Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.18576/amis/180623

Predictive Maintenance for Vehicle Performance using Bidirectional LSTM

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Received: 14 Aug. 2024, Revised: 9 Sep. 2024, Accepted: 2 Oct. 2024
Published online: 1 Nov. 2024

Abstract: The advancement of sensor and network technologies has led to an abundance of condition- monitoring and performance data, particularly in the automotive sector. This data and big data analytics offer opportunities to enhance predictive maintenance strategies. Various data preprocessing techniques, such as handling missing values and data normalization, are involved before the data is fed into the algorithm. The Feature selection process and Data splitting process also play a major role in determining which attributes in the data are more important and splitting the data for the testing and training process. The evolution of Deep Learning (DL) techniques becomes achievable to address potential equipment failures like a brake pad, fuel consumption, tire rotation, crankshaft detection, etc., and estimate the remaining useful life of the vehicle by using the algorithm bidirectional Long Short-Term Memory (LSTM) deep networks as a primary algorithm for predictive maintenance in vehicles.

Keywords: Predictive Maintenance, Deep Learning, Bidirectional LSTM, Performance Metrics, Consumer Preferences, Innovation

1 Introduction

In today's dynamic world, automobiles are essential for making the daily routine simple by facilitating transportation, business, and improvement in the automotive sectors. The unexpected vehicle breakdowns can disrupt daily schedules and result in weighty expenses and terms of safety [1,2,3,4]. To resolve these challenges, the automotive sector has embraced predictive maintenance as a powerful strategy to strengthen features of vehicles, optimize maintenance schedules, and enhance overall vehicle performance. Predictive maintenance necessitates advanced analytics and data-driven insights to predict when car components or systems will likely fail or need maintenance. By harnessing the power of DL, it becomes feasible to accurately estimate the remaining useful life of vehicle components, enabling proactive maintenance interventions before failures occur [5,6,7]. Stochastic methods and artificial intelligence (AI) approaches are systematically integrated to improve maintenance action optimization further and ensure timely and appropriate interventions to maintain vehicle performance and reliability [8,9,10,11]. Predictive maintenance employs preventive strategies to avoid breakdowns, adhere to service maintenance schedules, and reduce downtime, in contrast to relative maintenance, which attends to problems as they occur. This crucial method analyzes different functionality and patterns and forecasts maintenance needs by using data analytics, sensors, networks, and DL models [12,13,14,15]. Users may predict maintenance needs and spot trends and anomalies by using machine learning algorithms like

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Random Forest, Naive Bayes, and BiLSTM DL model. This improves vehicle performance and solidity while cutting downtime and costs [16,17,18,19]. Predictive car maintenanceis a dynamic process in real-time applications that continuously monitors and analyzes data streams from networked systems and onboard sensors [20,21,22]. These systems use sophisticated algorithms to identify irregularities, anticipate probable malfunctions, and recommend maintenance tasks instantly [23,24,25]. Onboard sensors, for example, can track tire pressure, engine vibrations, brake pad thickness, and many other factors. These data are then fed into predictive maintenance algorithms driven by LSTM networks.

2 Literature Review

In the automotive sector, predictive maintenance has recently become more popular. In their investigation of the difficulties of predictive maintenance, Patel et al. [26] argued in favor of preventative measures. They investigated Random Forests and Support Vector Machines (SVM). Wang et al. [27] used Decision Trees and K-means Clustering to assess condition-based predictive maintenance techniques for brakes. In the meantime, a thorough analysis of predictive maintenance in the automobile industry was carried out by [28], providing insights into a range of approaches and technology Gupta et al.'s evaluation of Deep Learning approaches (2022) focused on the effectiveness of algorithms such as CNNs and LSTM networks. With an emphasis on proactive scheduling and real-time monitoring. Liu et al. [29] presented an Internet of Things (IoT)-based predictive maintenance architecture designed specifically for automotive systems. Theissler et al. [30] case study on predictive maintenance for car fleets, and other researchers further show the value of data analytics [31,32,33,34].

Without mentioning any specific methods, Wang et al. [27] explored sophisticated techniques for improving car reliability. Kumar et al. [35] used algorithms like ANN and GBM to compare predictive maintenance models for car engines. Principal Component Analysis (PCA) and k-nearest Neighbors (KNN) were two of the machine learning approaches assessed by [36]. Last but not least, Buccafusco et al. [37] thoroughly analyzed predictive maintenance methods for car transmissions without mentioning the vehicle-specific algorithms.

