Deep Sequence Modeling of Dump Truck Sensor Data for Fuel Efficiency and Engine Health Prediction

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Abstract

The Fourth Industrial Revolution represents a shift to a more connected, digital world across all industries, including mining. The application of smart sensors will reduce site risks and fuel consumption, reduce equipment breakdowns, improve preventative maintenance, and improve equipment efficiency, including dump truck engines. Dump truck fuel efficiency is influenced by a number of real-world factors, including driver behavior, road and weather conditions, and vehicle specifications. Additionally, potential engine failures and other aspects can impact vehicle outcomes. By using dynamic on-road data to predict fuel consumption per trip, the industry can effectively minimize the expense associated with driving evaluations. Furthermore, analysis of data provides valuable insights into identifying the underlying causes of fuel consumption by analyzing input parameters. This paper proposes and evaluates novel models for predicting dump truck fuel consumption and engine failures in open-pit mining. These models combine the power of features derived from data collected locally by dump truck sensors and their analysis. The fuel consumption prediction architecture for open-top mining trucks using an improved Long Short-Term Memory (LSTM) model and a double-layer thick Deep Neural Network (DNN) forms the basis of the model design, which consists of two separate components. Multi-delay Recurrent Neural Network (RNN) models have been found to be efficient and accurate. The RNN architecture is applied to capture the cyclic components and complex rules in engine consumption data. This research relied on essential factors (route, vehicle speed, engine revolutions, and engine load). The proposed model outperforms existing models, achieving (MAE=0.0210), (RMSE=0.0294), (MSE=0.0009), and accuracy (R^2=0.9842), demonstrating that it can produce highly accurate predictions.

Keywords: Recurrent Neural Networks (RNNs); Fuel Consumption; Engine Failures; Deep Learning (DL); Mining Dump Trucks

1 Introduction

The Fourth Industrial Revolution 4, also known as Industry 4.0, represents a fundamental shift in the way we live, work, and interact. It is characterized by the convergence of technologies that blur the boundaries between the physical, digital, and biological realms [1]. The Fourth Industrial Revolution builds on the digital revolution that has been taking place since the middle of the last century integration of artificial intelligence (AI), the Internet of Things (IoT), and cyber-physical systems [2]. AI improves operational optimization through data-driven decision making, enabling precise control over drilling, blasting, and mining processes [3] AI-powered predictive maintenance minimizes equipment downtime by predicting breakdowns before they occur, thereby ensuring smooth operations and reducing maintenance costs [4]. In addition, AI significantly improves

DOI: https://doi.org/10.54216/FPA.210204

Received: February 07, 2025 Revised: May 31, 2025 Accepted: July 06, 2025

safety by monitoring environmental conditions and automating hazardous tasks with autonomous vehicles and drones [5]. Overall, integrating AI into open-pit mining not only improves productivity and cost efficiency, but also contributes to safer and more sustainable mining operations [6].Mining and transport complexes (MTC) are one of the basic elements of mineral extraction and one of the goals of digital transformation [7]. To achieve this transformation, all subsystems of an MTC must function in a coordinated manner. These include both stationary installations (e.g., gas stations, excavation and loading sites) and mobile assets (e.g., drilling rigs and dump trucks). An automated control system (ACS) is needed to monitor vehicle conditions, dispatch logistics, and control fuel and load management [8]. This study evaluates novel models for predicting dump truck fuel consumption and engine failures in open-pit mining. These models utilize data collected from truck sensors and apply a hybrid architecture combining Long Short-Term Memory (LSTM) and Deep Neural Network (DNN) models [9]. The model consists of two components: an LSTM–DNN and a double-layer dense neural network, with additional use of multi-delay Recurrent Neural Networks (RNNs) to capture cyclic and temporal dependencies [10]. like route, speed, engine load and engine revolutions. The MTC configuration includes stationary installations (gas stations, excavation and loading sites) and movable property (drilling rigs, vehicles). To control mobile assets, an automated control system (ACS) is required, responsible for data collection, dispatching, load and truck movement control, equipment condition monitoring, and tire usage control. Thus, the MTC structure is formed by many subsystems and elements characterized by a significant number of indicators [11].

The remainder of this paper is structured as follows: Section 2 presents related work on predictive maintenance and deep learning approaches applied to sensor data in industrial settings. Explaining the main factors affected the: fuel consumption and Engine Health issues. Section 3 outlines the problem definition and provides a system-level overview. Section 4 describes the dataset and details the pre-processing steps, including imputation, normalization, feature selection and Data splitting. Section 5 introduces the proposed hybrid LSTM-DNN architecture for multiclass engine failure prediction. Section 6 explains the experimental setup and discusses model interpretability and practical implications for smart mining applications, including training parameters and evaluation strategy. Section 7 presents the results, including performance metrics and analysis. Section 8 concludes the paper and outlines directions for future research.

2 Literature Review

The use of data to predict heavy truck fuel consumption in neural networks has been explored in several studies. An Artificial neural network (ANN) technique used to estimate the fuel consumption in mining dump trucks. The results demonstrated the considerable effect of mining trucks idle times in fuel consumption [12]. Estimate the truck 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 [13]. Focuses on benchmarking energy consumption and estimating minimum Specific Fuel Consumption (SFC) for dump trucks in mines, a generic model is presented to benchmark energy consumption for dump trucks in mines. The model estimates minimum specific fuel consumption and shows potential fuel savings [14]. 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 [15].

