AI-Enabled Predictive Maintenance Framework For Connected Vehicles Using Cloud-Based Web Interfaces

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Abstract—A predictive maintenance framework based on arti- ficial intelligence (AI) is presented. Connected vehicles transmit vehicle-generated data to a cloud server from multiple vehicles. The data is processed with the AI model to forecast vehicle main- tenance requirements and issues and for scheduling maintenance operations in advance. The results—displayed on an easy-to-use, cloud-based web interface—consist of multiple-choice dropdowns to select the desired query for the AI model for processing and forecasting. The web interface facilitates smooth access to the AI process results and allows users to analyze data and identify the maintenance needs of individual connected vehicles.

Index Terms—Data acquisition and transmission,Data prepro- cessing and feature extraction,Predictive modeling (e.g., machine learning or deep learning),Maintenance decision rules,Cloud and edge interactions,Web-based visualization and alerts,predictive maintenance, connected vehicle, AI, cloud, web interface.

I. INTRODUCTION

The growing relevance of predictive maintenance for con- nected vehicles hinges on harnessing data already stored by vehicle manufacturers. Application Programming Interfaces (API) now provide easier access to this data, enabling the construction of efficient maintenance models. Data sourced from several vehicles opens opportunities for maintenance specialists to better schedule required maintenance. The pro- posed AI-enabled predictive maintenance framework, designed with a cloud-based web interface, allows quick interaction with processed data through the model. These capabilities can enable predictive maintenance specialists to make informed decisions about developing fault causes, vehicle fleets, and maintenance schedules. The confluence of connected vehicle data and artificial intelligence algorithms—as opposed to pack- aged analytical solutions—creates a user-preferred relationship developed for application in all types of connected vehicles. Connected vehicles generate substantial amounts of environ- mental and operational data that, when properly preprocessed, can detect potential breakdowns in advance and alert vehicle owners. The framework aims to provide a unified platform en- abling maintenance specialists to execute algorithm-generated inspections and receive inspection results through a user- friendly cloud-based web interface. Such a platform supports timely, data-driven decisions on maintenance requirements.

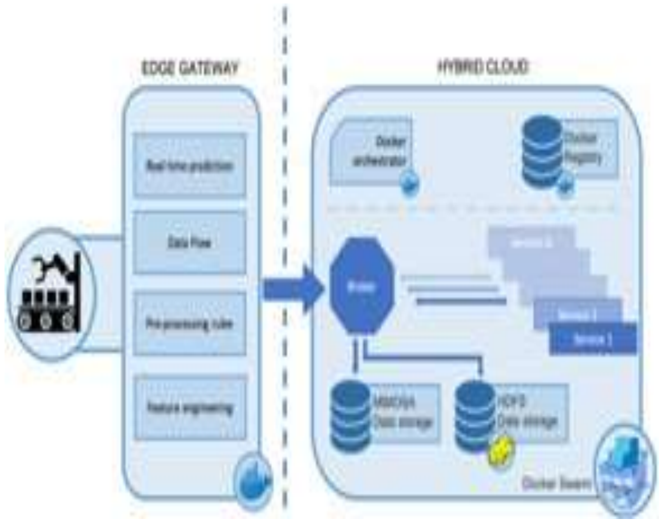

Fig. 1. Predictive Analytics in Robotics Industry

A. Background and Significance

Due to the recent development of connected vehicles, it is now possible to access information about the operational con- ditions of vehicles or their faults in real time from practically any place and at any time. However, frequently-diagnosed faults and potential future errors of vehicles cannot be suf- ficiently diagnosed yet. Accordingly, a predictive maintenance framework is proposed for the ongoing maintenance practices of connected vehicles by incorporating fault diagnosis for such models. The framework helps users investigate fault occur- rence probabilities in the past and their status at the time of query. The framework consists of data management and fault prediction segments, and it supports interaction with predictive maintenance algorithms through a web interface hosted on a cloud platform. Users may request fault diagnosis for specific parameters or assess the risk of various faults through the cloud-supported web interface. Predictive maintenance plays an essential role in enhancing performance and extending the service life of assets. In connected vehicles, maintenance operations are typically carried out only after a fault occurs or irregular performance is detected. A cloud-integrated artificial intelligence (AI) framework is introduced to overcome such limitations by enabling predictive maintenance in connected vehicles. Available information collected from connected ve-

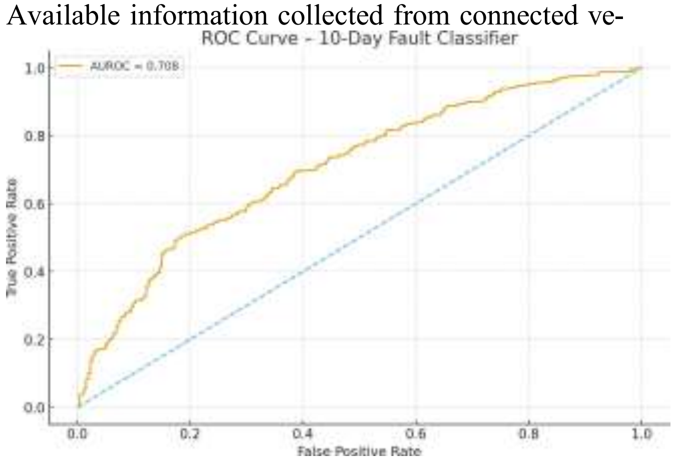

Fig. 2. ROC Curve – 10-Day Fault Classifier

Metric	Value
ROC AUC	0.5940099065899065
Precision (0)	0.933939393939394
Recall (0)	1.0
F1 (0)	0.9658414290191162
Precision (1)	0.0
Recall (1)	0.0
F1 (1)	0.0

