations ofthe recurrent neural anetwork (RNN) LSTM with dense layers is evaluated using test data gathered from a single journey. From Figuore (), the datas points that are in close proximity to the regression line suggest that the proposed model has the capability to effectively forecast fuels consumptions with minimal errors. Conversely, Outliers are present in the dataset if the data points are located far from the regression line. These anomalies can be ascribed to abrupt changes in engine and vehicle speed that the neural network failed to detect, see Figure 7.

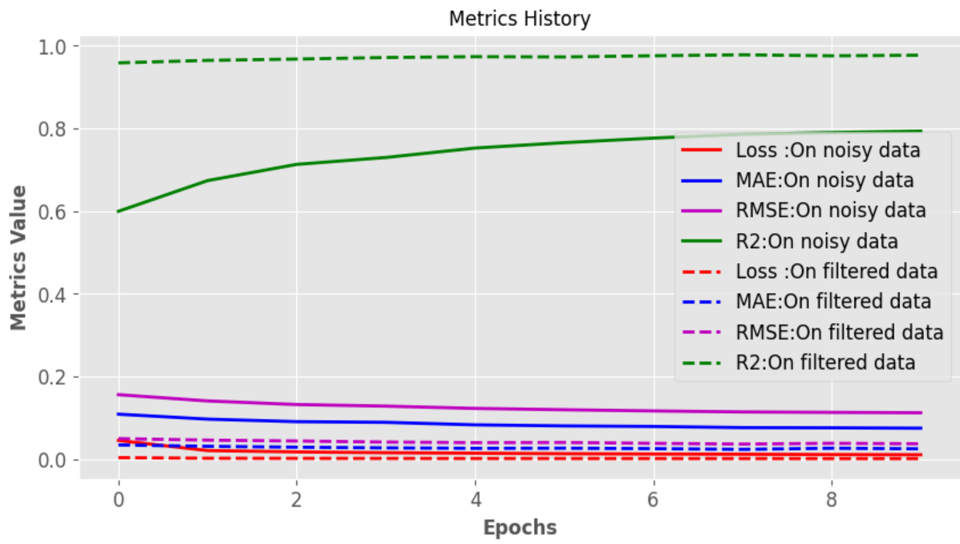

Figure 7. Metrics History.

The table 2 presents a comparative performance analysis of machine learning models for fuel consumption prediction. Metrics such as MAE, RMSE, and R2R^2R2 indicate model accuracy. The Artificial Neural Network (ANN) achieved the highest R2R^2R2 (0.9443) with 10 features, outperforming MLP NN, KNN, and Gradient Boosting in predictive capability.

Table 2. Performance testing on a dataset using our model.

Model	**MAE**	**RMSE**	***R²***	***No. features***	***Description***	***References***
MLP NN	0.0614	0.0772	**0.7854**		Excavator fuel consumption	
KNN	0.0595	0.0796	**0.7200**	**10**		[29]
Gradient Boosting (GB)	0.0582	0.0762	**0.7330**			
Artificial Neural Network (ANN)	0.0006	0.0010	**0.9443**	**10**	Dump truck fuel consumption	[30]

The cumulative fuel consumption is calculated by adding together the instantaneous fuel rate readings every second to determine the total quantity of fuel used by a vehicle. The model and the results are assessed using the performance metrics on noise data loss:0.0106, MAE: 0.021, MSE:0.0106, RMSR:0.1029, MAE:0.0698, R2:0.8267 and we obtained values on filtered data are loss:0.0008, MSE:0.0009, RMSE: 0.029, and R2 value is 0.984 for the training data.

The proposed model was compared in Table No. (3) with machine learning algorithms and techniques and artificial intelligence networks, where the accuracy R2 appeared lower, and the study proved that the proposed model gave us more efficiency and accuracy.

Table 3. Performance Evaluation of the Proposed LSTM-DNN Model.