The work focuses on data-driven analysis and forecasting of medium and heavy truck fuel consumption in general, and the work provides a data-driven analysis and forecasting of medium and heavy truck fuel consumption, and emphasizes the need for transparency in determining the most fuel-efficient truck models [16]. proposed a Back Propagation (BP) neural network model based on heavy truck driving behavior data, which was improved using genetic algorithm (GA), simulated annealing algorithm (SA), and genetic annealing algorithm (GSA) [17]. A back propagation fuel consumption prediction model based on the Cauchy Multi-Verse optimizer (CMVO) for plateau conditions, which showed improved prediction accuracy compared to other algorithms [18]. 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 [19]. Diesel engines are vital for the operation of dump trucks, and their failures can significantly impact productivity and operational efficiency. Failure types were categorized based on domain-specific thresholds for various critical parameters including issues with specific engine components and subsystems, as well as broader reliability concerns.

Failures in components like pinion gears are often linked to non-standard material compositions and improper treatment processes, leading to fatigue failures. Diesel Particulate Filter (DPF) Failures, such as pinhole, melt,

Received: February 07, 2025 Revised: May 31, 2025 Accepted: July 06, 2025

crack, and fouling failures, were linked to changes in the chemical composition and crystalline structure of the cordierite substrate. These failures compromise the emission control capabilities of the diesel engines [20]. The fuel supply system had the highest reliability, while the self-starting subsystem had the lowest. This analysis was based on statistical methods like the Common Beta Hypothesis test and Meta-analysis test. Analysis of after-sales maintenance data identified the fuel supply system as a major failure point, with electronic devices and high-pressure components being particularly vulnerable. The service background significantly affects engine life [21]. Methods such as Pareto analysis, Failure Mode and Effect Analysis (FMEA), and Systematic Cause Analysis Technique (SCAT) were employed to address performance issues in dump trucks. These methods helped prioritize and manage failures, with significant issues identified in low power errors, work lamp problems and engine start failures. Insufficient lubricity in diesel fuel has been identified as a major cause of engine failures, particularly in overhauled engines, resulting in piston seizures [22] .

3 System Overview and Problem Definition

Efficient fuel usage and engine health monitoring are critical components in open-pit mining operations, where dump trucks operate under high loads and harsh conditions. Unmonitored inefficiencies can lead to increased fuel costs, unplanned downtime, and equipment failure. This study addresses two key predictive maintenance tasks using real-world sensor data from dump trucks:

1. Fuel Efficiency Prediction: Estimating fuel consumption patterns based on operational parameters (load, speed, slope, and engine RPM).
2. Engine Health Classification: Detecting and classifying engine health status into predefined conditions based on critical sensor readings.

The model is designed to process multivariate time-series data and generate accurate predictions that can assist mine operators in optimizing fuel usage and planning preventive maintenance. This study contributes to the development of smart mining technologies, enabling real-time monitoring and predictive insights that enhance both energy efficiency and equipment longevity. Figure (1) presents a Flowchart for the proposal model.

The proposed pipeline consists of the following stages:

- Data Collection: Second-by-second sensor data is collected during operational trips, resulting in 3112 trip records and 40 raw features.
- Data Pre-processing: The dataset undergoes imputation, feature selection (25 key features), normalization, and transformation to improve model performance.
- Modeling: A hybrid deep learning architecture combining Long Short-Term Memory (LSTM) and Dense Neural Network (DNN) layers is used to capture temporal dependencies and feature interactions.
- Prediction and Evaluation: Fuel efficiency is modeled as a regression task, while engine health is framed as a multiclass classification problem. The models are evaluated using appropriate metrics such as MAE, RMSE, R^2 and confusion matrix.

4 Dataset Collection and Pre-processing

Data is read from the sensors while the dump truck is traveling, especially when loading heavy materials (this is where the engine load and torque are maximized. During road tests, the sensors output second-by-second data to a CSV file for each journey. Table (1) illustrate the data obtained from the tipper sensors, the CSV data contains (3112 rows) and (40) columns. A total of 25 features were selected for model training and testing based on their relevance and data quality. Records with more than 40% missing values were excluded, as preliminary testing showed that such entries degraded imputation accuracy and model reliability. This cutoff also aligns with thresholds commonly adopted in industrial sensor-data processing. for reduce dimensionality and improve learning efficiency. This selection was guided by domain knowledge, correlation heatmaps, and feature variance analysis, ensuring that highly informative and relevant attributes were retained. Table (2) represents the 25 selected features from the dataset.

DOI: https://doi.org/10.54216/FPA.210204

Received: February 07, 2025 Revised: May 31, 2025 Accepted: July 06, 2025

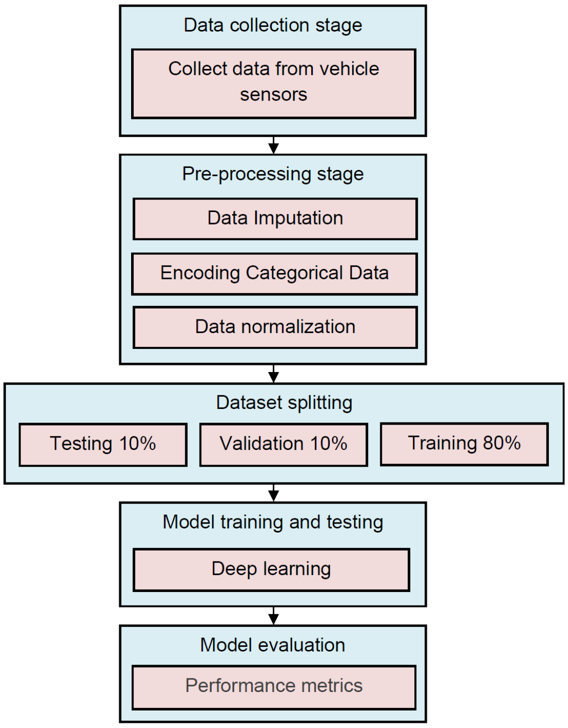

Figure 1: Flowchart proposal model.