hicles through on-board diagnostics and infotainment systems is stored in cloud storage, and the AI framework diagnoses fault probabilities in the braking systems of connected vehicles based on these collected data. The framework can be adapted to other fault diagnosis scenarios through a comprehensive processing and modeling procedure, and a user-friendly web interface is introduced to facilitate broad-scale usage of the framework.

EQ1:Feature extraction & preprocessing (derivations)

$$x^{i}, t(j) = xi, t(j), m\ j, xobserved, xmissing \qquad (1)$$

$$x\ i, t = \alpha x^{i}, t + (1-\alpha)x\ i, t-1, \alpha \in (0, 1]. \qquad (2)$$

$$x\ i, t = \sum_{k=0}^{w-1} \alpha(1-\alpha)^{k} x^{i}, t-k + (1-\alpha)^{w} x\ i, t-w. \quad (3)$$

II. Challenges and Limitations

The predictive maintenance of connected vehicles presents both technical challenges and data privacy risks. Failure to address such concerns can considerably limit the application of a predictive maintenance framework. In particular, interactions between testing drivers and testing vehicles become indis- pensable because the testing drivers should obtain accurate information about the test vehicles and then send appropriate commands to the vehicles. However, the testing vehicles can only upload the necessary information to the cloud but cannot download responses from the testing drivers, meaning that cloud-based web control functions should be enabled. Cloud computing is an architecture that divides the back-end of a data-processing platform into a front-end and a back-end.

The front-end usually consists of a browser and an operating system, whereas the back-end is an enormous collection of data storage servers, such as big data platforms. Cloud comput- ing is therefore a prospective architecture capable of solving the aforementioned limitation of predictive maintenance. In particular, one function of a cloud platform is to provide a web interface for data interaction between drivers and vehicles, so the control commands from the drivers can be passed to the cloud interface and then distributed to specific vehicles through the AnyData platform.

A. Technical Challenges

Monitoring and utilizing data generated by connected cars enables the development of vehicle maintenance frameworks capable of transmitting alerts as needed. Often, these frame- works operate using predictions derived from developed mod- els; such predictive maintenance models help identify main- tenance deficiencies within the vehicle. Recent approaches have incorporated artificial intelligence algorithms to examine connected car data for various applications, including mental burden assessment during driving, accident warning systems, automated maintenance scheduling, and decision-making re- garding ideal maintenance periods. Given the substantial data generated during a connected car's lifecycle, developers pro- pose implementing artificial intelligence algorithms capable of supporting complex analysis for diverse purposes. As predic- tive maintenance frameworks evolve, adding web interfaces to facilitate real-time data queries represents considerable design advancement. Accessibility remains a primary con- cern in development, and incorporating cloud services allows frameworks to be exposed via web pages built with various programming languages. Consequently, any user can interact with the framework by providing their data and receiving rapid analyses regarding the maintenance scheduling of their connected vehicle.

B. Data Privacy Concerns

Maintaining the confidentiality and privacy of customer data is a core priority for any business. Organizations recognize that a single breach of privacy or data security can result in a loss of customer trust and revenue. The Operating System (OS) privacy control in connected vehicles plays a crucial role in addressing these concerns. Connected vehicles collect vast amounts of data from sensors, cameras, automatic valet park- ing, weather services, among others. This data is transmitted to the cloud where AI-enabled predictive maintenance algo- rithms analyze and predict potential failures. Consequently, the data is displayed on the web interfaces of the connected vehicles for real-time interaction and exploration. The use of a cloud-based web interface in the predictive maintenance framework ensures real-time interaction with data generated by connected vehicles, giving vehicle owners a clear picture of their vehicle's condition and enabling prompt decisions. With the increasing demand for interaction between vehicle data and AI-based predictive maintenance algorithms, it is necessary to migrate data to the cloud. However, this migration process

