Autohealth - A Predictive Maintenance System for EVs

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Abstract— **Predictive maintenance plays a critical role in ensuring the reliability and efficiency of electric vehicles [EVs], particularly in preventing unexpected motor failures. This paper reviews the application of deep learning techniques, specifically Convolutional Neural Networks [CNN] and Long Short-Term Memory [LSTM] networks, for predictive maintenance in EVs. We analyze sensor data from electric motors. We look at how these models, combining L1 Regularization, Logistic Regression, and Random Forest, improve fault detection accuracy. It is preceded by a data analysis and followed by a discussion on machine learning and deep learning models used. A comparison of different models is done and CNN + LSTM emerges as the best possible solution, as it can capture spatial and temporal patterns in the data. Finally, we have the challenges and limitations of these models and give directions for future work including real-time monitoring systems and digital twin technologies.**

Keywords—: ***Predictive maintenance, electric vehicles, deep learning, CNN, LSTM, L1 regularization, logistic regression, random forest, sensor data analysis***

I. INTRODUCTION

The automotive industry is undergoing a rapid transformation due to advancements in digital technologies. With the integration of Industry 4.0 principles, there is a significant shift towards interconnected systems that blend traditional manufacturing with cutting-edge IT infrastructure. These digital innovations are driving improvements in data collection, production efficiency, product quality, and cost optimization. In the realm of vehicle maintenance, predictive maintenance [PdM] is emerging as a game-changer, leveraging sensor data and artificial intelligence [AI] to forecast potential failures, thereby preventing unplanned downtimes and enhancing operational safety [3].

Industry 4.0, which encompasses key technological trends such as the Internet of Things [IoT], big data, and AI, is revolutionizing automotive manufacturing. By enabling seamless communication between machines and sensors, this framework fosters real-time data analysis and decision-making, which is critical in maintaining the reliability of production processes. Within the automotive sector, the use of IoT and AI for predictive maintenance has enhanced the efficiency of vehicle fleets, transforming the way vehicles are monitored, maintained, and repaired [2, 3].

Predictive maintenance, a core application of AI and IoT in the automotive industry, marks a departure from traditional reactive and preventive maintenance strategies. Traditional models, such as reactive maintenance [where repairs are made after failures occur] or preventive maintenance [where routine servicing is conducted at set intervals], often lead to inefficiencies in cost and time management [8]. PdM offers a more intelligent solution by utilizing machine learning algorithms to assess the health of vehicle components continuously. This allows for early fault detection, which significantly reduces the likelihood of unexpected breakdowns and associated costs [9].

The evolution of machine learning techniques has played a pivotal role in the advancement of predictive maintenance. Tools such as the Autoregressive Moving Average [ARMA] model have been widely adopted for forecasting fault events in industrial settings, offering a robust foundation for future automotive applications [1]. By integrating these data-driven techniques, manufacturers can anticipate component failures with greater accuracy, enabling a proactive approach to vehicle maintenance that enhances both the reliability and longevity of automotive systems.

In the automotive sector, real-time data analytics are becoming the norm, particularly in predictive maintenance. Vehicles equipped with IoT-enabled sensors collect continuous streams of data, such as temperature, vibration, and performance metrics, which are then processed using AI algorithms to predict the remaining useful life [RUL] of critical parts. This capability allows for optimized maintenance scheduling, ensuring that repairs are conducted only when necessary, thus reducing maintenance costs and extending vehicle life spans [5, 6].

Predictive maintenance is particularly valuable in electric vehicles [EVs], where the condition of power electronics, battery systems, and motors must be closely monitored to prevent malfunctions. Machine learning techniques, including deep learning algorithms, are increasingly being used to improve the accuracy of these predictions. For instance, a study on the integration of AI into energy management systems for EVs highlights the potential of AI tools in extending battery life and improving overall vehicle performance [9, 11]. This integration of AI into EV maintenance not only enhances vehicle reliability but also contributes to sustainability efforts by minimizing energy wastage.

However, the implementation of predictive maintenance is not without challenges. The complexity of installing and maintaining IoT infrastructure, the need for significant investments in AI technologies, and the requirement for skilled personnel to manage these systems are among the major barriers to its widespread adoption [2, 20]. Despite these obstacles, companies that invest in predictive maintenance stand to benefit from reduced operational costs, improved vehicle safety, and longer asset lifespans.