Model	**Loss**	**MAE**	**MSE**	**RMSE**	***R²***		***No. features***
Our proposed LSTM-DNN	0.0106	0.0698	0.0106	0.1029	0.8267	**On noise data**	**25**
	0.0008	**0.0210**	**0.0009**	**0.0294**	**0.9842**	**On filtered data**	

4. Conclusion

Our study explained the modeling of afuel consumption in modern adump trucks in openpit mines based on the available data, using the recurrent neural network (LSTM) algorithm and combining it with deep learning using dense layers. An endeavor was undertaken to construct a framework utilizing a minuscule number of parameters gathered under diverse circumstances in order to educate a recurrent neural network. The framework is established on data and parameters that are effortlessly procured from the vehicle during its trip. The effectiveness metrics of R-squared (R2), mean squared error (MSE)/loss, mean absolute error (MAE), and root mean squared error (RMSE) show that an accurate predicted can be obtained by employing the model. Moreover, it can assist in diagnosing the vehicle's functionality in the event of a malfunction. The utilization of model and expeditious real-time prediction models will facilitate an enhancement in fuel consumption. This study can be extended to include more factors that affect gasoline use, such as time, GPS data, traffic information, route information, etc.

REFERENCES

[1] Wincono and J. R. Horman, "Analisis Pengaruh Kemiringan Jalan Angkut Terhadap Konsumsi Bahan Bakar Dump Truck Hino 500 FG 235 JJ," *INTAN Jurnal Penelitian Tambang*, vol. 2, no. 2, pp. 155-160, 2019.

[2] E. Siami-Irdemoosa and S. R. Dindarloo, "Prediction of fuel consumption of mining dump trucks: A neural networks approach," *Appl. Energy*, vol. 151, pp. 77-84, 2015.

[3] T. Bousonville, M. Dirichs, and T. Krüger, "Estimating truck fuel consumption with machine learning using telematics, topology and weather data," in *Proc. 2019 Int. Conf. Ind. Eng. Syst. Manag. (IESM)*, 2019, pp. 1-6.

[4] D. Mykola and S. Oleksandr, "Theoretical justification of factors of influence on fuel consumption of dump trucks in the process of unloading bulk cargo," *World Science*, vol. 2, no. 74, 2022.

[5] L. K. Sahoo, S. Bandyopadhyay, and R. Banerjee, "Benchmarking energy consumption for dump trucks in mines," *Appl. Energy*, vol. 113, pp. 1382-1396, 2014.