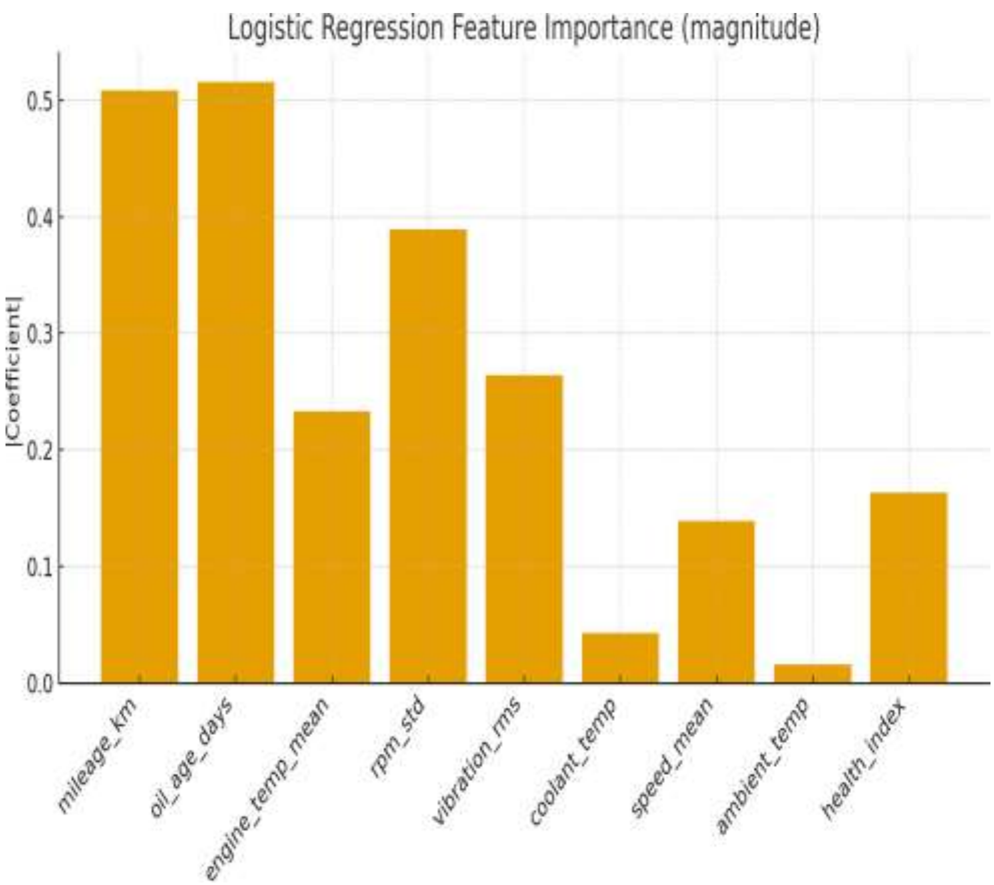

Fig. 3. Logistic Regression Feature Importance (magnitude)

Feature	Coefficient	OddsRatio(expβ)
engine temp	0.21412055905193458	1.2387719909681518
dtc count	0.1853223879419795	1.2036064057787235
rpm mean	-0.12895997016798505	0.8790091514300072
brake events	0.07570466190569163	1.078643962458204
mileage	0.04440717755492002	1.0454079348860732
ambient temp	-0.0014235988392011874	0.9985774139969452

raises several technical challenges and limitations, particularly concerning data privacy. Organizations are, therefore, seeking solutions that align with the Internet of Things (IoT) paradigm and comply with existing data privacy policies and guidelines in both the automotive domain and other domains where predictive maintenance models have been implemented.
EQ2:Predictive maintenance model (ML/AI-based)

$$Y_{i,t+h} \in \{0, 1\} \text{ for horizon } h = 10 \text{ days} \quad (4)$$
$$Y_{i,t+h} = 1 \iff \text{fault occurs in } (t, t+h]. \quad (5)$$

$$p_{i,t} = \Pr(Y_{i,t+h} = 1 \mid z_{i,t}) = \quad (6)$$
$$\sigma(\beta_0 + \beta^{\top} z_{i,t}), \sigma(u) = 1 + e^{-u}1. \quad (7)$$

$$L(\beta_0, \beta) = -n = 1 \sum m[y_n \log p_n + \quad (8)$$
$$(1 - y_n)\log(1 - p_n)] + 1 \ \beta \ 22. \ | \ | \quad (9)$$

III. Literature Review

The concept of preventative maintenance emerged during World War II when significant aircraft production was sup- ported by a strategy of replacement or repair schedule based on time in service (Kothamasu et al., 2006, Weerasinghe et al., 2022). During wartime, vulnerability was decreased and equipment availability was maintained by putting tight controls on protective maintenance. Even though these concepts proved to be fairly successful, it became apparent following the war that preventative maintenance was not always the most cost