Predictive maintenance has been shown to reduce maintenance costs by up to 12% while increasing production output by 25% in some sectors [9]. These significant savings highlight the long-term economic benefits of PdM, making it an attractive option for automotive manufacturers looking to stay competitive in the rapidly evolving industry. Furthermore, predictive maintenance supports enhanced vehicle safety by proactively addressing potential failures, reducing the risk of accidents caused by component malfunctions [16].

In conclusion, predictive maintenance is transforming the automotive industry by enabling smarter, data-driven approaches to vehicle maintenance and repair. By leveraging the power of AI, machine learning, and IoT, automotive manufacturers can optimize maintenance schedules, reduce downtime, and improve vehicle reliability. As the automotive sector continues to evolve, the adoption of predictive maintenance strategies will likely become a standard practice, providing both economic and operational advantages [3, 5].

II. LITERATURE REVIEW METHODOLOGY

The methodology employed in conducting this literature review is grounded in a systematic exploration of available research on predictive maintenance systems, particularly in the automotive sector. The approach primarily involved sourcing and synthesizing relevant academic papers, articles, and case studies from reputable journals, proceedings, and conference papers that address the intersection of predictive maintenance, artificial intelligence [AI], machine learning [ML], and Internet of Things [IoT] technologies.

A. Identification of Relevant Keywords

The first step in this methodology was to identify key terms related to predictive maintenance in the automotive industry and associated technologies. The keywords used included "predictive maintenance," "automotive sector," "machine learning," "electric vehicles," "IoT," and "artificial intelligence." This process ensured that the search encompassed all aspects of predictive maintenance, focusing on electric vehicle [EV] systems, power electronics, and battery management systems [5, 13, 20].

B. Selection of Research Databases

To ensure comprehensive coverage, multiple research databases were accessed, including IEEE Xplore, SpringerLink, and Google Scholar. These platforms are recognized for their extensive collections of peer-reviewed articles and technical papers. The selection was guided by the availability of papers relevant to predictive maintenance, ensuring that the final pool of studies covered both foundational theoretical frameworks and recent advances in technology [2, 3, 6].

C. Inclusion and Exclusion Criteria

The selection of papers was based on specific inclusion and exclusion criteria to maintain the focus on predictive maintenance in electric vehicles and automotive systems. The inclusion criteria were as follows:

- Papers published from 2017 to 2024, ensuring the timeliness and relevance of the research [1, 5].
- Studies specifically dealing with predictive maintenance strategies and their application in the automotive sector [7, 9].
- Articles that explore the use of AI, ML, and IoT technologies in enhancing the reliability and performance of EV systems [6, 20].

Papers that primarily focused on predictive maintenance in other industries [e.g., manufacturing or aerospace] without direct automotive applications were excluded unless they offered methodologies adaptable to the automotive context [8, 9].

D. Review and Classification of Literature

The next step involved reviewing and categorizing the selected papers based on their specific focus areas. The literature was divided into three primary categories:

- *Predictive Maintenance Approaches:* This category included papers that discuss general frameworks for predictive maintenance in automotive systems. Techniques like ARMA modeling, regression analysis, and statistical methods were reviewed for their applicability [1, 3].
- *Machine Learning and AI Integration:* Papers focusing on the integration of machine learning algorithms, such as neural networks, decision trees, and deep learning techniques, into predictive maintenance systems were reviewed. Special attention was given to their ability to predict vehicle component failures and optimize maintenance schedules [5, 6, 20].
- *IoT and Data-Driven Techniques:* The third category included literature on the use of IoT in predictive maintenance systems. These studies highlighted the role of real-time data acquisition and monitoring in predicting potential faults in electric vehicles [2, 13].

E. Comparative Analysis of Techniques

A comparative analysis was performed to identify the strengths, limitations, and challenges associated with different predictive maintenance techniques. Studies like the one by Baptista and Sankararaman [2021] using ARMA modeling were compared to machine learning approaches, such as the neural network models used in more recent works [1, 6]. This comparison provided insights into the accuracy, efficiency, and scalability of each method in real-world automotive applications.

