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Review Article

Vehicular Tracking System for Optimized Maintenance Strategy - Survey

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Abstract - *This abstract gives an overview of the importance and benefits of vehicle maintenance. With the advancement of technology nowadays, various improvements can be made in monitoring the condition of the car. Existing systems help coordinate key components of preventive maintenance, such as adhering to component replacement schedules, ensuring warning signs and addressing issues promptly. With proactive vehicle maintenance, drivers can minimize the risk of breakdowns and save on repair costs as well as improve road safety. This paper focuses on a review of existing maintenance systems and system recommendations that need to be improved to improve current progress.*

Keywords - *Maintenance strategy optimization, Predictive maintenance, Telematics, Vehicle diagnostics, Vehicle maintenance, Vehicular tracking systems.*

1. Introduction

In the automotive sector, vehicle tracking systems for preventative maintenance have become essential technologies that improve vehicle efficiency, safety, and dependability. These systems make use of the latest developments in GPS, GSM, and IoT technologies to offer predictive analytics and real-time monitoring. This guarantees that cars receive repair on time to avoid malfunctions and increase their operating lifespan.

Data on vibration, temperature, pressure, and electrical factors is now much more readily available due to the quick development of sensor and network technology. Sensors connected to the Internet of Things (IoT) produce billions of data points, which can provide real-time insights [1]. Predictive maintenance is made even more successful by integrating GIS with cutting-edge technology like machine learning and sensor data. For instance, it shows how GIS may make it easier to gather and analyze data on an automobile's lifecycle, which would improve maintenance forecasts [2].

The integration of IoT technology with automotive systems to improve the capabilities of conventional vehicles is a component of this transition. The self-driving automobile, an autonomous vehicle, demonstrates the sophistication of technology. With the aid of a sophisticated algorithm and sensors such as lidar, radar, camera, and GPS, an autonomous car can effectively adjust to changing road conditions without the help of a human driver. With the help of an Internet of Things sensor installed in the car, real-time data on vital parameters like fuel consumption, engine performance, and component health is continuously collected and sent to a centralized system for analysis. This wealth of data makes preventive maintenance procedures feasible, allowing maintenance staff to schedule maintenance proactively and spot issues. Additionally, in IR 4.0 situations, maintenance staff can discover and fix issues remotely, saving downtime, thanks to the remote monitoring and control capabilities offered by vehicle tracking systems.

Routine maintenance is crucial to guarantee maximum vehicle life for a user. For instance, replacing the oil at the appropriate intervals helps prevent friction-related engine damage. You should also inspect and adjust the air filter to keep the engine's air supply clean. Maintaining enough air pressure keeps tires from wearing down and increases their lifespan. It also keeps an eye on coolants, brakes, and other important parts and guarantees their appropriate operation.

Brake pads and belts should be checked frequently to ensure safety. A vehicle's maintenance program can be adhered to by following the manufacturer's recommended service plan, which frequently calls for routine inspections and replacements that are either infrequently fulfilled or spaced out. This includes inspecting the tires, brakes, and fluids, as well as changing the engine's oil and filter. Maintaining a regular eye out for warning signs, such as strange noises, vibrations, or dashboard indicator lights, can also aid in early problem detection and prevent more significant harm.

Preventive maintenance is essential to preventing traffic accidents since it calls for routine examination and servicing to address potential mechanical flaws before they worsen. The process of equipment replacement and maintenance is crucial to preventing collisions. By replacing vital parts like the tires, brakes, and lights, you can ensure that your car is safe to drive. Motorcycle crashes frequently occur at night when an automobile stops on the shoulder of the road, making it harder to see the stopped vehicle. Among other things, when the brakes fail to work properly, the car gets into more serious accidents, and more often than not, people die in them.

1.1. Research Gap

Implementation of predictive maintenance techniques and vehicular tracking systems to moving vehicle systems is still a relatively emerging territory despite their extensive research in industrial settings and stationary gear. In particular, there are not many comprehensive studies that address how real-time vehicular monitoring data can be used to optimize maintenance schedules for a range of vehicles. The area of deficiency is in the way predictive analytics and vehicle tracking technologies are used to create a data-driven, optimal maintenance plan. Moreover, the difficulties with data quality, sensor dependability, and the scalability of predictive models across many car kinds and operating conditions are frequently ignored by the research that is now available. Closing these gaps can result in more predictive maintenance models that work better, fewer breakdowns, lower costs, and better fleet management all around.