3 Domain

–Introduction to the Automotive Sector
The design, production, and distribution of automobiles, including cars, trucks, buses, and motorbikes, are the activities of a broad spectrum of industries included in the automotive sector. Technological improvements, safety standards, and environmental restrictions drive innovation and competitiveness in this industry, which is critical to the global transportation economy.

–Vehicle Components and Systems
Powertrain: The engine, transmission, and drive train components that produce and transfer power to move the vehicle are all part of the power train system. Through developments like hybrid and electric propulsion systems, power train technology advances aim to increase fuel economy, lower emissions, and improve performance.
Suspension and Chassis: The chassis houses the steering, braking, and suspension systems and provides the vehicle's structural support. Developments in materials and design have improved the performance and safety of suspension systems, which are essential for maintaining vehicle stability, handling, and ride comfort.
Electrical and Electronic Systems: Advanced electrical and electronic systems are used in modern cars for several purposes, including as connectivity, infotainment, safety features, and engine control. Key technologies in this field include vehicle-to-everything (V2X) communication, telemetric, and advanced driver assistance systems (ADAS) for increased convenience and safety.

–Emerging Trends and Technologies
Automobiles equipped with autonomous driving technology can navigate and function without human involvement, marking a paradigm leap in the field. Developments in sensors, artificial intelligence, and real-time data processing, which allow cars to sense and react to their surroundings, will make transportation systems safer and more effective.
Electric and Hybrid Vehicles: The transition to electrification seeks to lessen reliance on fossil fuels and lessen the environmental impact by promoting the use of electric and hybrid vehicles. Prioritizing battery technology, charging infrastructure, and range optimization can expedite the shift toward sustainable mobility options.
Vehicles that are connected: Advanced safety, navigation, and entertainment services can be made possible by connected vehicle technology, which allows for smooth connection between automobiles, infrastructure, and outside networks. Vehicles can now make educated judgments and maximize performance in real-time thanks to communication technologies that connect vehicles to infrastructure (V2I) and other vehicles (V2V), as well as cloud computing and data analytics.

–Regulatory and Market Dynamics
Tight emissions laws: To reduce pollutants and greenhouse gas emissions, strict emissions laws encourage car design and technology innovation. To meet pollution regulations while preserving performance and customer demand, automakers spend

money on R&D.Safety Standards: As new hazards and technology arise, safety is still the top priority in the automotive industry, and rules and standards are constantly changing to reflect this. To increase vehicle safety and lower traffic accidents, emphasis is being placed on crashworthiness, occupant protection, and active safety systems.
Consumer Preferences, Market Trends, and Technology: The automotive industry is impacted by changing consumer preferences, market dynamics, and marketing techniques, which affect product development and business models. Trends like electric mobility, shared mobility services, and connected features shape the future of mobility and investment decisions throughout the value chain.
Materials and Manufacturing Processes: Optimizing vehicle performance, durability, and economy requires a thorough understanding of the materials used in vehicle construction, such as steel, aluminum, and composite materials, as well as manufacturing processes like stamping, welding, and casting.
Testing and Validation: Strict procedures are necessary to guarantee that automobiles fulfill safety, quality, and legal requirements. This entails conducting numerous tests in real-world settings, including emissions, crashes, durability, and performance tests.
Supply Chain Management: Proficient knowledge in logistics, inventory control, and procurement is necessary to oversee the intricate web of manufacturers, distributors, suppliers, and retailers in the automotive supply chain. Effective supply chain management is essential to ensure product quality, control costs, and adhere to production schedules.
Autonomous Vehicle Diagnostics and Maintenance: The creation of diagnostic instruments and frameworks to identify and resolve car issues is crucial to guaranteeing automobile dependability and reducing unproductive periods. This coversapplying predictive maintenance algorithms, remote monitoring technologies, and onboard diagnostic (OBD) systems.
Vehicle Design and Styling: These aspects of a car are crucial in drawing in buyers and setting them apart from other cars on the market. To create aesthetically pleasing, functional, and aerodynamically efficient automobiles, one must thoroughly understand design principles, ergonomics, aerodynamics, and consumer preferences.
Environmental Sustainability: The automotive industry is becoming increasingly dependent on addressing environmental issues like resource depletion, carbon emissions, and air pollution. To meet sustainability targets and comply with regulations, eco-friendly technology such as lightweight materials, energy-efficient propulsion systems, and alternative fuels must be developed.