F. Identifying Gaps and Future Research Directions

A significant part of the review involved identifying gaps in the current literature. While the majority of papers focused on the technological advancements in predictive maintenance, few addressed the challenges related to implementation at scale. For instance, there is a need for more research into how machine learning models can be optimized for real-time data analysis without causing delays in vehicle operation [9, 10]. Furthermore, the integration of IoT-based data systems with existing automotive infrastructure poses both technical and cybersecurity challenges [2, 13].

G. Synthesis of Findings

The findings from this literature review were synthesized to create a comprehensive understanding of the current state of predictive maintenance in electric vehicles. The synthesis involved the integration of theoretical models with practical case studies, offering a balanced perspective on the opportunities and challenges in the field. For example, studies by Hu and Zhou [2021] on the application of machine learning algorithms in vehicle maintenance were combined with the work of Ravi et al. [2022] on case studies of successful predictive maintenance implementations [5, 6].

This template was adapted from those provided by the IEEE on their own website.

III. DESCRIPTIVE ANALYSIS OF THE LITERATURE

In predictive maintenance for electric vehicles, the dataset primarily comprises sensor data collected from various vehicle components, such as batteries, motors, and electronic control units. These sensors continuously monitor parameters like temperature, voltage, current, and vibrations. Such datasets can provide valuable insights into the operational state of the vehicle, allowing for early detection of potential failures [1, 4, 9]. The richness of this data enables the application of advanced analytical techniques and machine learning algorithms to predict maintenance needs before failures occur.

A. Preprocessing Techniques Employed

Preprocessing is crucial in ensuring the quality and reliability of the data used for predictive maintenance. This phase involves several steps:

- Data Cleaning: This step addresses any inconsistencies in the data, such as duplicate entries, incorrect values, or irrelevant features. For example, removing records with sensor malfunctions or calibrating sensors to correct erroneous readings is vital [3, 11].
- Feature Extraction: Key features are derived from the raw sensor data to highlight relevant patterns. Techniques like Fourier transforms may be applied to convert time-domain signals into frequency-domain representations, allowing for the analysis of vibration data to identify anomalies [6, 7].
- Handling Missing Values: Missing data can significantly impact model performance. Common strategies include imputation techniques [e.g., mean/mode imputation, interpolation] to fill in gaps, or remove of instances with excessive missing values to maintain dataset integrity [2, 12].
- Outlier Detection: Outliers in sensor data can skew results. Techniques such as Z-score analysis or the Tukey method can identify these anomalies, enabling corrective actions, such as removal or capping of extreme values [5, 11].
- Data Transformation: Normalizing or standardizing features ensures they contribute equally to the model's performance. This is particularly important for algorithms sensitive to the scale of input data, such as deep learning models [4, 10].

B. Deep Learning Models for Predictive Maintenance

1] Convolutional Neural Networks [CNN]

CNNs are adept at processing time-series data due to their ability to extract spatial hierarchies of features.

Convolutional Neural Networks are a family of deep models trained mainly on structured grid data, for example, images, or time series sensor data. CNNs outperform other deep learning models because their ability to automatically detect hierarchical features is what is primarily needed in those domains with huge precedence in recognizing patterns. In the case of predictive maintenance of an electric vehicle, CNNs take huge amounts of sensor data into account for detecting anomalies and predicting failures, thus making EV systems more reliable and safe.

One of the most fundamental strengths of CNNs is feature extraction, which does not require much manual engineering. In the case of EVs, sensors produce high-dimensional data, encompassing signals from accelerometers, gyroscopes, and temperature sensors. CNNs make use of convolution layers to learn spatial hierarchies in that data. The data can also be preprocessed and filtered to highlight abnormal signatures in vibration or temperature, which may be another indicator of component failure soon.

This way, feature extraction is automated, and the model will focus on the most relevant aspects of the data for improved prediction accuracy and efficiency. A typical time-series monitoring data set is typical with CNNs, especially with EV components. CNNs can easily capture temporal dependencies and trends by considering time as a spatial dimension. They can, when used for sensor data, analyze the vibration signal from an electric motor, say, over time and identify patterns before failure. This capability enables manufacturers and fleet operators to pursue predictive maintenance strategies and reduces the total downtime as well as the expenses while enhancing overall vehicle performance.