1.2. Problem Statement

Vehicle reliability and maintenance are major issues for the modern transportation industry. Keeping cars operating at peak efficiency and longevity has grown to be a major challenge as they get complicated. Conventional maintenance approaches, including reactive or time-based maintenance, frequently lead to greater operating expenses, unscheduled downtimes, and wasteful resource usage. Predictive maintenance, on the other hand, makes use of data-driven strategies, such as machine learning and Internet of Things-based sensors, to anticipate errors before they happen and enable proactive treatments. Predictive maintenance in automotive systems requires the use of vehicle monitoring systems to collect real-time data on wear and tear, engine health, fuel efficiency, and other performance metrics. This information is crucial for maximizing maintenance plans, cutting expenses, and raising vehicles' dependability and safety.

1.3. Objective

In addition to analyzing present shortcomings and outlining prospective avenues for future research and development, this study surveys current vehicle monitoring systems and their potential utility in developing optimized predictive maintenance techniques.

2. Literature Review

The value of preventative maintenance in extending the life of vital components has been demonstrated by several studies, making this research a crucial aspect of car ownership. Once industries have realized the fundamental risks and repercussions connected with adopting the Corrective Maintenance (CM) strategy for breakdowns, maintenance planning has generally been judged vital [3]. This finding establishes the preventive benefit of routine maintenance by lowering the need for expensive repairs. Furthermore, appropriate maintenance guarantees proper operations and seamless internal logistics while lowering life cycle costs [4].

In addition to its financial advantages, preventive maintenance has been well utilized in vehicle safety. According to research by Mena, Preventive car maintenance has many advantages, including protecting the environment, preserving driver and passenger safety, lowering fuel consumption and saving money, and guaranteeing that traffic laws are followed [5]. Moreover, prevention's contribution to environmental sustainability has received more attention in the past few years. According to research by Alex Antony, well-maintained vehicles have better fuel efficiency and produce less pollutants, which lowers their carbon footprint and contributes to larger environmental preservation initiatives [6].

Though there is a wealth of evidence supporting the advantages of preventative auto maintenance, not much is known about the impact of emerging technology on maintenance practices, such as vehicle diagnostic systems and predictive analytics. More research should look into how these developments might complement preventive measures, improving the efficacy and efficiency of auto maintenance. Overall, the study shows that preventative maintenance has numerous advantages, such as lower costs, more safety, and environmental sustainability. It also emphasizes how important it is to maintain the best possible performance and long-term viability of automobiles.

2.1. Vehicle Tracking Systems Comparative Analysis

Examples of vehicle tracking systems research are available in the literature (Table 1 - Appendix).

2.2. Usage-Based Maintenance

Adding usage-based maintenance to the present maintenance methods could provide an all-encompassing approach to equipment care. Usage-based maintenance monitors actual usage patterns and equipment performance data to determine the optimal time for maintenance chores. Variables such as running hours, cycles, or throughput might be examined when scheduling maintenance activities to account for the equipment's real-time operational requirements.

Usage-based maintenance lowers the risk of over- or under-maintenance by directly linking maintenance tasks to the equipment's actual usage and performance. This allows for a more individualized and efficient approach to equipment upkeep. Ultimately increasing equipment reliability and reducing downtime, this approach can further increase operational efficiency by ensuring that maintenance procedures are performed at the most convenient times. Organizations can also employ machine learning techniques and advanced analytics to examine consumption data from the equipment and identify any patterns or anomalies.

Pros: Maintenance is carried out when needed because it is tagged to actual equipment usage patterns. Through the use of real operational data to address wear and tear, it can aid in the prevention of premature failures. By eliminating needless repair on equipment that is not frequently utilized, maintenance efforts can be maximized.

Cons: Accurate tracking of equipment utilization is required for this option, which could be difficult for some assets. High demand could necessitate more frequent repair, which would lengthen downtime. The implementation of real-time monitoring and data collection systems is necessary for this approach, which can be expensive.