4 Problem Statement

Engine predictive maintenance solutions that are dependable are lacking, which presents serious obstacles to traffic management, safety, and the advancement of autonomous driving technologies. Conventional maintenance methods frequently lead to unanticipated malfunctions and downtime, raising the possibility of mishaps and traffic jams. The integration of smart mobility solutions, which aim to improve transportation efficiency, reduce carbon emissions, and reduce congestion, is hindered by the lack of proactive maintenance practices. Tailored predictive maintenance solutions utilizing cutting-edge technology like machine learning, deep learning, and IoT sensors are desperately needed to address these issues. By maximizing maintenance schedules, reducing downtime, and guaranteeing continuous engine performance, these technologies would enable smart mobility to reach its full potential and promote safer, more effective transportation networks.

The development of autonomous vehicle capabilities, traffic flow management, and road safety are all severely hampered by the lack of predictive maintenance plans for braking systems. Conventional maintenance techniques can increase the danger of accidents and traffic jams by causing unanticipated brake failures and operating delays. The smooth integration of intelligent mobility solutions—which aim to minimize traffic, cut emissions, and maximize transportation efficiency faces significant challenges without proactive maintenance frameworks. There is an immediate need for customized predictive maintenance solutions that make use of cutting-edge technology like machine learning, deep learning, and Internet of Things sensors in order to address these problems head-on. By ensuring continuous brake performance, reducing downtime, and revolutionizing maintenance planning, these technologies would fully realize the promise of smart mobility projects and foster safer, more efficient transportation networks.

5 Methodology

1. **Data Collection:**
   - Sensor Data Acquisition: The first stage is to collect data from the different sensors that are built into the car, such as oil pressure, temperature, GPS, and accelerometers.
   - Communication Protocols: Bluetooth, Wi-Fi, cellular networks, and other channels can all be connected through the MQTT (Message Queuing Telemetry Transport) protocol, which facilitates data transmission.
   - Data Characteristics: The gathered dataset includes a million rows and 32 unique attributes, reflecting various aspects of vehicle operation and condition.
2. **Data Preprocessing:**

- Handling Missing Values: Methods are used to address any missing data entries to maintain accuracy and completeness in the dataset.
- Duplicate Handling: To preserve data integrity and avoid redundancy, duplicate entries within the dataset were found and eliminated.
- Data Normalization: The Standard Scalar normalization approach is used to guarantee data comparability and consistency among various attributes.
- Label Encoding: Label encoding converts categorical data into a numerical representation that makes machine learning algorithms more easily work with it.

3. **Model Selection:**
   - Algorithms: A number of algorithms, such as Random Forest, Bidirectional LSTM, and Naive Bayes, are considered for their applicability in predictive maintenance jobs.
   - Criteria: To determine the most effective approach, models are compared using performance criteria such as recall, accuracy, precision, F1-score, RMSE, and ROC curves.
4. **Model Evaluation:**
   - Performance Metrics: Various performance metrics, such as accuracy, confusion matrix analysis, precision-recall curves, and ROC (Receiver Operating Characteristic) curves, are used to evaluate the chosen models thoroughly.
5. **Implementation:**
   - Choosing the Best Model: Bidirectional Long Short-Term Memory (LSTM) is found to be the best model because of its exceptional accuracy and predictive power in identifying temporal connections in the data.
   - Frontend Development: To interface with the chosen model, a frontend system is created. This allows for the real-time detection of maintenance warnings and the prompt implementation of interventions to avert possible failures.

6 Process Flow of Proposed Algorithm

Fig. 1 shows the process flow of the proposed algorithm. The data is collected with 32 attributes and a million rows, and the data undergoes the data preprocessing technique, where it handles missing values, removes duplicates, and data normalization. Then it, preprocessed data moves for the feature selection process; after the data are split into testing and training data the model selection process of ML and DL algorithms are used; after the model is evaluated based on performance metrics, the best model is deployed into the front end.

- **Initial Model Selection:** The process commences with evaluating baseline algorithms, including Naive Bayes and Random Forest. These algorithms serve as foundational frameworks for predictive maintenance, offering initial insights into fault detection and maintenance scheduling.

Fig. 1: Process Flow Diagram.