To enhance its prediction capability, CNNs can be combined with other deep architectures such as LSTM networks. This hybrid approach helps the model to rely on the complementary advantages of both architectures; CNNs perform very well in spatial feature extraction, whereas LSTMs work well in sequential dependencies. The use of these models allows for better performance in predictive maintenance systems in terms of predicting failures from historical sensor data with more accuracy. As a result, this will have effective scheduling and much better uptime in vehicles.

Numerous studies and industry implementations prove the success of CNN in predictive maintenance. For example, a few studies have reflected how CNN can recognize the states of an electric motor after analyzing the vibrations, thus providing timely interventions before catastrophic failure. Recently, automotive companies have used CNN in real-time health monitoring of a battery and other critical components of the vehicle to realize proactive decisions on maintenance and thus enhance the car's lifecycle.

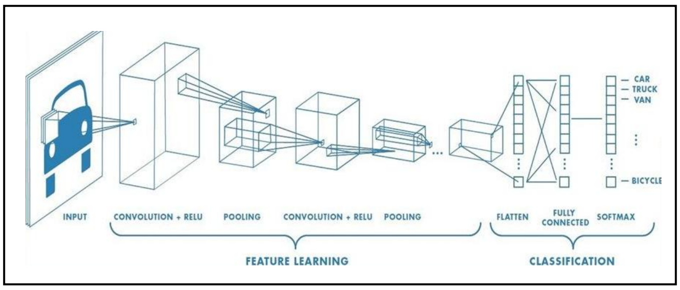

Fig. 1. CNN Working in Layers

2] Long Short-Term Memory [LSTM]

Long Short-Term Memory [LSTM] networks are a specialized type of recurrent neural network [RNN] designed to learn from sequences of data, making them particularly well-suited for tasks that require modeling temporal dependencies. In the context of predictive maintenance for electric vehicles [EVs], LSTMs are invaluable for analyzing time-series sensor data generated by various vehicle components. Unlike traditional RNNs, which struggle with long-term dependencies due to issues like vanishing gradients, LSTMs incorporate memory cells that enable them to retain information over extended sequences. This architecture is crucial when predicting failures or maintenance needs based on historical data.

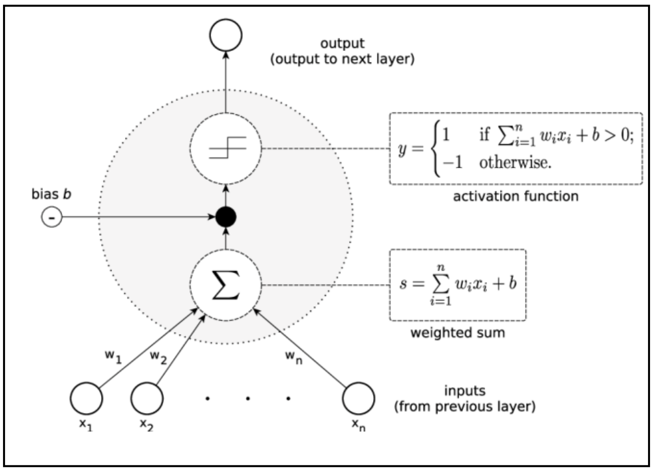

Fig. 2. LSTM Neural Structure & Working

The inherent design of LSTMs allows them to selectively remember or forget information, making them exceptionally effective for processing sensor data collected over time. For instance, in electric vehicles, LSTMs can be trained on sequences of data such as motor temperature, battery voltage, and vibration readings. By utilizing a series of gates [input, forget, and output gates], LSTMs can dynamically adjust their memory based on the relevance of the information being processed. This capability is vital for applications like early failure prediction, where understanding patterns and trends from past sensor readings can significantly influence maintenance decisions.

In the realm of predictive maintenance, LSTMs are particularly adept at capturing anomalies in sensor data that may signal impending failures. For example, they can analyze the historical performance of an electric motor, detecting shifts in operational parameters that deviate from the norm. By learning from previous patterns, LSTMs can identify subtle changes in the data that may indicate potential issues, allowing for timely interventions before a failure occurs. This predictive capability not only enhances the reliability of EVs but also reduces operational costs by minimizing unplanned downtime and optimizing maintenance schedules.