2.3. Time-Based Maintenance

Using a time-based maintenance schedule in addition to Utilization-based maintenance can lengthen the equipment's lifespan and enhance overall performance. Time-based maintenance involves doing routine maintenance chores at prearranged intervals, regardless of how frequently the equipment is used. In order to lower the likelihood of unscheduled equipment breakdowns, this preventative strategy ensures that all required maintenance including lubrication, inspections, and part replacements is completed on time.

By combining usage-based maintenance and time-based maintenance, a comprehensive maintenance plan can be created that considers the wear and tear that the equipment really undergoes, as well as the need for routine repair to prevent any issues. This integrated strategy has the potential to maximize equipment durability and minimize downtime, ultimately leading to optimal operational efficiency.

Pros: Since maintenance chores are planned at predetermined times, they are easy to implement and monitor. It offers a methodical approach to scheduling and planning maintenance. Guarantees routine maintenance and inspections, which can aid in the early detection of problems.

Cons: If equipment is underutilized or runs in less demanding conditions, it may result in over-maintenance and fails to take into consideration changes in the ways that equipment is used, which could lead to needless maintenance or lost maintenance opportunities. There is an increased chance of unanticipated breakdowns if maintenance schedules are not suitably matched to the state of the machinery.

2.4. Predictive-Based Maintenance

In addition to usage- and time-based maintenance programs, there is also predictive-based maintenance to think about. This approach uses data analytics and cutting-edge technologies to forecast when equipment repair is necessary based on the actual health of the assets. Predictive maintenance uses sensor data, machine learning algorithms, and historical performance data to forecast equipment faults in the future accurately. This makes it possible to carry out preventative maintenance procedures before issues arise.

Numerous benefits come with predictive-based maintenance, including decreased downtime, improved safety, and even greater cost savings by averting unnecessary repairs or maintenance. Organizations can optimize equipment reliability and operational efficiency by implementing predictive analytics to shift from reactive and preventative maintenance to a more planned and data-driven maintenance strategy. Maintenance is necessary for reinforced concrete constructions to be durable and safe. Upkeep teams can prevent more deterioration by closely monitoring the reinforcement's state and promptly identifying any indications of corrosion.

Pros: It makes use of monitoring technologies and data-driven analytics to anticipate equipment breakdowns before they happen, allows for the scheduling of maintenance only when it is absolutely necessary and saves money and downtime. Enhances asset availability and dependability by proactively resolving problems before they become more serious.

Cons: It may be difficult and expensive to adopt because it requires sophisticated data collection, processing, and predictive modeling capabilities. It depends on precise data and predictive algorithms, both of which can be difficult to create and keep up to date. A substantial investment in technology and knowledge may be necessary for the initial setup and integration with current systems.

2.5. Why Predictive-Based Maintenance is often the Best Choice

While minimizing their shortcomings, predictive-based maintenance combines the advantages of time- and use-based techniques. Utilizing sophisticated data analytics and predictive modeling methods, predictive maintenance:

- Minimizes downtime and lowers the possibility of unplanned breakdowns, improving operational efficiency and productivity;

- Anticipates equipment failures before they occur, enabling proactive maintenance actions to be taken;
- Targets interventions only when essential, optimizing maintenance efforts and lowering overall maintenance costs;
- Offers insightful information about the functionality and health of the equipment, facilitating more intelligent resource allocation and decision-making.

Predictive-based maintenance is the go-to option for many businesses wishing to improve their maintenance strategies because, although it may involve an initial investment in technology and knowledge, the long-term advantages in terms of increased reliability, decreased downtime, and optimized maintenance costs frequently outweigh the initial costs.

The goal of the study is to ascertain whether preventive car maintenance methods may enhance an automobile's lifespan, performance, and safety. A comprehensive review of the literature will be carried out as part of this project to identify critical factors and best practices for preventive maintenance. After that, a survey of vehicle owners will be conducted to assess their opinions regarding routine maintenance, their knowledge of warning signs, and their adherence to service schedules advised by the manufacturer.