4.1 Data Pre-Processing

The raw data, collected from dump truck sensors during open-pit mining operations, consists of 40 parameters measured at one second intervals across 3,112 recorded trips. Before feeding the data into the deep learning models, several pre-processing steps were performed to improve data quality, enhance model performance, and reduce computational complexity. for our model the pre-processing stage containing:

4.1.1 Data Imputation

Responsible of removing features with a high percentage of missing values (more than 40%) were considered for several reasons: Features with a substantial percentage of missing values might lack sufficient data integrity or quality, potentially impacting the reliability of those features. High missing value percentages can bias the understanding or representation of those features, leading to inaccurate conclusions or models. Fewer features with a significant number of missing values simplify the dataset, reducing computational complexity during analysis or modeling. Eliminating these features can speed up data processing and model training, especially in scenarios with large datasets. Features with substantial missing values might introduce noise into the model or hinder its ability to learn meaningful patterns. Removing such features might enhance the generalization ability of the model by reducing overfitting. The threshold of 40% is arbitrary and should be determined based on domain knowledge, understanding the specific dataset, and the significance of each feature to the task at hand [23].

4.1.2 Encoding Categorical Data

To increase the performance of models, pre-processing categorical data with One-Hot Encoding is necessary [24]. This approach converts categorical variables into a format that machine learning algorithms can use. To make them more accessible to machine learning algorithms, it converts category variables to a binary format. One-Hot Encoding creates binary columns (0s and 1s) [25], with each column representing one category. Only one column in each set of binary columns will contain a 1 (indicating the presence of that category) while the others will be 0s. Reasons for using One-Hot Encoding:

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Table 1: Samples of data read from tipper sensors in csv file, full dataset contains 3112 rows and 40 columns.

Index	len	Speed	Latitude	Longitude	Instant Weight	Lateral Slope	Height	Fuel Level (L)
0	10	5	54.159399	87.121072	221.0	4.00	287.0	NaN
1	13	11	54.159434	87.121223	221.0	3.00	288.0	NaN
2	15	8	54.159445	87.121263	221.0	3.00	288.0	NaN
3	18	9	54.159449	87.121298	223.0	3.00	288.0	NaN
4	21	8	54.159459	87.121334	224.0	3.00	289.0	NaN
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
3107	2218	5	54.152425	87.120592	217.0	5.00	363.0	NaN
3108	2219	4	54.152436	87.120615	219.0	2.00	363.0	NaN
3109	2221	4	54.152442	87.120635	221.0	2.00	363.0	NaN
3110	2222	4	54.152448	87.120657	224.0	2.00	362.0	NaN
3111	2223	3	54.152458	87.120678	225.0	1.05	362.0	NaN

Table 2: Features set used in the model.

No.	Feature	Description
1	Path	The route the dump truck follows when moving between locations.
2	Speed	Current speed of the dump truck (km/h).
3	Engine Speed	Engine rotational speed (RPM).
4	Load Capacity	Carrying capacity of the dump truck at its maximum, measured in tons.
5	Current Engine Load	Current load on the engine (%).
6	Longitudinal Inclination	Vertical alignment of the road in the longitudinal direction.
7	Lateral Slope	Horizontal slope across the road surface.
8	Dump Truck Model	Identifier for the dump truck model.
9	ICE Fuel Consumption	Estimated fuel consumed by the internal combustion engine per trip unit.
10	Fuel Consumption	Actual fuel reading in the tank.
11	Right Rear Cylinder Pressure	Pressure measurement indicating component movement at the right rear cylinder.
12	Left Rear Cylinder Pressure	Pressure measurement indicating component movement at the left rear cylinder.
13	Dump Truck Type	Classification or type of dump truck.
14	Status: Loaded Moves Forward	Indicates when a loaded dump truck is moving forward.
15	Status: Loaded Moves Backward	Indicates when a loaded dump truck is reversing.
16	Status: Loaded Stands	Indicates when a loaded dump truck is stationary.
17	Estimated Engine Torque Output	Engine torque output as a percentage of reference value.
18	X-Axis Acceleration	Acceleration along the X-axis.
19	Y-Axis Acceleration	Acceleration along the Y-axis.
20	Z-Axis Acceleration	Acceleration along the Z-axis.
21	Latitude	Geographic latitude of the dump truck's location.
22	Slope	Averages incline of the road on which the dump truck operates.
23	Instant Weight	Current weight of the dump truck (loaded or unloaded).
24	Longitude	Geographic longitude of the dump truck's location.
25	Track Length (len)	Length of the road or path segment the dump truck is traveling on.

- Machine learning models work with numerical data. One-Hot Encoding transforms categorical variables (like color, gender, country) into numerical format without imposing any ordinal relationship between categories.
- Avoids implying any ordinal relationship between categories that ordinal encoding might impose. For example, 'low', 'medium', 'high' might mistakenly suggest a sequential order if encoded numerically.
- Prevents a model from assuming a false hierarchy in categorical variables, thereby improving the learning process and model performance.

4.1.3 Data normalization

It is a crucial pre-processing step in machine learning that involves transforming the features of a dataset to a standard scale without distorting the differences in the ranges of values [24]. It's done to bring all features onto a similar scale or range, which offers several benefits:

- Helps the optimization algorithms converge more quickly, as it avoids extreme weight updates that can slow down the learning process.

DOI: https://doi.org/10.54216/FPA.210204

Received: February 07, 2025 Revised: May 31, 2025 Accepted: July 06, 2025

- Ensures that all features contribute proportionally to the learning process.
- Stabilizing the training process by ensuring that the weights and biases don't fluctuate significantly, which could slow down or prevent convergence.
- Datasets often contain features with different units and scales. Normalization brings them to a common scale, making the comparison and analysis easier.