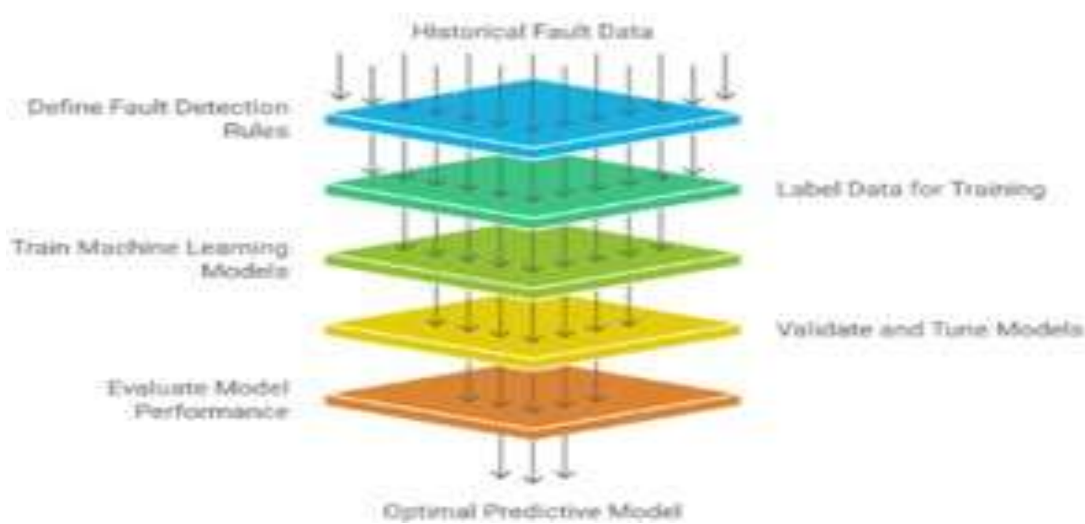

Fig. 4. Hybrid Predictive Maintenance for Building Systems

and resource-effective approach. The basic issues of deliber- ately replacing components based on time in service revolved around the costs or lack of availability of the parts as well as the unpredictability of the failure mode. That is, whenever the components were removed for replacement, these components may have been just as likely to function properly for a long time into the future as they were to fail immediately after being replaced. This issue was of concern not only from a cost standpoint, but also from a safety and maintenance schedule standpoint (Levy, 1995). Further literature review delves into these existing models for predictive maintenance of connected vehicles and highlights the relevant state-of-the-art in the domain.

A. Existing Predictive Maintenance Models

Existing predictive maintenance (PM) models vary widely in their approach. Concurrently, advancements in cloud com- puting bring new opportunities, particularly when a cloud- based Web interface complements data-driven algorithms. The framework described for connected vehicles proves effective, with cloud-based services limiting the use of on-premises resources and many end users preferring a Web interface for interacting with real-time data. Connectivity of vehicles plays an important role in PM. By analysing fault codes and other data transmitted from a connected vehicle, the proposed PM framework predicts the urgency of required maintenance and shows the OEM recommended action. The model can handle a range of faults and recommends different maintenance sched- ules. Last, a Web interface developed using Google Cloud Platform (GCP) enables dealers and OEMs to interact with real-time data transmitted from all connected vehicles. The framework is tested using a car follow-up analysis, which identifies an engine oil replacement requirement. It is then applied to a fault-log analysis that requires immediate fix.

B. Cloud Computing in Automotive Applications

Cloud computing can be utilized for the data processing and analysis of automotive vehicles in the future. Studies performed in this area have proposed novel methods and architectures using information technology and data science with main focus on information sharing. Connected vehicles use streaming data to provide online information about the traffic situation. Additionally, the cloud computing concept is proposed to implement vehicular data storage and anal- ysis. Existing cloud computing platforms can be extended to implement a novel V2V sharing information software application using the cloud computing concept as the back-end vehicle–vehicle data storage and analysis supporting system. However, architectural issues and implementation details of such a platform have not been presented. The implementation of Fault Detection Identification and Recovery (FDIR) is not yet operating efficiently on automobiles. One approach com- prised a cloud computing Workshop Sign on Modem (WSM) Box for fault detection in automobile FDIRs. However, the results were limited to the detection of vehicle parameters such as data on Engine temperature, RPM and Neutral gear position status. Energy consumption and security are two major challenges for cloud-based applications for connected vehicles. An architecture was proposed that considered real- time big data with the aim of reducing energy consumption in the framework. The main concern was data transfer between different channels, which was addressed by incorporating the encryption–decrypt action during transfer using an energy- efficient network coding technique. Vehicular sensors form the main source of data for the vehicle management system. Storing and running different services was a critical issue in the past owing to limited resource in-vehicle sensors. A frame- work was proposed, and a cloud-based processing architecture was developed for a connected vehicle management system. The framework supports the security and privacy of vehicle data during cloud processing. Furthermore, a model for the incorporation of middleware services was also presented for fault detection and predictive maintenance. Despite cloud com- puting platforms offering several applications, their utility in predictive maintenance was not explored in detail. Moreover, with growing concern regarding the security of vehicle data, data privacy was also analysed.

IV. Framework Overview

Predictive maintenance leverages data analysis tools and techniques to detect anomalies in operational environments and mitigate the risk of failures proactively. Cloud computing is transformed into an elastic service that provides on-demand and facile access over the Internet, supplying storage and pro- cessing resources anytime and anywhere. Since the emergence of cars, the need for their maintenance has been obvious. Common maintenance strategies include preventive mainte- nance, corrective maintenance, and predictive maintenance. Recently, Location-Based Service coverage has been utilized to develop a web-based interface that simplifies data loading and extraction, making it an effective property for predictive maintenance. Data generated by connected cars contains in- formation about the condition of the car and its components. Studying this data enables the implementation of predictive maintenance by anticipating the future condition of the parts and informing the driver accordingly. The proposed framework aims to provide such information through a web interface hosted on the Google Cloud Platform. The designed algorithm predicts the probability of failure within the upcoming 10 days for various components; incidents exceeding a 50

A. Architecture of the Framework

The harmonised interaction between prediction-driving components is crucial to the development of any predictive maintenance framework, especially the flow of data through the involved algorithms. For connected vehicles, the aggre- gated data that lie at the root of prediction provide neces- sary historical context and enable delicately placed temporal comparisons. After being collected from multiple sources, the telematics data are processed via indicative selection and treatment mechanisms before being directed to either fault-prediction or service-scheduling modules, where an AI- algorithmic approach is leveraged. The outcomes are then displayed to the user through an interactive web interface, which incorporates data-filtering capabilities to help the driver quickly comprehend the system status. Descriptive flights through each major component in the data stream paint a fuller picture of the overall architecture of the predictive-maintenance framework. Game engines, mapping programs, and predictive models rely heavily on generation, reception, or manipulation of data to achieve their desired purposes. Likewise, the algorithm of choice is chiefly responsible for processing data and generating useful outcomes for the user, but it is only with the assistance of a web interface integrated on a cloud platform that the algorithm's effectiveness can be fully realised. Such a setup provides service to the end user throughout the vehicle's life on the street, facilitating a straightforward connection between vehicle and user.