Additionally, by comparing the costs and benefits of normal maintenance versus those of unplanned breakdowns and repairs, the study will investigate the economic consequences of preventative maintenance. Furthermore, the study will look into how proactive maintenance indicator monitoring reduces the risk of accidents and how preventive maintenance and vehicle safety are related.

The study aims to evaluate the environmental impact of preventative maintenance by comparing the emissions and fuel economy of vehicles that receive regular servicing to those that do not. Lastly, the research will investigate how technology innovations like predictive analytics and car diagnostic systems can improve preventive maintenance procedures.

The overall goal of this proposed study is to shed light on the effectiveness of preventative car maintenance techniques and their many advantages, which will help guide policy recommendations and best practices for car owners and other industry stakeholders.

The selected papers on vehicle predictive maintenance show that integrating diverse data sources, such as real-world fleet maintenance records, GIS data, and operational data, significantly enhances the accuracy of predicting vehicle failures. Studies utilizing advanced machine learning models, including Random Survival Forest (RSF), Long Short-Term Memory (LSTM) networks, and Seq2Seq models with Gated Recurrent Units (GRU), have demonstrated improved prediction outcomes by effectively handling complex time- -series and sparse datasets. For example, the integration of GIS data with maintenance records using deep learning models, such as the M-LSTM and Cox Proportional Hazard Model, has shown to be successful in estimating cars' Remaining Usable Lives (RUL) [2]. Similarly, incorporating geographical data into Time-Between-Failures (TBF) modeling has improved the accuracy of deep neural networks in predicting automobile maintenance needs [2]. Furthermore, models utilizing constrained-time-based algorithms have shown improved generalization for vehicle maintenance prediction by considering time constraints and enhancing model interpretability [21].

Additionally, explainable AI models for predictive maintenance applications have been developed using synthetic datasets, providing new ways to understand and interpret machine learning models in industrial settings [22]. Other approaches, such as the use of IoT-based architectures and Consensus Self-Organised Models (COSMO) for real-time predictive maintenance of vehicle fleets, have shown promising results in improving prediction accuracy by dynamically selecting sensors based on vehicle data [23]. Moreover, constrained Seq2Seq neural network models have also demonstrated improved prediction performance compared to traditional methods, suggesting a strong potential for application in vehicle maintenance prediction [24].

However, the complexity of data integration and issues with data availability and quality also pose serious obstacles to these integrated techniques. Sparse data, missing values, and variations in data readouts necessitate sophisticated preprocessing and model tuning to achieve reliable results [19]. While the strengths of data-driven predictive maintenance models are evident, as they allow for better planning and reduced vehicle downtime, future research is needed to optimize these models to be less dependent on complex and hard-to-acquire datasets. There is also a growing emphasis on leveraging explainable AI to improve model interpretability and user trust, as indicated by comprehensive literature reviews on the subject [20].

The development of constrained and explainable models provides pathways to address these challenges and enhance model adoption in practical settings [21, 22]. The integration of IoT-based dynamic sensor selection and constrained neural network models further enriches the landscape of predictive maintenance solutions, offering new dimensions for research and application [23, 24]. Overall, while the field shows considerable promise, enhancing data accessibility and refining model performance are critical areas for future exploration.

3. Proposed Materials and Methods

From data collection to model deployment, there are multiple processes involved in applying machine learning algorithms to handle On-Board Diagnostics II (OBDII) parameters for vehicle maintenance prediction, listed as follows.

3.1. Data Gathering

3.1.1. OBDII Parameters

Gather selected information from the vehicle's OBDII system. Certain data points are deemed vital vehicle parameters and can be accessed using the OBDII interface. These include engine RPM, vehicle speed, throttle position, coolant temperature, and error codes.

3.1.2. Additional Data Sources

For a more thorough analysis, data from other sources can be included, such as maintenance records for historical context and GPS data for tracking vehicle speed and location.

3.2. Data Preprocessing

3.2.1. Cleaning

Remove or correct missing or erroneous data points.

3.2.2. Normalization

Scaling numerical input to a standard range or distribution improves the performance of many machine learning methods.