4.1.4 Data splitting

In this study,the dataset sorted down into three primary sets categories:

1. The training: the most significant component of the dataset, taking up to (80%) of the overall dataset contents. this category primary function is to train the models while simultaneously modifying the weights through the learning process and checking the training proper outcomes.
2. The validation: take (10%) from the sensors data set, this portion utilized in order to assess the model via the modification of the hyperparameters, it has an indirect influence on the models and is not applied for the purposes of learning.
3. The testing: also take (10%), this group utilized to guarantee an objective and accurate evaluation of the models after the training procedure completion.

4.1.5 Feature Transformation

The collected data must accurately reflect the underlying reality for much improves model performance. 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. 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.

5 The Proposed Model Architecture

The proposed DL architecture comprises a fusion of two distinct neural networks. Conversely, one cannot disentangle these two networks or execute independent training, thereby yielding a singular model. RNNs and LSTM networks are commonly used for time series forecasting due to their ability to capture sequential dependencies and patterns within the data. 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 time steps. For training, we chose 100 time steps for each patch (batch size = 100), while prediction will be for 5 future time steps. The training process lasted for 10 epochs. Using 2 LSTM layers followed by Dense layers in a forecasting model has these advantages.

Additionally, there are other parameters involved in determining the power and efficiency of a lorry engine

1. Gross vehicle mass (GVM), which is the sum of the empty truck mass and the payload.
2. Truck speed.
3. Total Resistance (TR), which is the sum of Rolling Resistance and Slope Resistance when the truck is traveling against a road gradient.
4. Resistance Force, which is the force acting between the tires and the ground to propel the truck.

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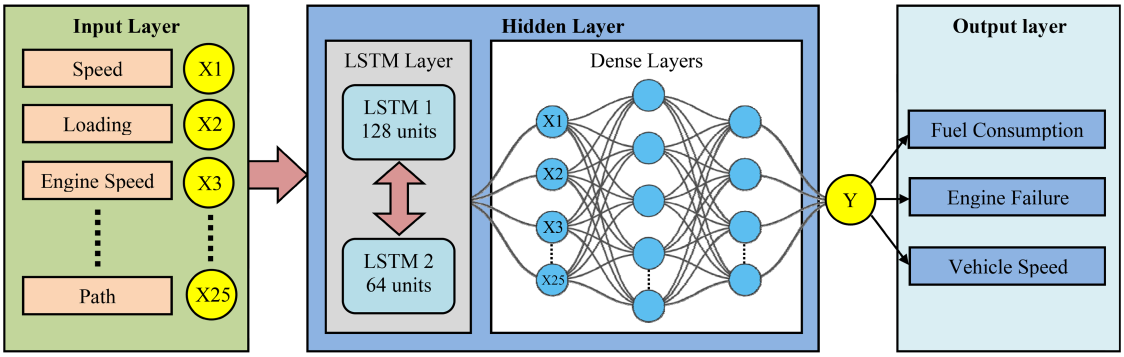

Figure 2: Proposed LSTM-DNN Model architecture.

Predicting DL model for fuel consumption and engine failure presented of modern dump trucks based on information from their sensors in various driving scenarios and on different roads, taking into account the influence of external variables. The model uses 40 parameters, from which we extract 25 features as input data, comprising, truck load,route, engine speed, engine load, vehicle speed, among others. figure (2) represent a diagram of the architecture used in the proposed LSTM-DNN model.

In this study, engine failure is defined as any trip record during which critical sensor readings exceed predefined safety thresholds. For example, the engine temperature exceeding 105°C, abnormally high fuel consumption increased for more than 40 L/h, or sustained other parameter data values beyond the expected operational limit. These thresholds were selected based on domain expert recommendations and manufacturer specifications. Each trip was labeled as either:

- Normal (0): All parameters remain within safe operating ranges.
- Failure (1): One or more key parameters exceed failure thresholds persistently, signaling potential engine malfunction or unsafe operation.

6 Experimental Setup and Discussion

LSTM networks were developed to mitigate the diminishing value problem seen by conventional RNNs while learning long-term correlations in consecutive input. LSTMs may retain information for prolonged durations because to their memory cells and gating processes. The memory cells are regulated by three principal gates: (input, forget and output) gates. This method demonstrates the implementation of LSTM Networks via TensorFlow. figure (3) illustrate the training and testing processes.

Using 2 LSTM layers followed by Dense layers in a predicted model has specific advantages:

1. LSTM layers are designed to handle sequential data by maintaining memory over time. This allows them to capture long-term dependencies within time series data, which is crucial for accurate forecasting.
2. Multiple LSTM layers (stacked LSTMs) enable the model to learn more complex temporal patterns and relationships present in the time series data, capturing both short-term and long-term patterns.
3. Stacked LSTM layers allow the network to learn hierarchical representations of the temporal data, where each layer extracts and refines features from the previous layer, potentially improving the model's ability to capture intricate patterns.
4. The addition of Dense layers after LSTM layers enables the model to learn higher-level representations and mappings from the learned temporal features to the target variable for forecasting.
5. The flexibility of the architecture allows for adjustments in the number of LSTM layers, units in each layer, and Dense layers based on the complexity and characteristics of the data.

