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Machine Learning Applications in Predictive Maintenance for Vehicles: Case Studies

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Abstract

The trend in the automotive industry has shifted from wanting the connected car, which uses the internet to fulfill the infotainment needs of the driver and the passengers, to acquiring the capability to manage the massive amount of vehicle data to enable new profitable opportunities such as maintenance-as-a-service. This real-time maintenance is possible using machine learning (ML) applications to develop predictive maintenance (PdM) algorithms. This creates a new realm focusing on preventing the unscheduled broken state of expensive automotive parts such as the clutch of an automatic transmission, as the breaking of a single part can affect the behavior of the whole vehicle.

This paper aims to help move the PdM industry even further, with an up-to-date insight into new available technologies and highlight potential applications for vehicle PdM, with a list of use cases that can be studied for future development. Additionally, for each use case, the most suitable data sources are also listed. Such a list is extremely helpful to researchers and developers, especially in the vehicle maintenance field, to understand exactly which sensor has to be developed and installed, in which area it is available, and with which resolution and accuracy.

Keywords: Machine Learning Applications, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM),Computer Science, Data Science,Vehicle, Vehicle Reliability

1. Introduction to Predictive Maintenance in Vehicles

In the automotive industry, predictive maintenance refers to monitoring the condition of vehicle subsystems or components, diagnosing potential faults or defects, and predicting when the vehicle requires maintenance. For example, on a braking system, predictive maintenance can monitor sensor feedback to identify if the brake pad is wearing down and alert the driver. Predictive maintenance in vehicles requires sophisticated sensing technology and a robust capability to process information from these sensors and identify patterns and trends in the condition of various vehicle components. An advanced form of predictive maintenance includes a model trained with large data sets to manage incoming live sensor data, evaluate the vehicle's condition and recommend action or send alerts.

We identified 26 case studies and applications where machine learning (ML) methods, such as decision trees, random forests, support vector machine (SVM), neural network, nearest neighbor, and clustering algorithms, Gaussian processes, naïve Bayes, bootstrapping, and AdaBoost, were used in predictive maintenance application for vehicles. Most of the vehicle predictive maintenance (VPM) case studies focused on the following sub-systems: powertrain components, such as engine and transmission; electrical systems and components, mainly batteries and circuits; and tire pressure and temperature monitoring. The remaining 41% of case studies are distributed among different auxiliary but relevant sub-systems. Since most of the vehicle sub-systems consist of high-speed rotating machinery and related components and most case studies applied ML for predictive maintenance, the scope has been categorized as assessing vehicle motion and machine component wear. The general breakdown of the case studies is approximately 50% powertrain, 20% electrical system, and 30% auxiliary system.

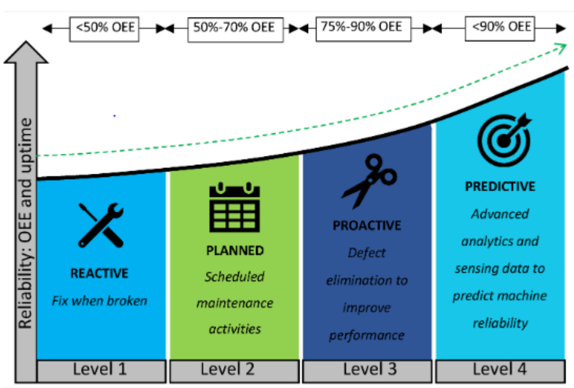

Fig :1: Machine Learning in Predictive Maintenance

1.1. Definition and Importance

The discipline of ensuring the correct functioning of vehicles, wind turbines, mining drills, and any other sort of machine is generally known as maintenance. When maintenance is carried out following predictive procedures, such procedures are generally described as predictive maintenance. Predictive maintenance is the standard philosophy in most essential industrial fields, such as airlines, shipping, power distribution companies, telecommunication systems, health systems, etc. The airplane maintenance scenario is a valid example that reflects the significance of predictive maintenance. This importance is also endorsed by the American Society of Mechanical Engineers, which reports, through studies in conjunction with the Adams Associates, that every $1 spent on predictive maintenance may result in $10 to $25 saved.