3.2.3. Characteristic - Feature Engineering

Using the raw data, develop additional features that could be more indicative of maintenance requirements. For instance, determining the rate of change of specific parameters or aggregating data into relevant time intervals.

3.3. Exploratory Data Analysis (EDA)

To comprehend the distributions, trends, and relationships within the data, statistical analysis and graphical visualizations can be conducted. The features that are most important for forecasting maintenance requirements can be found using this procedure.

3.4. Selecting an Appropriate Machine Learning Model

3.4.1. Regression Models

These are used to forecast continuous values, like the amount of time until a specific component fails.

3.4.2. Classification Models

When forecasting discrete results, such as the necessity or absence of a specific maintenance procedure. Other algorithms, such as Neural Networks, Gradient Boosting, and Random Forest, can be utilized to determine which of these models performs the best for the predictive maintenance tasks on hand.

3.5. Feature Selection and Dimensionality Reduction

Reduce the amount of input features to enhance model performance and lessen overfitting. Use methods like Principal Component Analysis (PCA) or feature significance scores from tree-based models.

3.6. Model Training and Validation

Separate the data into training and testing sets so that the performance of the chosen models may be reliably evaluated. Cross-validation techniques must be used to ascertain how well the chosen machine-learning model will perform with unknown data. Use proper metrics to assess the performance of the model (e.g., MSE for regression tasks use RMSE, or F1 score, recall, precision, and accuracy for classification tasks).

3.7. Hyperparameter Tuning

To enhance model performance, optimize the model's hyperparameters using methods like Grid Search or Random Search.

3.8. Deployment

Position the model in a working setting where it can interpret and forecast real-time data from OBDII systems. To keep the model accurate over time, ensure the system can be retrained with fresh data on a regular basis.

3.9. Observation and Upkeep

Observe for drifts or changes in patterns that could have an impact on forecasts in the model's performance and data input. Modify the model as needed to account for fresh information or adjustments to the requirements for vehicle maintenance.

3.10. Feedback Loop

Establish a feedback loop to gather information about the accuracy of the maintenance forecasts, with continuous effort to utilize the extracted information to further fine tune and enhance the model. Using OBDII data, this method offers a thorough strategy for leveraging machine learning for predictive maintenance on vehicles. The specifics can change according to the available data, the kinds of vehicles, and the exact maintenance outcomes to be forecasted.

4. Conclusion

An important development in automotive technology is the application of machine learning algorithms to process OBDII parameters for anticipating vehicle maintenance, providing a proactive approach to vehicle care and management. This approach makes use of machine learning and the abundance of data provided by OBDII systems to forecast maintenance requirements before they develop into serious problems. The procedure includes gathering and preparing data, examining and evaluating the data to spot trends, choosing and developing suitable machine learning models, and putting these models to use in the real world by making predictions. The careful preparation of the data, the deliberate feature engineering, and the selection of appropriate machine learning models that correspond with the particular maintenance prediction aims are critical components of this approach's effectiveness. The predictive skills can be greatly improved, and a more comprehensive picture of the vehicle's health can be obtained by integrating additional data sources, such as GPS and previous maintenance records.

Furthermore, in order for the machine learning models to adjust to new data and evolving patterns and maintain their accuracy and applicability over time, ongoing monitoring and updating is necessary. By incorporating a feedback loop, models can be improved based on real maintenance results, increasing the predicted accuracy even more.

In conclusion, there is potential for a revolution in car diagnostics, maintenance, and management through the application of machine learning to OBDII information for maintenance prediction. It provides a proactive maintenance strategy that may lower repair costs and downtime while also increasing vehicle longevity. However, putting such a system into place calls for a thorough understanding of data science, machine learning, and automotive technology, in addition to a dedication to constant model evaluation and development.