- **Evaluation and Enhancement:** Upon evaluating the initial models, the algorithm assesses their performance metrics, including accuracy and precision. Although it shows intermediate accuracy levels of 64% and 68%, respectively, more sophisticated approaches must be used to achieve higher precision and recall.
- **Integration of Bidirectional LSTM:** The algorithm integrates Bidirectional LSTM networks to obtain greater robustness and accuracy. One kind of RNN that is particularly good at identifying temporal patterns and sequential dependencies in sensor data is the bidirectional LSTM. By utilizing its bidirectional architecture, the model is able to learn from data situations in the past and the future, allowing for more accurate predictions.
- **Training and Refinement of the Model:** The algorithm builds and trains the neural network model after integrating the Bidirectional LSTM. The model adjusts its parameters to decrease prediction errors and maximize accuracy using optimization techniques like gradient descent and backpropagation throughout iterative training iterations.
- **Performance Evaluation:** Following model training, the algorithm evaluates the Bidirectional LSTM model's performance using a range of in-depth metrics, such as accuracy, precision, recall, F1-score, RMSE, and ROC curves. By comparing these signs to preset criteria and industry standards, the algorithm assesses these indicators and determines the predictive maintenance system's efficacy.
- **Iterative Improvement:** The suggested technique incorporates an iterative improvement process in which upcoming improvements are informed by feedback from model performance. The algorithm is continuously improved by monitoring predictive accuracy and system dependability, guaranteeing that

it can adjust to changing operational conditions and maintenance needs.

7 Overview of Proposed Algorithm

Naive Bayes Classifier: The classifier ascertains the probability that a given instance belongs to each true or false class label based on the observed feature values. Next, the class label with the highest probability percentage is assigned to the instance.

Performance: RMSE, or root mean square error, is computed for this statistic using the average of the difference between the expected and actual class labels. In this case, the RMSE is 0.561, which represents the classifier's average error size.

Accuracy: The accuracy of the Naive Bayes classifier is indicated by the percentage of correctly categorized instances in the test set compared to all the cases, which is 61.65%.

Confusion Matrix: The confusion matrix, which displays the number of true positives, true negatives, false positives, and false negatives, offers a thorough analysis of the classifier's performance. It aids in assessing how well the classifier can identify examples that belong to each class label.

Classification Report: The classification report provides metrics like recall, precision, and F1 score for every class label. Recall is the percentage of True Positive predictions from all actual positive instances, whereas precision is the percentage of True Positive forecasts from all optimistic predictions. The F1-score, which assesses the classifier's performance fairly, is the harmonic mean average of precision and recall.

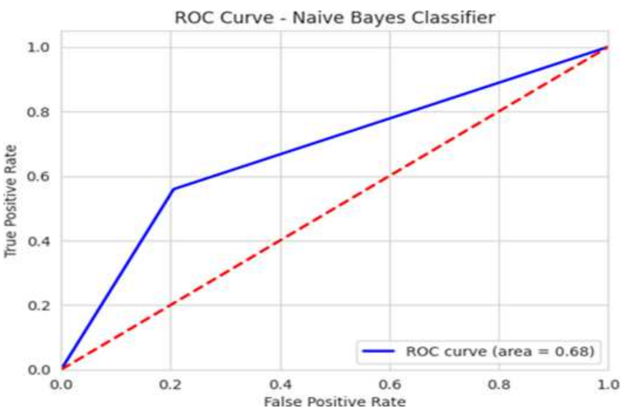

Fig. 2: ROC Curve–Naïve Bayes Classifier.

Fig. 2 represents that; the ROC curve visually depicts a classifier's trade between correctly identifying True Positives and incorrectly labeling False Positives across various threshold settings.

–The Random Forest classifier technique: The RF Classifier is an ensemble learning technique that builds several decision trees during training and delivers a class that is the mean prediction regression or class classification mode of each individual tree. To increase generalization and resilience over a single tree, it mixes the predictions of several different decision trees.

–Performance: Root Mean Squared Error, or RMSE: This statistic calculates the average difference between the actual class labels and the anticipated class labels. The RMSE in this instance is 0.561, reflecting the classifier's average error magnitude.

–Accuracy: The percentage of successfully categorized instances in the test set that is used is 68.5%, indicating the accuracy of the Random Forest classifier.

–Confusion Matrix: The amount of true positives, true negatives, false positives, and false negatives in the confusion matrix indicates the classifier's performance in detail. Sessing the classifier's accuracy in correctly classifying cases that correspond to the class label is helpful.