B. Components of the System

The AI-enabled framework for predictive maintenance leverages a rich volume of data collected by connected ve- hicles and implements various models using machine learning approaches. To capitalize on the benefits of ultramodern cloud computing, a cloud-based web interface has been developed that not only records a large amount of data but also inputs extensive information into predictive models. This cloud-driven set of algorithms provides a user-friendly environment, enabling users to dynamically switch between models using the same input data. Predictive maintenance emerges as a crucial aspect not only for sufficient vehicle operation but also as a significant source of revenue. In contrast to reactive main-tenance—performing service actions post-failure to maintain functionality—and preventive maintenance—which involves routine scheduling to prevent failures—predictive maintenance determines the optimal conditions for maintenance actions and effectively reduces the likelihood of breakdowns. This feature offers valuable guidance for optimizing maintenance schedules and budgets. Maintenance costs rank as the third major expen- diture in vehicle fleets, exceeded only by depreciation and fuel

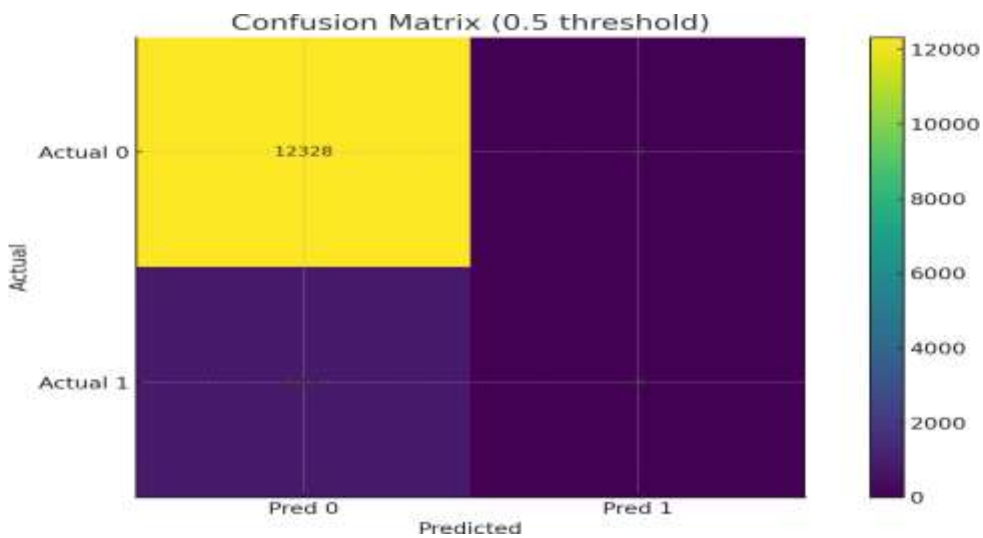

Fig. 5. Data Collection, Data Entry & Data Management

Confusion Matrix (Counts)

	Pred 0	**Pred 1**
Actual 0	12328	0
Actual 1	872	0

costs. Paying meticulous attention to preventive maintenance not only reduces operational costs but also decreases pollutant emissions, thus minimizing the vehicle fleet's overall impact on the atmosphere. The Cloud provides access to telematics data from any device connected to the Internet. It is well known that the amount of data generated within telematics is immense, and ensuring its quality and privacy is vital.

Obtain- ing millions of data points containing valuable information that can be used to make maintenance predictive systems feasible is considered a great advantage. The Web Interface represents the means through which any user connected to the Cloud can enjoy and take advantage of the predictive capabilities for their vehicle.

EQ3:Sensor data acquisition (sampling model)

, =, +, , [,] = 0, V ar(,) = 2xi, t = si, t + $\epsilon_{i,t}$, E[$\epsilon_{i,t}$] =
0, V ar($\epsilon_{i,t}$) = σ^2 ϵ
(10) $\int$
xi, k = D1 (k − 1)DkDxi, tdtorxi, k = M 1ℓ
(11) $\sum$
= 1 Mxi, tk, ℓ.

V. Data Collection and Management

The first critical step for enabling predictive maintenance of connected vehicles is the collection of vehicle data. Connected cars shed abundant information describing their operating status and health conditions, making data collection and intel- ligent utilization essential. Thanks to advancements in audio- video capture techniques and communication technologies, telematics data can be efficiently gathered and stored in the cloud from various on-board sensors. Four categories of vehicle data are considered: vehicle operating data, diagnostic reports, environmental data, and user inspection. Each category provides valuable performance parameters supporting mainte- nance. The second consideration involves data management, requiring high-quality data sources to feed predictive mainte- nance algorithms. Although predictive models—such as fault detection algorithms or remaining useful life estimators—are not new, a rise in cloud computing enables a user-friendly web interface connecting end-users to back-end AI algorithms. Data quality management techniques enhance sourcing pro- cesses by cleansing erroneous or inconsistent data. Privacy concerns associated with storing connected vehicle data in the cloud are also addressed to maintain user trust and comply with regulatory requirements.