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References

[1] Mayur P. Chaudhari, and Manoj B. Chandak, "Predictive Analytics for Anomaly Detection in Internet of Things Enabled Smart Cold Storage Warehousing," *Helix*, vol. 8, no. 5, pp. 3941-3945, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[2] Chong Chen et al., "An Integrated Deep Learning-Based Approach for Automobile Maintenance Prediction with GIS Data," *Reliability Engineering & System Safety*, vol. 216, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Behnam Einabadi et al., "Dynamic Predictive and Preventive Maintenance Planning with Failure Risk and Opportunistic Grouping Considerations: A Case Study in the Automotive Industry," *Journal of Manufacturing Systems*, vol. 69, pp. 292-310, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Geert Waeyenbergh, and Liliane Pintelon, "A Framework for Maintenance Concept Development," *International Journal of Production Economics*, vol. 77, no. 3, pp. 299-313, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[5] Alex Fernando Llerena Mena et al., "Vehicle Preventive Maintenance: A Comprehensive Analysis of its Impact on Society, Economic, and Environmental Factors in General Villamil Playas City," *South Florida Journal of Development*, vol. 5, no. 1, pp. 65-75, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[6] Alex Antony, The Environmental Benefits of Regular Car Maintenance, Midtown Center auto Repair, 2024. [Online]. Available: https://midtowncenterautorepair.com/the-environmental-benefits-of-regular-car-maintenance/

[7] Masoumeh Rahimi et al., "A Review on Technologies for Localization and Navigation in Autonomous Railway Maintenance Systems," *Sensors*, vol. 22, no. 11, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] Paul S. Frame, "Computerized Health Maintenance Tracking Systems: A Clinician's Guide to Necessary and Optional Features," *The Journal of the American Board of Family Practice*, vol. 8, no. 3, pp. 221-229, 1995. [CrossRef] [Google Scholar] [Publisher Link]

[9] M. Atanasio, Abdul Samad Shibghatullah, and Shayla Islam, "Developing A Mobile Application for Fleet Vehicle Tracking," *2022 1st International Conference on AI in Cybersecurity (ICAIC)*, Victoria, TX, USA, pp. 1-5, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] Amir Mukhtar, Likun Xia, and Tong Boon Tang, "Vehicle Detection Techniques for Collision Avoidance Systems: A Review," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no.5, pp. 2318-2338, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[11] John Schiavone, "*Preventive Maintenance Intervals for Transit Buses*," Technical Report, World Transit Research, 2010. [Google Scholar] [Publisher Link]

[12] Dinesh Suresh Bhadane et al., "A Review on GSM and GPS Based Vehicle Tracking System," *International Journal of Engineering Research and General Science*, vol. 3, no. 2, pp. 351-353, 2015. [Google Scholar] [Publisher Link]

[13] Swapnil Waykole, Nirajan Shiwakoti, and Peter Stasinopoulos, "Review on Lane Detection and Tracking Algorithms of Advanced Driver Assistance System," *Sustainability*, vol. 13, no. 20, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[14] Florin Leon, and Marius Gavrilescu, "A Review of Tracking, Prediction and Decision Making Methods for Autonomous Driving," *Mathematics*, vol. 9, no. 6, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[15] Jaco Prinsloo, and Reza Malekian, “Accurate Vehicle Location System Using RFID, an Internet of Things Approach,” *Sensors*, vol. 6, no. 6, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[16] Z. Ye et al., “Vehicle-Based Sensor Technologies for Winter Highway Operations,” *IET Intelligent Transport Systems*, vol. 6, no. 3, pp. 336-345, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[17] Uferah Shafi et al., “Vehicle Remote Health Monitoring and Prognostic Maintenance System,” *Journal of Advanced Transportation*, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[18] Danilo Giordano et al., “Data-Driven Strategies for Predictive Maintenance: Lesson Learned from an Automotive Use Case,” *Computers in Industry*, vol. 134, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[19] Chong Chen et al., “Automobile Maintenance Prediction Using Deep Learning with GIS Data,” *Procedia CIRP*, vol. 81, pp. 447-452, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[20] Sergii Voronov, Mattias Krysander, and Erik Frisk, “Predictive Maintenance of Lead-Acid Batteries with Sparse Vehicle Operational Data,” *International Journal of Prognostics and Health Management*, vol. 11, no. 1, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[21] Fabio Arena et al., “Predictive Maintenance in the Automotive Sector: A Literature Review,” *Mathematical and Computational Applications*, vol. 27, no. 1, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Qingping Wang, Haowen Wang, and Haixia Pan, “A Constrained-Time-Based Algorithm for Vehicle Maintain Prediction,” *5th International Conference on Information Science, Electrical, and Automation Engineering*, vol. 12748, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Stephan Matzka, “Explainable Artificial Intelligence for Predictive Maintenance Applications,” *Third International Conference on Artificial Intelligence for Industries (AI4I)*, Irvine, CA, USA, pp. 69-74, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[24] Patrick Killeen, Iliju Kiringa, and Tet Yeap, “Unsupervised Dynamic Sensor Selection for IoT-Based Predictive Maintenance of a Fleet of Public Transport Buses,” *ACM Transactions on Internet of Things*, vol. 3, no. 3, pp. 1-36, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[25] Ozlem Guven, and Hasan Sahin, “Predictive Maintenance Based on Machine Learning in Public Transportation Vehicles,” *Mühendislik Bilimleri Ve Araştırmaları Dergisi*, vol. 4, no. 1, pp. 89-98, 2022. [CrossRef] [Google Scholar] [Publisher Link]