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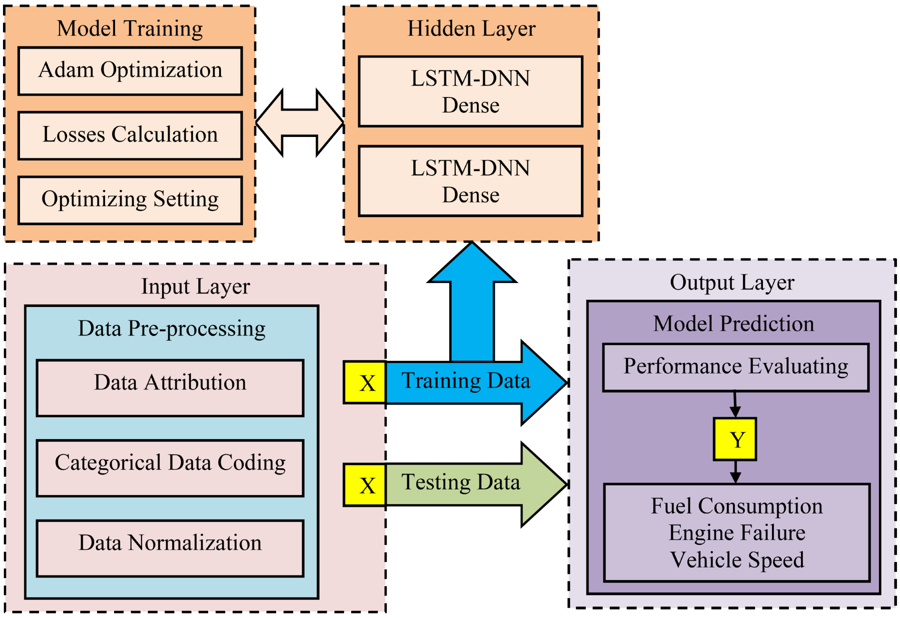

Figure 3: Diagram showing the stages of training and testing data.

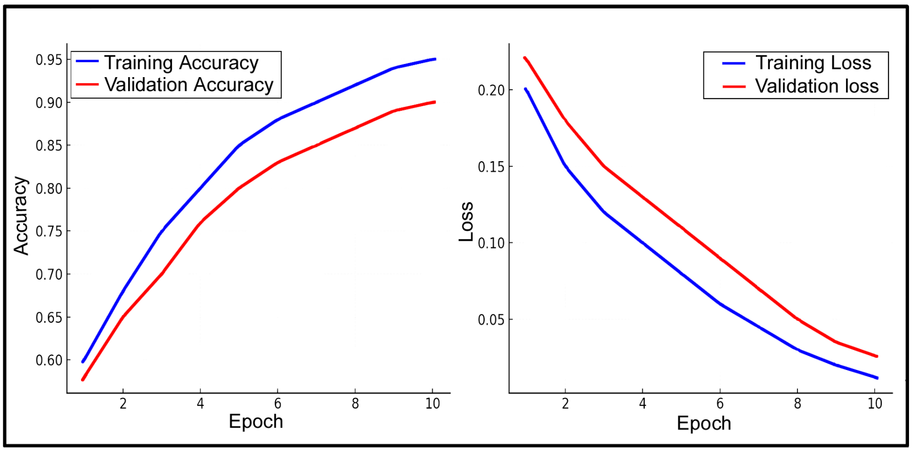

Figure 4: Proposed LSTM-DNN Model (a) Accuracy of Training and Validation, (b) Loss Function.

The model was trained on a data sample after doing the above mentioned pre-processing techniques and we got very promising results where, loss: 0.0122 - val_loss: 0.0262. figure (4): (a) show the training accuracy and (b) show loss function, both training and validation losses consistently decreased over the 10 epochs. the hyperparameters of the modele listed in table(3).

- Load Libraries and Datasets: importing the requisite libraries, including: (sklearn, numpy, pandas, tensorflow and matplotlib).
- Data Preparation and Scaling: this step includes:
  - Use the dataset for dump truck sensor using LSTM.
  - perform time period investigation by import data collection from the dump vehicle's sensor.
  - Use MinMaxScaler to make the data range between [0, 1] so the model can train properly.
- Generating Sequences and Partitioning Data: produce patterns from input data and separate the dataset to testing and training subgroups. The raw data set reformed according to the specifications of LSTM input.
- Constructing LSTM Model: This phase entails delineating and assembling the design of the LSTM structure. The framework has 2 LSTM layers, each with 128 units, followed by a layer of 64 units to mitigate overfitting. The model culminates in a Dense layer with two layers in order for predicting an

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Table 3: Proposed model hyperparameters.

Hyperparameter	Value	Description
Batch Size	100	Number of time steps per input patch during training.
Epochs	10	Number of full training passes over the dataset.
Sequence Length	100	Length of the input sequence (time steps) fed to the LSTM model.
Prediction Horizon	5	Number of future time steps to predict.
LSTM Layers	2	Number of stacked LSTM layers in the architecture.
LSTM Units (Layer 1)	128	Number of memory units in the first LSTM layer.
LSTM Units (Layer 2)	64	Number of memory units in the second LSTM layer.
Dense Layers	2	Number of fully connected layers after LSTM layers.

individual outcome.

- Model training and testing: The model trained using 100 time-steps each patch (batch size = 100), whereas the prediction for 5 subsequent period steps evaluated. The training extended throughout 10 epochs. Upon completion of training, the Optimizer was Adam, Learning Rate was 0.001 and the Activation Functions were ReLU for hidden layers and softmax for the output layer in classification and linear for regression output, the model is employed to generate predictions on the test collection, and Root Mean Squared Error (RMSE) is computed in order to evaluate efficiency.
- The data was randomly shuffled but kept consistent across experiments to prevent data leakage. Overfitting was monitored using validation loss and early stopping techniques.