[6] D. Mykola and S. Oleksandr, "Theoretical justification of factors of influence on fuel consumption of dump trucks in the process of unloading bulk cargo," *World Science*, vol. 2, no. 74, 2022.
[7] T. Bousonville et al., "Data driven analysis and forecasting of medium and heavy truck fuel consumption," *Enterp. Inf. Syst.*, vol. 16, no. 6, pp. 1856417, 2022.
[8] Y. Zhou et al., "Prediction model of fuel consumption of heavy truck based on improved BP neural network," in *Proc. 2022 IEEE Intl Conf. Dependable, Autonomic, Secure Comput., Intl Conf. Pervasive Intell. Comput., Intl Conf. Cloud Big Data Comput., Intl Conf. Cyber Sci. Technol. Congress (DASC/PiCom/CBDCom/CyberSciTech)*, 2022, pp. 1-6.
[9] C. Chenxi et al., "Research on vehicle fuel consumption prediction model based on Cauchy mutation multiverse algorithm," in *Proc. 2022 9th Int. Forum Electr. Eng. Autom. (IFEEA)*, 2022, pp. 1-6.
[10] C. Chenxi et al., "Research on vehicle fuel consumption prediction model based on Cauchy mutation multiverse algorithm," in *Proc. 2022 9th Int. Forum Electr. Eng. Autom. (IFEEA)*, 2022, pp. 1-6.
[11] G. Pereira et al., "Fuel consumption prediction for construction trucks: A noninvasive approach using dedicated sensors and machine learning," *Infrastructures*, vol. 6, no. 11, pp. 157, 2021.
[12] S. Katreddi, "Development of Machine Learning based approach to predict fuel consumption and maintenance cost of Heavy-Duty Vehicles using diesel and alternative fuels," 2023.
[13] A. Bhoraskar, "Prediction of fuel consumption of long haul heavy duty vehicles using machine learning and comparison of the performance of various learning techniques," 2019.
[14] S. Ren et al., "Investigation of Heavy-Duty Vehicle Chassis Dynamometer Fuel Consumption and CO2 Emissions Based on a Binning-Reconstruction Model Using Real-Road Data," *Atmosphere*, vol. 14, no. 3, pp. 528, 2023.
[15] S. N. Mohanty, L. E. L. Lydia, M. Elhoseny, M. M. G. Al Otaibi, and K. Shankar, "Deep learning with LSTM based distributed data mining model for energy efficient wireless sensor networks," *Phys. Commun.*, vol. 40, pp. 101097, 2020.
[16] F. Perrotta, T. Parry, and L. C. Neves, "Application of machine learning for fuel consumption modelling of trucks," in *Proc. 2017 IEEE Int. Conf. Big Data (Big Data)*, 2017, pp. 1679-1687.
[17] Q. Zhang, Y. Bu, B. Chen, S. Zhang, and X. Lu, "Research on phishing webpage detection technology based on CNN-BiLSTM algorithm," *J. Phys. Conf. Ser.*, vol. 1738, pp. 012131, 2021.
[18] J. Brownlee, *Long short-term memory networks with python: Develop sequence prediction models with deep learning*. Machine Learning Mastery, 2017.
[19] S. G. Jing, F. B. Li, and X. Ma, "Digital Mining Control Management System in an Open Pit Based on GIS/GPS/GPRS," *Key Eng. Mater.*, vol. 467, pp. 207-211, 2011.
[20] H. Altiti, R. Alrawashdeh, and H. Alnawafleh, "Open Pit Mining," in *Mining Techniques: Past, Present and Future*, 2021, pp. 1-10.
[21] H. Amankwah, "Mathematical optimization models and methods for open-pit mining," Ph.D. dissertation, Linköping University Electronic Press, 2011.
[22] Z. Jian and O. G. Troyanskaya, "Predicting effects of noncoding variants with deep learning-based sequence model," *Nat. Methods*, vol. 10, no. 9, pp. 931-934, 2015.
[23] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436-444, 2015.
[24] A. Garcia-Garcia et al., "A survey on deep learning techniques for image and video semantic segmentation," *Appl. Soft Comput.*, vol. 70, pp. 41-65, 2018.
[25] S. K. Pal and S. Mitra, *Multilayer Perceptron, Fuzzy Sets, Classification*, 1992.
[26] N. Kussul et al., "Deep learning classification of land cover and crop types using remote sensing data," *IEEE Geosci. Remote Sens. Lett.*, vol. 14, no. 5, pp. 778-782, 2017.
[27] A. Sherstinsky, "Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network," *Physica D: Nonlinear Phenomena*, vol. 404, pp. 132306, 2020.
[28] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735-1780, 1997.
[29] N. Christanto, "Optimization of Exponential Moving Average (EMA) and Moving Average Convergence Divergence (MACD) trading strategy on Trading Foreign Exchange," 2021.
[30] A. K. Saim, F. N. Kumah, and M. N. Oppong, "Predicting Mining Excavator Fuel Consumption using Machine Learning Techniques," *Adv. Eng. Design Technol.*, vol. 2, pp. 1-5, 2020.

[31] S. Katreddi and A. Thiruvengadam, "Trip based modeling of fuel consumption in modern heavy-duty vehicles using artificial intelligence," *Energies*, vol. 14, no. 24, pp. 8592, 2021.