The integration of LSTM networks with CNNs represents a powerful approach for predictive maintenance in electric vehicles. While CNNs excel at extracting spatial features from complex data, LSTMs provide the temporal context necessary for understanding how those features evolve over time. This hybrid model leverages the strengths of both architectures, allowing for improved accuracy in failure prediction. By combining the ability to analyze the intricate patterns in sensor data with the understanding of temporal relationships, this approach offers a robust solution for maintaining the health of electric vehicle systems.

The real-world applicability of LSTMs in predictive maintenance is further supported by various studies and industry applications. Research has demonstrated the effectiveness of LSTMs in predicting battery failures in electric vehicles by analyzing historical charging patterns and operational data. These models have shown a high degree of accuracy in forecasting when a battery might reach critical levels of degradation, enabling proactive maintenance actions that extend the life of the battery and enhance overall vehicle performance.

LSTMs also play a significant role in developing digital twin technologies, where virtual representations of physical systems are used to simulate and analyze real-time performance. By integrating LSTM networks into these systems, manufacturers can continuously monitor the condition of electric vehicles, utilizing real-time sensor data to predict potential failures. This not only improves maintenance strategies but also enhances the overall user experience by providing insights into vehicle health and performance.

In conclusion, LSTMs are an essential component of predictive maintenance strategies for electric vehicles. Their ability to model temporal dependencies and analyze time-series data enables them to predict failures with remarkable accuracy. As the automotive industry continues to embrace advanced analytics and machine learning, the role of LSTM networks will become increasingly critical in enhancing the reliability and efficiency of electric vehicle systems.

3] Regularization and Accuracy Improvement Techniques

L1 Regularization: L1 regularization, also known as Lasso regularization, is a strong machine-learning technique to avoid overfitting in the improvement of the model performance. In particular, L1 regularization within predictive maintenance for electric vehicles controls the complexity of a model and improves the interpretability of the results. Adding a penalty term proportional to the absolute value of the coefficients to the loss function makes L1 regularization encourage sparsity in model parameters. This means that it reduces the number of features used in the model by driving some of the coefficients to zero, thereby making the model simpler and easier to interpret.

L1 regularization can thus be quite useful in applications of predictive maintenance, especially when big datasets are common and contain many features: finding the most relevant predictors in sensor data such as temperature, pressure, and vibration measurements a more compact, influential feature set and, hopefully, better generalizability to unseen data. This is especially useful in the EV field, where determining key failure indicators can be crucial to early intervention and cost savings in maintenance.

The L1 regularization influence, however, goes beyond simply adding to the accuracy of a model. In the case of models applied to predictive maintenance, it actually can do much greater than that to improve the predictability of a model because it does not suffer much from the overfitting pitfalls often found when handling complex, high-dimensional datasets. For instance, in a predictive model for predicting time to battery failure from historical charging patterns with additional usage data, L1 regularization would prevent the model from becoming one that memorizes the training data but learn to generalize. The improvement in predictions is consequentially accompanied by an improvement in maintenance strategy.

It also comes in handy in improving the interpretability of machine learning models. The prediction offered by predictive maintenance improves dramatically if considered that which features are more important or contribute the most in terms of the predictions so that insight for the engineers and data scientist is obtained through L1 regularization for the most impactful features, and sensor readings are prioritized among other related sources of data. It is extremely helpful in the manufacturing industry like automotive where actionable insights may become a cost saver to a very large extent while increasing safety.

Another advantage of L1 is that it often works well with other techniques, such as cross-validation and feature scaling. Such integration may further improve effectiveness when aiming for predictive maintenance scenarios. Practitioners could combine L1 regularization with other techniques to fine-tune their model for optimal performance while keeping it robust against overfitting [6, 10].

4] Other Techniques

To further enhance model accuracy, several techniques can be applied:

- Dropout: This regularization method randomly sets a fraction of the input units to zero at each update during training, which helps prevent overfitting by ensuring the model does not rely too heavily on any one feature [3, 11].
- Batch Normalization: This technique normalizes the input of each layer, allowing for faster training and improved stability of the learning process [2, 6]. By mitigating the problem of internal covariate shift, batch normalization helps maintain the flow of gradients throughout the network.
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IV. *COMPARATIVE MACHINE LEARNING MODELS*

A. Logistic Regression

Logistic regression is a statistical model commonly used for binary classification tasks, such as predicting whether a vehicle will experience a failure.