Appendix

Table 1. Vehicle tracking systems comparative analysis

Author(s)	Title	Strengths	Weaknesses	Type
Masoumeh Rahimi, et al. [7]	A Review of Technologies for Localisation and Navigation in Autonomous Railway Maintenance Systems	A comprehensive evaluation of localization and navigation methods in rail systems, highlighting the critical need for high accuracy in autonomous operations.	Focus primarily on railway systems, which might limit applicability to broader vehicle tracking systems.	Literature Review
P. Frame [8]	Computerize d Health Maintenance Tracking Systems: A Clinician's Guide To Necessary And Optional Features	Detailed guide on necessary and optional features for health maintenance tracking, promoting preventive health care.	Published in 1995, the technological context may be outdated for current vehicle tracking systems.	Literature Review
M. Atanasio et al. [9]	Developing A Mobile Application for Fleet Vehicle Tracking	Focus on improving transportatio n operations with technology to prevent drunk driving, showcasing the application development process.	Specific focus on preventing drunk driving, which may not cover other preventive maintenance aspects.	Research Article
Amir Mukhtar et al. [10]	Vehicle Detection Techniques for Collision Avoidance Systems: A Review	Offers a comprehensi ve survey on vehicle detection methods using vision for improving safety on the road.	Limited to collision avoidance, which is a subset of the broader preventive maintenance topic.	Literature Review
J. Schiavone [11]	Preventive Maintenance Intervals for Transit Buses	Addresses preventive maintenance for transit buses, focusing on maintaining service reliability and safety.	Specific to transit buses and might not be directly applicable to other types of vehicles or tracking systems.	Case Study
Dinesh Suresh Bhadane [12]	A Review Paper on Vehicle Tracking using GPS and GSM	Reviews GPS and GSM technology for vehicle tracking, highlighting its utility in security and fleet management.	The focus is more on tracking capabilities rather than the preventive maintenance aspect.	Literature Review
S. Waykole et al. [13]	Review on Lane Detection and Tracking Algorithms of Advanced Driver Assistance System	Analyzes tracking and lane detection algorithms for driver-assisted systems.	It mainly focuses on lane detection, which is only a part of vehicle tracking for preventive maintenance.	Literature Review
Florin Leon et al.[14]	A Review of Tracking, Prediction and Decision Making Methods for Autonomous Driving	Discusses critical aspects of autonomous driving, including tracking and prediction, which are essential for preventive maintenance.	Broad focus on autonomous driving, with less emphasis on preventive maintenance strategies.	Literature Review
J. Prinsloo & R. Malekian [15]	Accurate Vehicle Location System Using RFID, an Internet of Things Approach	Proposes a novel system combining RFID with GPS and GSM for accurate vehicle tracking, especially where GPS fails.	Specific to environments where GPS is unreliable, it may not cover all preventive maintenance needs.	Research Article
Z. Ye et al. [16]	Vehicle-based sensor technologies for winter highway operations	Reviews technologies for efficient winter road maintenance, contributing to vehicle safety and preventive maintenance.	Focuses on winter conditions, limiting applicability in other seasons or environments.	Lite ratu re Review