A. Data Sources

Data serves as a vital tool for predicting maintenance needs for connected vehicles. It offers a wealth of information with the right quality and size. Modern vehicles come equipped with sensors and systems that generate data regarding various conditions such as engine performance, speed, location, and driving behavior, aiding in effective vehicle management. A collection of web-based portals is presented to view and search recent or historical predictive maintenance data for connected vehicles. These portals utilize cloud computing to facilitate the execution of connected vehicle predictions, providing an initial interface for users to retrieve all information from the connected vehicle prediction algorithms. These predictions help detect any probable faults in the vehicles and allow for detailed data exploration and visualization in real time. The data might originate from various connected vehicles, enabling users to perform open-data analysis, examine predicted faults in connected vehicles worldwide, confirm the results of vehicle fault predictions, and investigate traffic congestion conditions. The investigative approach to open data analysis verifies the connected vehicles maintenance-fault data. Open-data analysis represents a specific form of data-mining analysis driven by particular analytical objectives and achieved by applying online analytical solutions and discovery tools to shared active data. For effective data-mining analysis, the gathered data must meet certain minimum standards, ensuring legitimacy, organized storage, regular updating, consistent maintenance of the information, and systematic cataloging. Data mining tasks encompass summarization, clustering, classification, associa- tion, and trend analysis. The classification technique catego- rizes entities into specified groups based on characteristics and patterns, employing different methods such as the Decision Tree method. Clustering divides data into meaningful, homo- geneous groups that are useful for interpretation and analysis.

B. Data Processing Techniques

Connected vehicles are gradually entering the mass market and represent an important part of the Internet of Things (IoT). A variety of external sensors and onboard diagnostics collect data, which can be leveraged to develop applications that provide an improved driving experience. In previous research, predictive analysis of connected vehicle data has shown that it is possible to accurately forecast fault occurrences related to emissions and other hard failures. However, enabling user in- teraction with the predictive functions remains a challenge, as these are typically presented as reports delivered via email. To address this limitation, an AI-enabled predictive maintenance framework that employs a cloud web interface is proposed. The framework integrates data gathered from multiple sources to generate actionable insights for preventive maintenance. Handling connected vehicle data via the cloud opens new possibilities for real-time interaction through web interfaces. In the proposed system, data is uploaded to the cloud, and an interactive cloud web interface can be queried to provide infor- mation at any time. Data from a Ford Transit Connect vehicle is used as a testbed, demonstrating the practical benefits of key metrics related to emissions and vehicle faults when presented through a cloud web interface. From a technical perspective, the primary advantage is that it enables direct querying of the predictive maintenance framework through Google Cloud services.The PLCM model for the battery management system in UAVs was developed using a combination of supervised and unsupervised learning algorithms by applying Long Short- Term Memory (LSTM) and k-means clustering algorithms by pooling several signals from asynchronous sensors, such as voltage, current, and temperature.
EQ4:Health Index (HI) estimation

$$HIn = 1 - max(e) - min(e)en - min(e). \quad (12)$$

$$HIi, t = sigmoid(g0 + \sum_{j} gjzi, t(j)), \quad (13)$$

VI. Predictive Maintenance Algorithms

Various predictive maintenance algorithms are presented here, fed by monitored data directly. They propose integrating the artificial intelligence step with cloud computing to over- come limitations caused by data quality. Indeed, innovative paradigms for predictive maintenance are developed with real- time sensory data collected from the working environment as input. At the same time, new trends and requirements of cloud

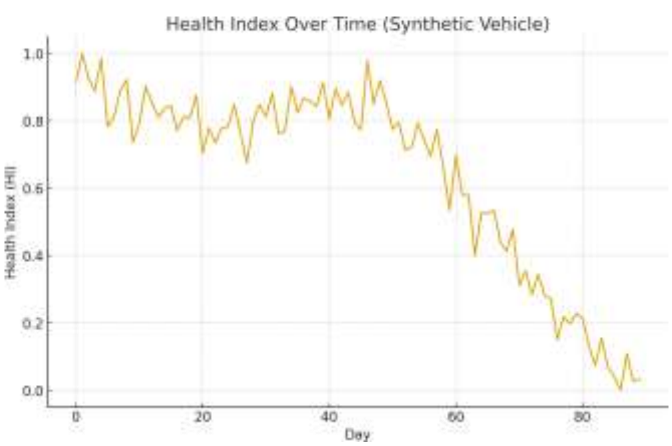

Fig. 6. Health Index Over Time (Synthetic Vehicle)

computing are considered and designed as the foundation to provide advanced threshold analysis and timely warning services in order to ensure product operation and risk manage- ment. Predictive maintenance models are applied to connected vehicles. Since cloud computing plays an important role in the development of connected systems and vehicles, within the framework, the functions are embedded in an interactive web interface running in the cloud.