7 Results and Evaluation

The research introduce a DL model for two parameters (fuel consumption , engine failure) prediction using data from sensors installed on trucks vehicle. Subjecting variety of environmental parameters was considered during sensor data gathering. Data input to the model comes from 25 various features, including the following: truck load, route, load percentage (%), engine speed in revolutions per minute (RPM), speed in kilometers per hour (Km/h), and etc. We trained with 100 time steps per patch (batch size=100) and used 5 time steps in the future for prediction. There were a total of ten epochs throughout the learning and training processes. The loss graphs display the MAE and MSE on the validation and training sets of data, respectively. Loss plots for training and validation data show very little divergence in the generalization gap, which means the model, fits the data well. Testing data acquired during a single journey is used to confirm the generalizability of the LSTM dense-layer RNN. The results of the practical experiment are shown in Figure (4), which indicate that the anticipated and real values converge for fuel consumption as we mentioned in table (2) feature No. 10 .

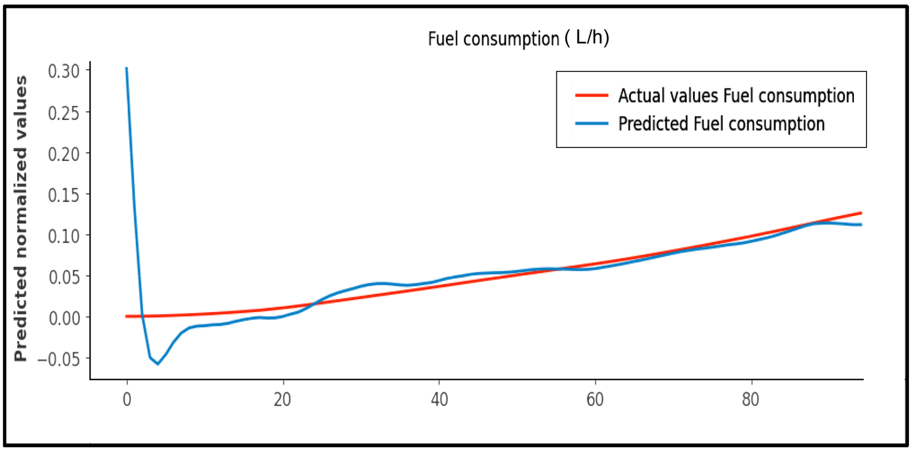

Figure 5: Fuel consumption proposed model prediction and actual values.

The purpose of predicting the speed of dump trucks is to improve operational efficiency, enhance safety measures, manage fuel consumption, minimize maintenance costs and improve the management of the entire fleet.

DOI: https://doi.org/10.54216/FPA.210204

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The concept of fuel utilization in dump trucks refers to the amount of fuel consumed by these vehicles over a certain period of time or distance in carrying out their assigned tasks of transporting and disposing of materials. Fuel consumption of dump trucks is affected by a number of elements, including the design of the vehicle, the conditions under which it operates, driver behavior and adherence to maintenance protocols. A comprehensive understanding of these elements is essential to improve fuel efficiency and reduce operating costs. The prediction of motor failures (motor running at maximum load and voltage) is shown in Figure (5) and (6) Showing the actual and expected values converge, for both dump truck speed in (km/h) and engine speed in (RPM) which indicating the success of the practical experiment.

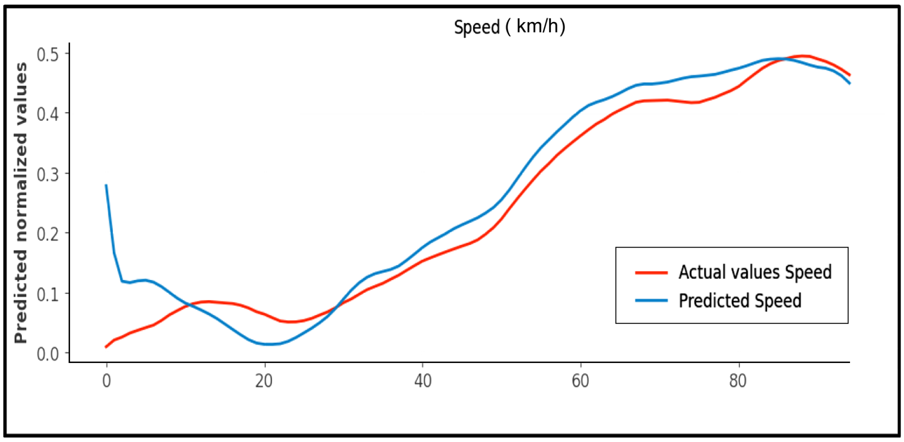

Figure 6: The predicted speed of the dump truck while traveling.

The phenomenon of diesel engine 'overspeed' or 'engine speed' manifests itself when the speed gets out of control and soon exceeds the rated speed, emitting a roar and large amounts of black or blue smoke billowing out of the exhaust pipe. Exceeding diesel engine speed not only causes serious damage to engine components, but can also endanger personal safety.

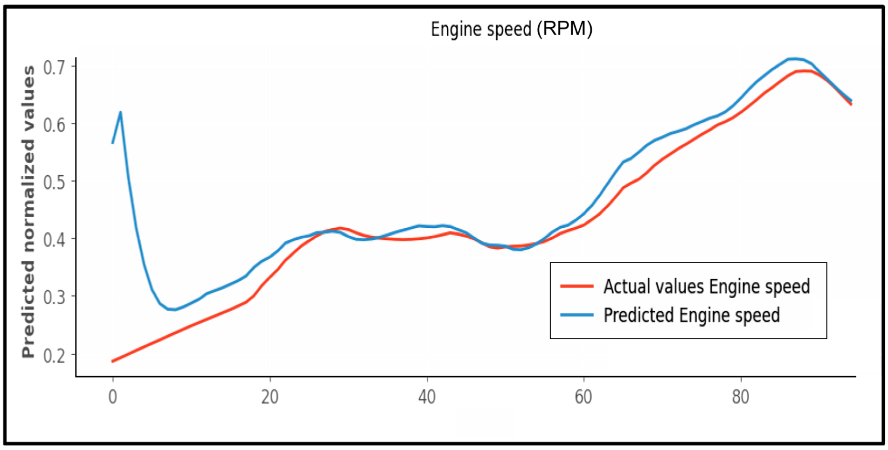

Figure 7: Proposed model engine speed prediction and actual values.