–Metrics like Precision, Recall, and F1-score are included in the classification report for every class label. Recall calculates the percentage of True Positive predictions from all real positive instances, whereas precision calculates the percentage of True Positive forecasts from all positive predictions.

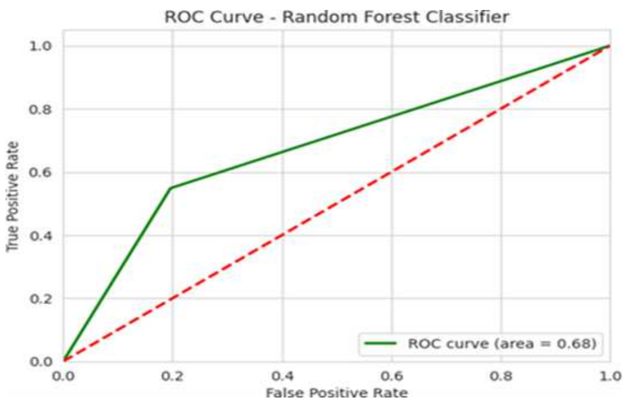

Fig. 3: Random Forest Classifier's ROC Curve.

The Random Forest classifier's ROC curve, which shows how well it distinguishes between genuine positives and false positives at various threshold values, is shown in Fig. 3. Bidirectional LSTM Classifier:

–By processing sequential input bidirectionally and capturing dependencies in both forward and backward directions, the Bidirectional LSTM classifier makes use of a Deep Learning architecture.

–Performance: Test Loss: The average difference between the actual and predicted class labels, or test loss value of 0.342, shows how well the ML and DL models performed in reducing prediction mistakes.

– Accuracy: Test Accuracy: The Bidirectional LSTM classifier's accuracy is 82.26%, which represents the percentage of correctly identified instances among all the examples in the test set.
– Precision: The percentage of True Positive forecasts among all positive predictions is measured by precision. The classifier's accuracy in identifying the positive cases is demonstrated by its 48.39% precision in this instance.
– Recall: The percentage of True Positive predictions made out of all real positive occurrences is known as recall. With a recall value percentage of 32.26%, the classifier's sensitivity to falsely detect positive cases is demonstrated.
– F1-score: This balanced indicator of the classifier's performance is the harmonic mean of the precision and recall. The F1-score in this instance is 38.71%, which indicates the classifier's overall efficacy in terms of recall and precision.

Fig. 4 depicts the ROC curve for the Bidirectional LSTM classifier, offering insights into its overall ability to a discriminate between true positives and false positives across various threshold settings which is used.

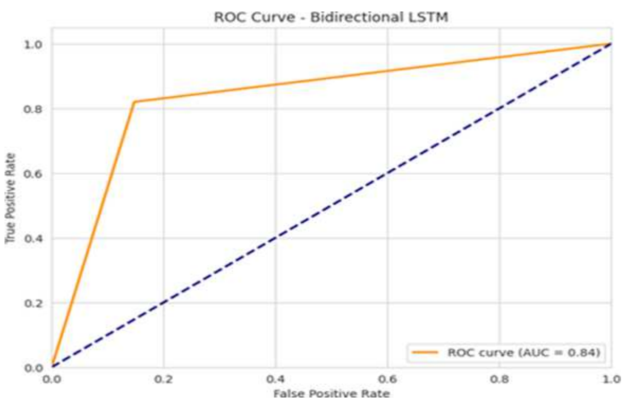

Fig. 4: ROC CURVE–Bidirectional LSTM.

8 Result and Analysis

Model Evaluation and Performance

The trained and evaluated several Machine Learning models to predict maintenance flags based on the given features. Among these models, the Bidirectional LSTM deep neural network demonstrated superior performance compared to other algorithms such as NaiveBayes and Random Forest.

The Bidirectional LSTM model was constructed with two Bidirectional LSTM layers, each consisting of 64 units and utilizing the ReLU activation function. Additionally, two Dense layers with 64 neuron and ReLU activation were incorporated, followed by a final layer which is Dense layer with a sigmoid activation function for binary classification tasks.

Table 1 shows that the BiLSTM model achieved the highest accuracy among the three algorithms, reaching 82%. However, compared to the Naive Bayes model and Random Forest methods, its precision, recall, F1-score, RMSE, and ROC Curves metrics are relatively low.