A. Machine Learning Approaches

Machine learning is a popular method for predicting the quality of a product or process. The analysis and predic- tion steps have been utilized in several areas of predictive maintenance research. In previous PLCM models, techniques such as “model building,” “fault detection,” “diagnosis,” “prog- nosis,” and “maintenance scheduling” were developed using supervised or unsupervised learning algorithms. Booth de- veloped an expert system for condition-based maintenance. Other researchers have used a Hidden Markov Model (HMM) to estimate the condition of a product. Khan and Coleman proposed meta-model-based fault diagnosis of the battery management system in UAVs using several machine learning classification algorithms. The selection of a model depends on the problem setup, data availability, quality and quantity of data, and interpretability of the model. In the literature, the most commonly used methods for prediction and estimation are Logistic regression, Support Vector Machine (SVM), De- cision trees, Gradient boosting, and Random forest algorithms. Their performance is comparable with Neural Network models in several domains. These popular classification algorithms can be categorized as supervised learning. Supervised learning is the most popular approach for developing a classification problem. In this framework, stepwise model development was achieved through logistic regression, Random Forest classifier, K-nearest neighbors, Decision Trees, Gradient boosting, and Multi-Layer Perceptron Classifier.

B. Statistical Methods

Predictive maintenance algorithms can also be categorized by the distinction between AI/Machine Learning methods and Classical/Statistical methods, which are representations of Data-Driven and Model-Based approaches. Model-Based methods utilize mathematical models to derive an optimal sys- tem test based on the exploitation of the pseudo-measurements, resulting in test coverage optimization used in the context of fault and failure detection. In contrast, Data-Driven methods are built on statistical and AI/Machine Learning algorithms; these ML algorithms have already been used to detect failures recently. Literature shows that the following methods have been practiced recently: Decision Tree, Random Forest, Sup- port Vector Machine, Neural Network, k-Nearest Neighbors, and Logistic Regression. Previous sections have outlined an AI-enabled predictive maintenance framework applied to con- nected cars. While AI algorithms process vehicle-embedded sensor data for prediction, cloud computer infrastructures offer accessible interaction with both input and output data through dedicated web interfaces. From this perspective, an additional on-line component is introduced, enabling control over the collection and preprocessing steps of sensor data and supporting real-time analysis of prediction results. Both elements—analysis algorithms and the web interface—are implemented, configured, and deployed within the major cloud platform provided by Google. The following paragraphs review the framework’s main features before detailing the development of the cloud dashboard supporting maintenance operations.The operation of CAV engines demands as large a fleet as possible. The failure or degradation of engine perfor- mance often results in service interruption for CAV operations. Condition-based maintenance of a CAV is therefore essential to ensure continuous operation and to realize safe services. However, the CAV does not have a specialized maintain-and- repair (M&R) center. On-demand repair can be expensive and time-consuming for CAV operation. The future M&R plan for the engine needs to be evaluated in advance.
EQ5:Discrete-time hazard (use when labels are per interval)

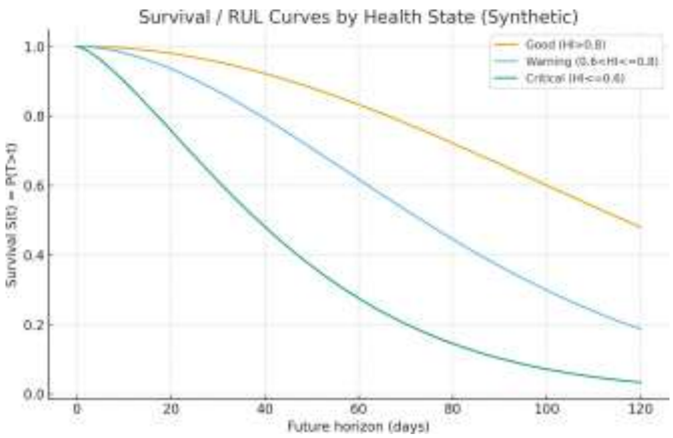

Fig. 7. Survival / RUL Curves by Health State (Synthetic)

the web interface. Within the implementation of the web interface, various programming languages supported different levels of interaction with the cloud. By leveraging RESTful web services, HTTP GET requests sent out by a Javascript program built within the web interface triggered the predictor model to obtain the latest prediction results.

A. Development Environment

AI-enabled predictive maintenance has been the subject of considerable interest in predictive maintenance, particularly in the context of connected vehicles, expressing the desire to use cloud-based web interfaces to support the interaction with the predictive maintenance algorithms. The field of connected and autonomous vehicles (CAV) has experienced significant progress over the past few decades. Cloud computing has continuously offered new opportunities for cross-domain in- dustrial revitalization. Industry 4.0 and its associated technolo- gies will lead to a fundamental change in the manufacturing ecosystem. Modern industry calls for rather complex network capabilities that are usually offered by cloud-based platforms, such as Amazon Web Services, Advanced Micro Devices, and Alibaba Cloud. The current focus is mainly on AI and cloud

$$h_u(z) = \Pr(T \in I_u \mid T \geq I_u, z) = 1-\exp\{-\exp(\alpha_u+\theta^{\top} z)\}, \quad (14)$$

$$S_U(z) = \prod_{u=1}^{U} (1 - h_u(z)), \quad \Pr(T \leq I_U) = 1 - S_U(z). \quad (15)$$

VII. Implementation of the Framework

The system was realized within a MATLAB programming environment that supported all data manipulation, processing and modelling capabilities. Predictive maintenance for con- nected vehicles relates to the specific topic of cloud computing. A cloud-based web interface can, for instance, display data originating from connected vehicles and allow user interac- tions with the data. Hence a cloud service was provided and leveraged. The predictor models were implemented in MATLAB and executed on the cloud service. The models then generated the prediction for query requests that came through platform services.