1) Pros of CNN Compared to Logistic Regression

- Feature Extraction: CNNs are designed to automatically extract hierarchical features from complex data, such as images or time-series sensor data, without requiring extensive manual feature engineering. This contrasts with logistic regression, which relies on predefined features and assumes a linear relationship between them and the outcome variable [21].
- Handling Complex Data: CNNs excel at processing high-dimensional data, particularly spatial and temporal data, making them well-suited for tasks such as motor vibration analysis and image recognition. Logistic regression, on the other hand, struggles with such complexity and may fail to capture the intricate patterns necessary for accurate predictions [14].
- Non-linearity: CNNs utilize non-linear activation functions [like ReLU] between layers, allowing them to model complex relationships. Logistic regression is inherently linear, which can limit its effectiveness when dealing with non-linear data distributions often found in real-world applications [2].
- Scalability: CNNs can scale effectively with larger datasets, improving their accuracy as more data becomes available. This is particularly important in predictive maintenance, where large amounts of sensor data can be collected over time. Logistic regression may not perform as well with large datasets, especially if the relationships among variables become more intricate [7].

2) Cons of CNN Compared to Logistic Regression

- Complexity and Training Time: CNNs are significantly more complex than logistic regression, requiring more computational resources and longer training times. This complexity may not be justified for simpler predictive maintenance tasks, where logistic regression could provide sufficient accuracy with less overhead [7].

- Interpretability: Logistic regression models are often easier to interpret, providing clear insights into the impact of each feature on the predicted outcome. This interpretability is crucial in industries like automotive maintenance, where stakeholders need to understand the reasoning behind predictions. CNNs, while powerful, operate more as "black boxes," making it challenging to interpret their decision-making processes [7].
- Overfitting: Although CNNs are powerful, they are also more prone to overfitting, particularly when trained on small datasets. Regularization techniques are necessary to mitigate this risk, adding to the model's complexity. Logistic regression, being simpler, is less susceptible to overfitting in cases with limited data [19]
- Data Requirements: CNNs require large amounts of labeled data to perform well, especially in supervised learning tasks. If labeled data is scarce or costly to obtain, logistic regression may provide a more practical solution due to its ability to perform adequately with smaller datasets [15].

B. Random Forest

Random Forest turns out to be very effective in dealing with large volumes of sensor data from batteries, motors, and control systems. In a high-dimensional space and often noisy, it is hard to gain actionable insights that can be used for predictive maintenance. Random Forest reduces this complexity by building a hypothesis by aggregating the predictions coming from multiple trees, thus reducing variance and improving the overall accuracy of the prediction.

One of the strengths of Random Forest is that it can rank features by importance, which might be extremely useful in a predictive maintenance framework. It will allow engineers to understand which parameters in the model form the core identification of soon-to-happen failures based on what they contribute to the model's predictions. For example, if a motor's vibration reading remains the strongest predictor of failure, then maintenance teams know to track that reading more closely, so interventions can be taken before the failure will happen. This increases operating efficiency and helps in proper resource allocation, so efforts are not wasted on areas where there is no pressing need for maintenance.

Further, its in-built capacity to intelligently handle missing values and outliers makes Random Forest apt for typical situations associated with the real-world conditions of EV operations. In any reality, sensors may fail or send noisy data due to environmental reasons. Most algorithms that work on full datasets break down when there are discrepancies. And what's really interesting about Random Forest is that it can still predict correctly even in the face of those discrepancies.

Another area in which Random Forest shines is its ability to scale and adapt. It can be easily applied to several types of data, ranging from structured numerical types such as temperature and voltage readings to categorical data like conditions in operation and past maintenance records. This makes Random Forest an all-purpose tool for predictive maintenance, which allows different sources of data to be streamlined into one maintenance model.

It generally outperforms other traditional machine learning algorithms, such as logistic regression and support vector machines in multi-class classification, which is the most common type of classification for predictive maintenance tasks. Moreover, its ensemble nature allows for understanding complex interactions between features without exhaustive hyperparameter tuning, making modeling easier for data scientists and engineers.