The resistance torque of a diesel engine is commonly referred to as the 'current engine load'. The average effective voltage is often used to express the load because it is proportional to the torque. Speed and load determine the efficiency of the diesel engine. When the diesel engine speed remains constant, the load characteristic shows how other important operating factors relate to each other. figure (7) present the different between the predicted and actual values of engine load. Current engine load as a percentage (%). This value represents the actual engine output torque compared to the maximum possible torque at the current engine speed.

The instantaneous fuel consumption values at each second must added together to obtain total fuel consumption and engine fault state. Performance measures To assess the efficacy of the model and its training set,

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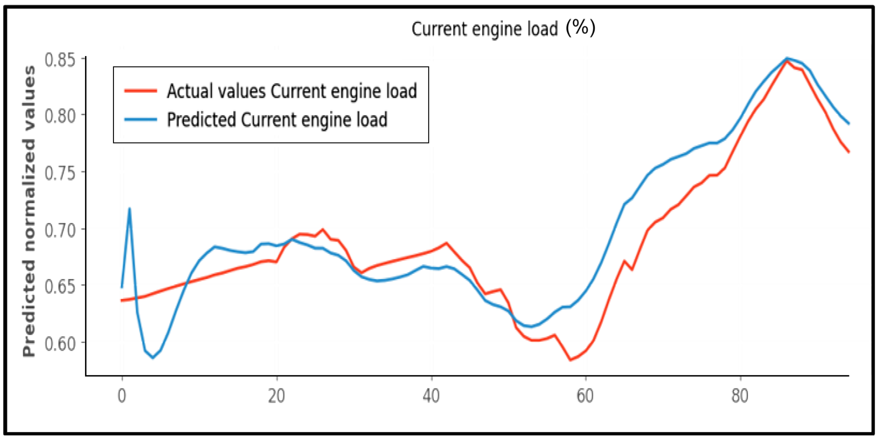

Figure 8: Proposed model current engine load prediction and actual values.

performance metrics are employed. When applied to new, unknown data, the LSTM-DNN model performs admirably. Figure (8) shows the matrix history where the matrix values depend on the torque factor. In order to determine the overall fuel consumption of the vehicle and also to calculate the total engine state (speed and load) during operation, the instantaneous engine states per second must be summed to get the total engine state.

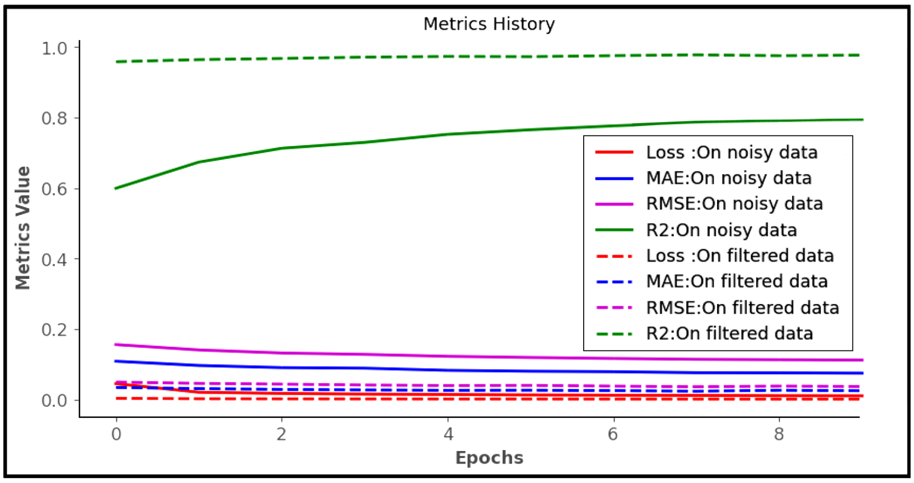

Figure 9: Comparison of total fuel consumption prediction using LSTM-DNN dense layers.

Figure (10) shows the performance of the model across 10 training epochs using both noisy and filtered datasets. The filtered data consistently resulted in improved performance across all metrics, validating the effectiveness of the preprocessing steps. The confusion matrix visualizes classification performance for two classes: (Normal Operation and Inefficiency / Engine Fault). The filtered data model achieved an accuracy of (97.5%), significantly outperforming the noisy data counterpart (80.7%). In contrast, the filtered data model demonstrates a clear improvement in correctly identifying all classes, with minimal false positives and false negatives. This indicates that filtering out noisy or irrelevant features substantially contributes to the model's precision and robustness in operational settings.

7.1 Performance Evaluation

To evaluate the effectiveness of the proposed models for fuel consumption prediction and engine health classification, a set of widely accepted performance metrics was employed. These metrics provide a quantitative assessment of model accuracy, error distribution, and generalization ability across different tasks. For the