B. Integration with Cloud Services

Several challenges need to be considered, such as limited bandwidth, node overload, file availability, security and pri- vacy of data, and latency-sensitive applications. Cloud com- puting supports resource sharing, massive storage, data center management, and processing power, all based on centralized and scalable architectures where IoV data storage can be handled. By uploading computationally heavy fault diagno- sis models, fault prediction models, and auto-maintenance scheduling algorithms to the cloud, the limited computing power of on-board devices can be solved. In this regard, a novel AI-enabled predictive maintenance framework support- ing various cloud services through a cloud-based web portal for connected vehicles is developed. Predictive maintenance models and maintenance schedules can be easily uploaded to the cloud, and prediction results and practical maintenance plans can be conveniently acquired. Information collected by connected vehicles can be fed to the cloud, executed against the predictive maintenance models, and then displayed to the users through the cloud-based web interface. Users are free to perform various maintenance-management tasks through the web portal, which supports fault detection, fault diagnosis, proactive fault prognosis, and maintenance scheduling func- tions for connected vehicles.

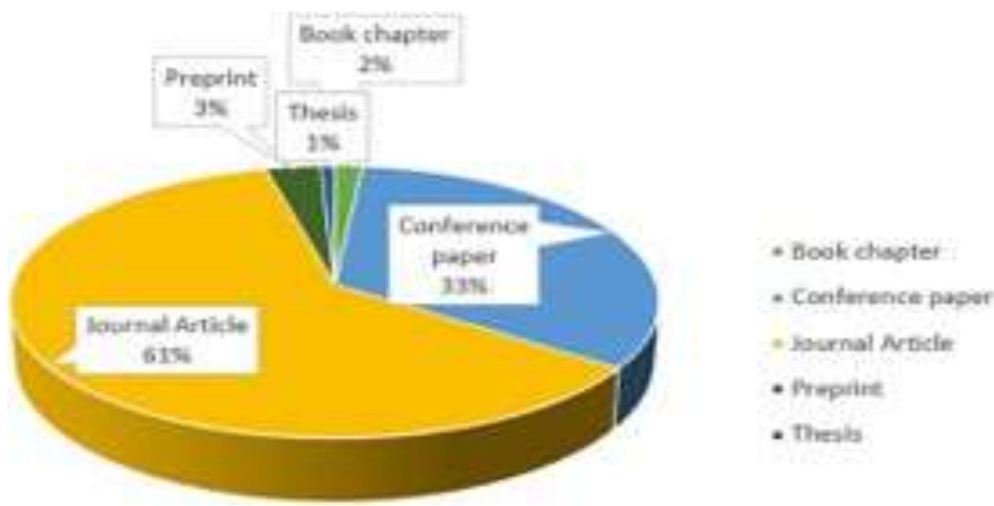

Fig. 8. Artificial intelligence driven predictive maintenance in vehicles

CONCLUSION

Predictive maintenance is increasingly regarded as an im- portant topic in the area of embedded systems. A lot of effort has been applied to the development of such maintenance systems. More and more vehicles are being equipped with the technology necessary to offer services of the connected vehicle concept. Data collected from connected vehicles can be used to collect technical information and estimate the state of vehicle components. The continuous growth in the usage of cloud platforms facilitates the creation of new systems and offers services that require analysis, processing, or storage of large amounts of data. By implementing an artificial intelli- gence enabled predictive maintenance framework applicable to connected vehicles and employing a web interface hosted in a cloud platform, predictive maintenance web environments can be developed and deployed in an easy way. The usage of such services in the cloud allows the connected vehicle and customer service areas to securely interact with the data generated and saved in the cloud platform in near real time.

C. Future Trends

Web interfaces developed for AI-enabled predictive main- tenance in connected vehicles clearly demonstrate the vast possibilities that arise when such maintenance algorithms are integrated with cloud platforms. Extending the analysis to other vehicle types—ranging from agricultural to heavy machinery—and to various conditions, including driving be- havior monitoring, is therefore both feasible and promising. These insights shape perspectives on the future directions of AI-assisted predictive maintenance for connected vehicles. Technical challenges emerge from the considerable volume of data generated by connected vehicles. Transmitting this data to the cloud can impose substantial costs and extend delays, prompting the consideration of edge computing for some vehicle types and applications. Incomplete data exacerbates problems, as errors introduced by missing values compromise model accuracy. Open issues include testing data collection in real-world conditions and assessing user acceptance. Data pro- tection concerns underscore the importance of complying with privacy regulations by storing user-related information with end users rather than central organizations. Public institutions in the automotive industry should thus encourage mitigation strategies that fully leverage the benefits of connected vehicles while assuring potential users of data privacy.

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