Table 2. Current research work comparative analysis

Article Title and Author	Dataset	Methodology and Algorithm Use	Strengths	Research Gap
Vehicle Remote Health Monitoring and Prognostic c Maintenance System, Uferah Shafi, et al. [17]	Consis ts of 150 sensor data collected from 70 Toyota vehicles	Data generation using an OBD2 scanner (ELM 327) to collect vehicle real-time sensor data, Feature selection using expert input and PCA, Classification on using Random Forest, Decision Tree, SVM, k- NN Algorithms.	Combinati on of smartphone / wireless technology and machine learning to develop a real-time vehicle monitoring and fault prediction system, Focus on ignition, fuel, exhaust, cooling vehicle subsystems, use of sensor data and feature selection for fault prediction.	The research gap addressed the challenge of implementing effective prognostic maintenance systems for vehicles, the complexity of vehicle systems, the limited availability of sensor data, and the high cost of onboard diagnostics. Creating a machine learning-based real-time car monitoring and failure prediction system that evaluates sensor data.
Data-driven strategies for predictive maintenance: Lesson learned from an automotive use case, Danilo Giordano et al. [18]	Dataset D, which contains 388 cycles of data collected from the engine under test using Program A and Programm B	• Utilizing the data-driven PREPIPE method to forecast the state of oxygen sensor clogging • Performing several preprocessing steps: • Selecting the most important signals • Determining the optimal time window size • Transforming ng the signals into suitable features • Selecting the top feature set • Evaluating the impact of including historical information • Comparing the performance of different classification algorithms • Evaluate the effect of temporal dependencies, 10- fold cross-validation and time series cross validation is used.	Investigation and optimization of each step of the predictive maintenance pipeline, and the comparison with state-of-the-art deep learning architectures, the “strength of research” in this paper is high.	Data-driven framework called PREPIPE for predictive maintenance in the automotive domain, which can correctly identify critical situations before a sensor reaches a critical condition, supports domain experts in optimizing the design of the pipeline and has performance comparable to state-of-the-art deep learning methodology while maintaining interpretability. The authors also make the PREPIPE code available as open-source, suggesting the framework is general-purpose and can be adapted to other use cases.

Table 3. Dataset comparative analysis

Study Author	Dataset Characteristics	Data Sources	Methodologies	Strengths	Weaknesses
Chong Chen [2]	Real- world fleet maintena nce dataset, includes GIS data, sensor data, maintenance data	UK fleet company data, GIS data integration from multiple sources	M-LSTM (Merged Long- Short Term Memory), Cox Proportional Hazard Model (PHM).	Effective use of deep learning for integrating different data types and improving RUL prediction accuracy.	Requires extensive GIS data and integration, which may not be available for all regions.
Chong Chen [19]	GIS- enhanced dataset for modeling Time- Between-Failures (TBF).	Real- world automobile maintena nce records with GIS data.	Deep Neural Networks (DNN) with GIS data for TBF modeling.	Improved prediction accuracy with the inclusion of environmental data.	High dependency on GIS data, which can increase computational cost and complexity.
S. Voronov [20]	Sparse, non- equidista nt vehicle operation al data focused on lead- acid batteries.	Vehicle workshop visits and over-the-air readouts.	Random Survival Forest (RSF), Long Short- Term Memory (LSTM), and data imputation algorithms.	Strong management of non- equidistant and sparse data, appropriate for irregular maintenance logs.	High complexity in dealing with missing data and variations in data readouts between vehicles.
Fabio Arena [21]	Various datasets, including sensor data (vibration, temperature, etc.) and vehicle operational data.	Literature review of multiple automotive PdM studies.	Statistical inference, stochastic methods, AI techniques including ML and DL models.	Comprehen sive review of existing techniques, useful for understanding the landscape of automotive PdM.	Lack of experimental validation; relies on secondary data from various sources.
Qingping Wang [22]	Real- world time-series data from vehicle maintenance records.	Data from vehicle fleets and operational time- series records.	Seq2Seq neural network structure with Gated Recurrent Unit (GRU), attention mechanismms.	Improves generalization ability by considering time constraints in predictive modeling.	Requires high- quality time-series data and complex model training processes.