This suggests a trade-off between reliably identifying actual positives and lowering false positives or false negatives, even if the BiLSTM model successfully recognized a higher percentage of cases overall. It also exhibited concerns with recall and precision. With a fairly low RMSE percentage of 34%, the Bidirectional LSTM model outperformed the other algorithms regarding regression prediction, indicating that, on average, its predictions were closer to the actual values. Although it had lower precision, recall, and F1-score, the Bidirectional LSTM model was the preferred choice for this particular task overall due to its higher accuracy and prediction accuracy.

Superior Performance of Bidirectional LSTM

Improved predictive accuracy resulted from the Bidirectional LSTM architecture's remarkable ability to capture temporal dependencies and patterns in the data. The Bidirectional LSTM model showed improved performance in comprehending sequential data by utilizing both forward and backward information flow, which is essential for our time-series prediction task. Furthermore, because the Bidirectional LSTM model could preserve long-term dependencies while lessening the vanishing gradient problem, it outperformed traditional machine learning methods like the Random Forest and Naive Bayes algorithms.

9 Deployment

The frontend interface was created using the use of modern web technologies, such as HTML, CSS, and JavaScript, to create a user experience that is responsive and simple to use. In order to make it simple for users to traverse the system and access pertinent features and functionalities, the interface was created with usability and accessibility in mind.

Figure 5 illustrates how users are greeted with an easy-to-use dashboard that offers a summary of the predictive maintenance system when they approach the frontend interface through the designated URL and port number. The dashboard could have several elements and displays, such as:

– System Status: This provides an overview of the predictive maintenance system's current state, including any alarms, model changes, or ongoing maintenance tasks.

Table 1: Measures of Performance.

Algorithm	Measures of Performance				
	Precision	Recall	Accuracy	F1 Score	RMSE
Navie Bayes	0.67	0.63	61%	0.64	56%
Random Forest	0.71	0.70	68%	0.71	55%
Bidirectional LSTM	0.77	0.90	82%	0.84	34%

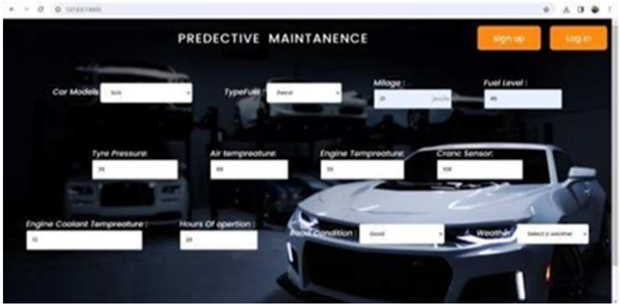

Fig. 5: Web User Interface.

- –Prediction Results: The most recent forecasts produced by predictive maintenance models are shown. This could contain data like odds, suggested courses of action, and anticipated maintenance occurrences.
- –User Controls: Input fields and user-friendly controls that let users adjust parameters, note upkeep needs, and communicate with the system. Options to add fresh data, modify model parameters, or create personalized reports can be among them.
- –Notifications and Alerts: Real-time notifications and alerts to inform users of critical events, anomalies, or maintenance needs. These notifications help users stay informed and proactive in managing maintenance activities.

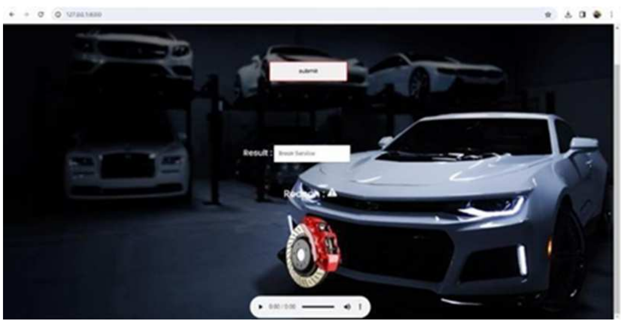

Fig. 6: Break Service Alert.

The predictive maintenance alert for brake service shown in Fig. 6 indicates an impending requirement for brake system maintenance or repair. This proactive alert allows prompt action to guarantee vehicle safety and peak performance.

Fig. 7: Crank Shaft Replacement Alert.

Fig 7 presents a predictive maintenance alert for crankshaft replacement, signalling the need for proactive action to address potential issues with the crankshaft before they escalate. This alert system aids in preventing unexpected failures and maintaining the engine's reliability.