DOI: https://doi.org/10.54216/FPA.210204

Received: February 07, 2025 Revised: May 31, 2025 Accepted: July 06, 2025

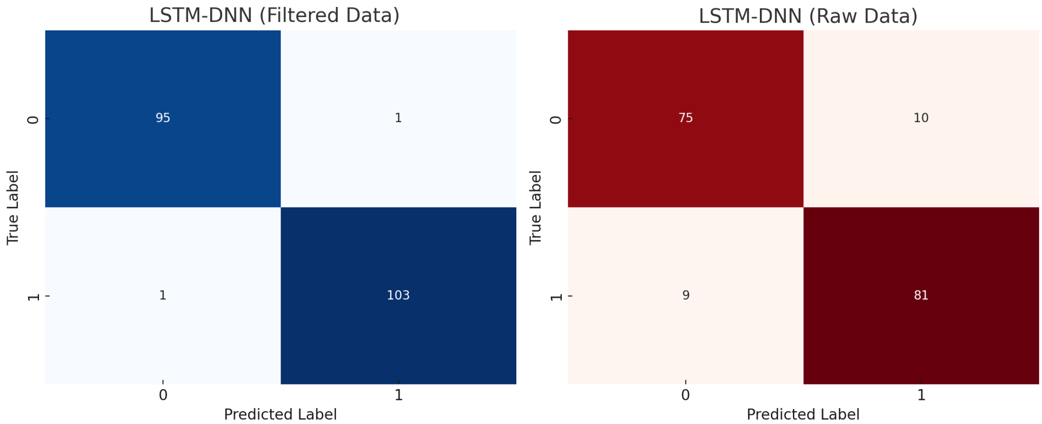

Figure 10: Confusion matrix comparison between the proposed LSTM-DNN model trained on raw sensor data (right) and filtered data (left).

fuel consumption prediction task and engine health classification task, four key metrics were used [26]: Mean Absolute Error (MAE): Measures the average magnitude of the prediction errors, providing a straightforward interpretation of how far the predicted values are from the actual ones on average. MAE is less sensitive to outliers than squared-error metrics.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{1}$$

Mean Squared Error (MSE): Captures the average squared difference between predicted and actual values. It penalizes larger errors more heavily and is useful for highlighting models that make occasional large mistakes.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{2}$$

Root Mean Squared Error (RMSE): Represents the square root of MSE and retains the same unit as the target variable, making it more interpretable. It also provides an overall sense of prediction accuracy.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{3}$$

Coefficient of Determination (R^2 Score): Indicates the proportion of the variance in the dependent variable that is predictable from the input features. A value close to 1.0 reflects a highly accurate model, while a value near 0 suggests that the model fails to capture the relationship in the data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{4}$$

where, y_i = actual value for instance i, $\hat{y}_i$ = predicted value for instance i, $\bar{y}$ = mean of actual values and n = total number of instances. These regression metrics together provide a comprehensive view of the model's predictive power, error dispersion, and robustness.

Confusion Matrix: To provide a detailed breakdown of the model's predictions versus actual labels, allowing insight into which classes are most commonly misclassified. These evaluation metrics were chosen to ensure both regression accuracy (for fuel prediction) and classification reliability (for engine health) were fully and fairly assessed. The results demonstrate that the proposed hybrid model performs robustly across both tasks.

Tables (4) show the practical experiment results of the proposed DL model using LSTM-DNN with an average number of data (3112) with 40 parameters. We extracted 25 features. Filtered LSTM-DNN model significantly outperforms all others in R^2 accuracy (0.9842).Even with more features; it maintains low MAE and RMSE, showcasing model strength and robustness. The use of sensor data pre-processing (filtering) proves critical to performance gains.

DOI: https://doi.org/10.54216/FPA.210204

Received: February 07, 2025 Revised: May 31, 2025 Accepted: July 06, 2025

Table 4: Performance Comparison.

Model	MAE	MSE	RMSE	R^2	No. of Features	Data Type
Multilayer Perception (MLP)	0.0614	0.0596	0.0772	0.7854	10	Sparse
k-Nearest Neighbors (KNN)	0.0595	0.0633	0.0796	0.7200	10	Sparse
Gradient Boosting (GB)	0.0582	0.0581	0.0762	0.7330	10	Sparse
Artificial Neural Network (ANN)	0.0006	0.0001	0.0010	0.9443	10	Cleaned
Proposed LSTM-DNN (Raw Data)	0.0698	0.0106	0.1029	0.8267	25 (from 40)	With Noise
Proposed LSTM-DNN (Filtered)	0.0210	0.0009	0.0294	0.9842	25 (from 40)	Filtered

8 Conclusion and Future works

Instead of depending on a single model for various activities utilizing different fuels, loads, paths, and other factors, this work aims to construct a complete model that is capable of accounting for unexpected outcomes in the data, especially when a large amount of data may not be available. For the model, large amounts of data were collected from sensors associated with heavy diesel vehicles in mining and transportation complexes. This paper developed a hybrid predictive maintenance model in which data undergo several processing steps followed by filtering. This model combines recurrent neural networks (RNN) and a Long Short-Term Memory (LSTM) algorithm combined with deep learning (DL) layers that influence the time series, facilitating real-time understanding of fixed and random effects during each journey. Unobserved test data from various sets is used in assessing the model's functionality, and it shows decent performance, providing predictions that in most cases exactly match the actual values. Model achievement analysis on test data indicates it generalizes well to both visible and invisible datasets during the training phase. Using predictive data and analytical tools enables fleet managers to make informed decisions that improve productivity, reduce costs, and ensure reliable and safe operations. While alternative fuels are becoming more mainstream, their use is still below projections. Organizations should prioritize vehicle maintenance data captured regularly utilizing sophisticated technologies, given the state of data capturing technology. Additional characteristics, including the highest and lowest temperatures, may be considered for future implementation. This will pave the way for the development of more robust prediction and investigating the model performance over electric vehicles. Models that identify the reasons contributing to elevated maintenance expenses might assist fleet management organizations in comprehending the influence of various parameters on vehicle maintenance. Future work will explore the integration of the predictive system into IoT-based platforms for real-time edge deployment. In smart mining environments, such integration would enable continuous monitoring of dump trucks, immediate anomaly detection, and preventive maintenance alerts, thereby improving safety and operational efficiency.

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Received: February 07, 2025 Revised: May 31, 2025 Accepted: July 06, 2025