Relating to the specific case of railway companies with declining revenues, the choice of predictive maintenance methods for railway vehicles is essential since these vehicles constitute the backbone of any rail service. This also occurs in the mining and offshore industries and the windmill power industry. In all these cases, the cost of unscheduled maintenance is particularly high. The same aspects seem to be present in aviation, where an unscheduled engine event may cost between a few hundred thousand dollars, for a minor issue still under warranty, up to many millions for a worst-case related to a financial gross performance loss. Finally, note the potential impact on environmental issues relating to aircraft landing and take-off cycles.

1.2. Challenges in Traditional Maintenance Approaches

Given time, mechanical devices will inevitably degrade. In domains as diverse as aviation engines, lasting mechanical systems (from space satellites to human bones) have been designed and operated, keeping a close eye on their non-replacement target component. Predictive maintenance, or monitoring of equipment condition, is increasingly being used to prioritize and optimize maintenance activities such as inspections, rebuilds, or replacements.

Predictive maintenance has much to offer in the often challenging realms of machinery and vehicles. The rewards are not only economic but also increased safety and assured readiness. The Monitor and Fault Diagnosis Research Thrust has a wealth of experience in utilizing statistical process control techniques to monitor stability and then detect and diagnose degradation. (Note, however, that our group is not focusing on basic research in aviation engine system diagnostics, a mature area in which our colleagues will continue to excel.) Our research portfolio includes applications related to rotorcraft, commercial aircraft, spacecraft, automotive components and systems, and air traffic control equipment.

2. Fundamentals of Machine Learning in Predictive Maintenance

Predictive maintenance applies machine learning to forecast when maintenance work will be required on assets. It promises to be less costly than traditional preventative maintenance that is based on time intervals rather than the actual usage and wear. In the vehicle domain, diagnostic trouble codes have long been used for generating predictions. Now, more advanced sensing capturing continuous vehicle data enables more powerful machine learning. Specifically, the use of predictive maintenance about a connected car generates substantial data volume, velocity, and variety. Advanced AI is critical for transforming this big data into value. This paper presents two case studies based on predictive maintenance algorithms. In both instances, these applications have been developed for a business-to-consumer car rental application. These case studies are analyzed in more detail in subsequent sections.

The use of machine learning is key in differentiating predictive maintenance from traditional maintenance where the work is performed on a set schedule. Predictive maintenance forecasts the future condition of equipment, which in turn allows you to intervene at the appropriate time by performing appropriate maintenance, repair, or replacement. Predictive maintenance not only finds the "sweet spot" where the cost of maintenance equals the cost of degradation or wear, but it also increases the uptime of equipment. Potential issues are foreseen, meaning assets can be fixed before they fail, scheduling downtime at a time that is convenient for the end user.

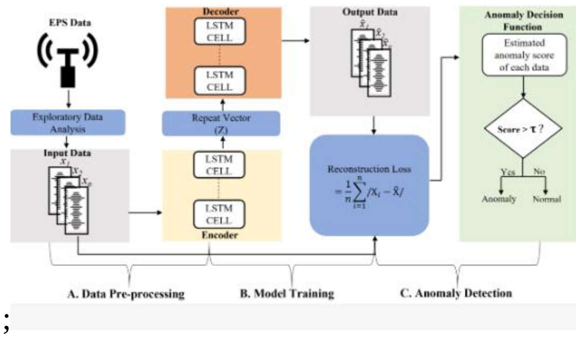

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Fig :2 : Framework of proposed anomaly detection

2.1. Supervised vs. Unsupervised Learning

The broken-down vehicle information can be analyzed as supervised learning. For classification tasks, Random Forest and Support Vector Machine (SVM) are very popular tree-based classification algorithms. For regression tasks, Random Forest, Gradient Boosting Machine (GBM), Gaussian progress regression, and SVM methods are employed. When approaching a new task or question in this class, several predictive capabilities can be used, such as time series analysis and modeling, image analysis, and sound analysis. Time series analysis includes checks, distance statistics, and model prediction-based methods. Image analysis includes feature extraction and feature learning, as well as object detection and object dot detection. For sound analysis, task-based label assignment, spatial detection, and manual review are used.