10 Summary

Sensor data is gathered as part of the Optimizing Vehicle Performance through Predictive Maintenance initiative using the MQTT protocol to retrieve it. The gathered data has been preprocessed using StandardScaler to eliminate null and duplicate values and apply label encoding in conjunction with data normalization methods.

Compared to the current approach, the proposed Bidirectional Long-Short-Term Memory (LSTM) model fed the preprocessed data produced a maximum accuracy of 0.82. Additional assessment metrics, including precision, recall, F1-score, root mean square error (RMSE), and Receiver Operating Characteristic (ROC) curve, were computed and shown. Ultimately, the model is implemented for real-world uses, proving it is still useful after development.

11 Conclusion

An important step toward improving asset management procedures and operational effectiveness in industrial settings is creating a predictive maintenance system with an easy-to-use front-end interface. We have shown the capacity to precisely forecast maintenance requirements and identify possible equipment breakdowns before they occur by utilizing cutting-edge machine learning approaches, such as BiLSTM networks.

The Bi-LSTM model outperformed the other machine learning models, demonstrating its ability to capture maintenance data's long-range dependencies and temporal dynamics. By using the temporal character of data, Bi-LSTM networks provide a potent tool for enhancing asset reliability, cutting downtime, and optimizing maintenance plans.

Additionally, by creating a front-end interface, stakeholders will have an easy-to-use platform to communicate with the predictive maintenance system and obtain insights that can be used. The interface's simple controls, notifications, and real-time visualizations will help users take proactive maintenance management and make well-informed decisions.

Predictive maintenance system integration into operational workflows promises to advance asset management practices' innovation and ongoing development. By utilizing predictive insights, organizations may reduce unplanned downtime, maximize resource allocation, and improve overall operational efficiency.

12 Future Enhancement

An attractive direction for future research is integrating sensor data from the vehicle to track variables like fuel economy, crankshaft condition, brake pad wear, and engine coolant temperature while driving. By directly integrating sensors into the vehicle's systems, real-time data may be gathered and processed to provide insights into a variety of elements of the vehicle's performance and health.

Subsequent investigations may create intelligent monitoring systems that employ machine learning algorithms to evaluate sensor data, anticipate possible maintenance problems, or enhance vehicle efficiency. This might entail:

1. Sensor Integration: Using sensors integrated into the car's parts to collect pertinent data while it's moving continuously. These sensors might be accelerometers to track brake pad wear, fuel flow sensors to track fuel usage, and temperature sensors for engine coolant.
2. Data Collection and Processing: Setting up systems for effectively gathering, storing, and preprocessing sensor data. This can entail creating algorithms to handle and filter the incoming data as well as building data gathering systems inside the car.
3. Predictive maintenance: ML algorithms examine sensor data and find issues or maintenance requirements. For example, predictive algorithms could determine when to replace brake pads based on wear patterns or spot anomalies in engine coolant temperature that indicate potential issues.
4. Optimization Techniques: Sensor data can be used to maximize vehicle effectiveness and performance. One way to do this is to create algorithms that modify engine parameters in response to real-time sensor feedback to reduce fuel consumption or improve engine performance.
5. User Feedback and Visualization: Designing intuitive dashboards or interfaces that give drivers useful information gleaned from sensor data. Real-time monitoring of vital data, maintenance alerts, or suggestions for improving driving habits to increase vehicle longevity are a few visualizations that could be included.

Acknowledgement

The authors thank all the respondents who provided valuable responses and support for the survey. They offer special gratitude to INTI International for publishing the research work, particularly to INTI International University for funding its publication, and acknowledge the partial funding support provided by the Electronic Marketing and Social Media Department, Economic and Administrative Sciences, Zarqa University.

Funding

The authors offer special gratitude to INTI International University for the opportunity to conduct research and publish the research work. In particular, the authors would like to thank INTI International University for funding the publication of this research work. Also, we extend our heartfelt gratitude to all research participants for their valuable contributions, which have been integral to the success of this study.

Conflict of Interest

The authors have no conflict of interest to declare.

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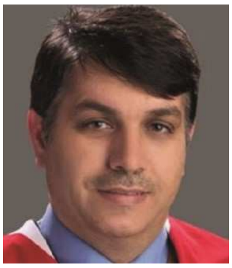

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