V. DISCUSSION

Considering predictive maintenance for electric vehicles [EVs], the choice between using Convolutional Neural Networks [CNNs] and logistic regression is critical due to the distinct characteristics of the data and the nature of the problem at hand. CNNs excel at automatically extracting features from complex datasets, particularly when dealing with high-dimensional inputs such as images and time-series sensor data. This capability allows CNNs to uncover intricate patterns that traditional models, like logistic regression, may overlook due to their linear assumptions.

Logistic regression, while simpler and more interpretable, operates under the assumption of linearity, making it less effective when relationships between input features and outcomes are non-linear. This limitation is particularly pronounced in predictive maintenance scenarios where sensor data may exhibit complex interdependencies and non-linear behavior. CNNs can model such complexities, capturing temporal and spatial features through convolutional layers, which is essential in understanding behaviors such as motor vibrations or temperature fluctuations.

Moreover, CNNs are adept at processing larger datasets, a common scenario in predictive maintenance applications where extensive sensor data is collected over time. As the volume of data increases, CNNs typically improve in accuracy, whereas logistic regression may plateau in performance due to its simplistic nature [9]. However, this increase in accuracy comes at the cost of computational complexity and longer training times, making CNNs resource-intensive compared to logistic regression, which is computationally lightweight and quicker to train.

Interpretability also plays a significant role in model selection. Logistic regression provides clear coefficients that indicate the impact of each feature, making it easier for stakeholders to understand and trust the model's predictions. In contrast, CNNs often operate as "black boxes," which can complicate the understanding of how predictions are made, posing challenges in environments where model transparency is crucial, such as automotive safety can bring at the same time are really computationally expensive, especially with regard to large data and many trees. This can lead to training times that are longer and also consumption of resources, such that it might be a concern for very tight budget constraint organizations or ones requiring real-time predictions. Moreover, although interpretability of feature importance is available with the model, its decision process often may be less clear compared to simpler models, which makes it hard to communicate findings with non-technical stakeholders

VI. CONCLUSION

This review paper has dwelled in detail on the predictive maintenance techniques on electric vehicles, particular to CNNs, LSTM networks, logistic regression, and random forest algorithms. Each one of these displays a different degree of success as the approaches handle the complexities of sensor data collected from an EV, such as motor vibrations, temperature, and torque measurements. The primary strength in this regard is for CNNs to automatically extract relevant features from complex high-dimensional data like cases in time-series and sensor applications, thereby being complemented by LSTMs capturing deeper insight into predictive patterns of temporal dependencies inherent in sequential sensor readings.

Other traditional machine learning models, such as logistic regression and random forest, are easy to understand and straightforward to implement but fail to capture the nonlinear and complex pattern imposed on this type of data. However, some CNNs and LSTMs can outperform these models in terms of accuracy and ability to make better predictions but at a much higher cost of computation and decreased interpretability. But the performance-explainability trade-off is a significant challenge in most practical industrial applications, notably in the automotive domain, where transparency and model validation are crucial for regulatory compliance and safety.

While most of the related work above is innovative, there are significant gaps between what is currently being developed and what is available for application in predictive maintenance models of EVs. The main weakness in deep learning models is their lack of real-time applicability. Current versions often exhibit high latency and are not well-suited to handle real-time streaming data, thereby raising questions about their applicability in real-world predictive maintenance systems. Another key gap relates to the problem of unbalanced datasets. Since failure events of EVs are scarce compared to normal operating data, the associated models can be potentially skewed by such an imbalance. So typically, at least some of the adverse effects thereof would have to be mitigated by approaches like synthetic data generation, reinforcement learning, or hybrid modeling.

Further study in this area should involve the development of IoT technology and 5G integration network, which promises much in direct real-time monitoring and predictive maintenance. Research on digital twins and cloud-based architectures that offer continuous updates dynamically in models to achieve faster and more reliable failures detection in EVs is worthy of pursuit in the future.

In summary, the field, in itself, is still at its nascent stages; cutting-edge models-CNNs and LSTMs, in particular-represent the future of predictive maintenance for EVs. Therefore, it would be expected that key issues in regions such as real-time performance, model interpretability, and dataset imbalance are crucially expected to inform the research for driving these technologies forward into larger-scale commercial applications.

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