In failure prognostics, predictive capabilities are quantified by approaching time-series analysis, data-driven, and physics-based methods. The vehicle downtime for repair operations is detected using the quality control charts technique. The absolute importance of different sensor features in diagnosing failure rotor clusters for the vehicle's electrical occupied data is determined by decision trees. The vibration-based predictor model for the estimation of the remaining useful life of monitored features is created for the adjacent working cracks through a novel non-local fatigue-induced simulation algorithm, including short cracks merging dynamics and the theory of damage mechanics. It can be seen from the available research work that supervised learning methods employed are more accurate and effective when compared with unsupervised learning methods for diagnosing vehicle-damaged features. The limitations of supervised learning methods are that they cannot sometimes capture the real relationship between features. Due to increased dimensionality in data, overfitting can also be a further shortcoming of the supervised methods.

2.2. Common Algorithms Used in Predictive Maintenance

In machine learning, predictive maintenance for vehicles is quite a diverse problem and can have different types such as failure prediction, Remaining Useful Life (RUL) prediction, etc., depending on the context and use case. Also, predictive maintenance is generally a supervised machine learning problem - with (censored) vehicle time series data as inputs, and time to failure (for individual components) as output. Through this section, I detail the common algorithms that are used for predictive maintenance problems and discuss their advantages and limitations.

Many predictive maintenance use cases work with (censored) time series data, but a lot of the core machine learning pipelines themselves are generic, and generic algorithms for time series forecasting can be used. For real-world solution development, even common models work well and there are many considerations like memory efficiency, scalability, online & incremental learning, model interpretability, coupling with anomaly detection, etc., that have to be thought through. Some of these machine learning models include exponential smoothing, ARIMA, Bayesian structural time series, Prophet, quantile regression, recurrent neural networks, transformers, etc. My previous articles detail various aspects that have to be considered for developing and deploying solutions with such machine learning models. Then there's also the processing of the raw vehicle time series data. Characteristics like noisiness, missing values, feature engineering needs, etc., have to be considered.

3. Data Collection and Preprocessing for Vehicle Maintenance

Vehicles, such as rail systems and buses, are expensive assets for public transportation companies. In addition to providing high levels of support to customers by offering schedules and frequencies of services, it is essential to guarantee that these farms are reliable and that maintenance does not cause failures or accidents. When the topic addressed is predictive maintenance for vehicles, the collection and preprocessing of data are fundamental for subsequent constructive works. This chapter presents a summary of specific ML algorithms for predicting relevant vehicle failures.

This task is particularly challenging mainly because of the characteristics of the systems such as large datasets, raw data collection and preprocessing, and challenges in offering both algorithms and experimental tests. Case studies of vehicle fleets in organizations in several countries and five new approaches for predicting relevant faults based on much information and knowledge in vehicles and scheduling components are presented and discussed. The results show that several combinations of the ML algorithms agree with the data of the case studies independent of the utilized measures.

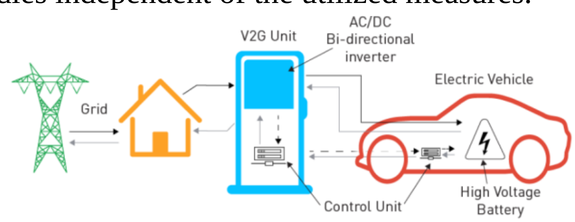

Fig : 3 : Future Trends in Battery Management System

3.1. Sensors and IoT Devices in Vehicles

Transportation companies, both traditional public transport and modern rail or road operators, spend significant investments in maintaining the readiness and performance of their vehicles to safely and efficiently meet passengers' requirements. Today, commercial vehicles have IoT devices and onboard sensors that collect rich and near real-time data about vehicle health, their surrounding environment, and service conditions. Thanks to the automation in data collection processes, transportation companies are looking for innovative solutions able to use this data to provide early warnings of vehicle failures, en-route guidance to avoid dangerous problems, and knowledge on the lifetime of mechanical or electric components of vehicles. The increasing hazard of congestion caused by the rising number of vehicles sharing the same roads or overcrowded public transport systems moved automotive research from the study of security and comfort applications to onboard vehicle systems based on information exchange with infrastructure. This led to the development of innovative intelligent transportation systems (ITS) aimed at making road and public transport more secure and fast.

3.2. Data Cleaning and Feature Engineering Techniques

To consume large volumes of data, feature engineering will often need to be implemented before being passed into machine learning models. There may be time gaps between readings where sensor readings are not being made, and to address this, we can use a hybrid approach. We addressed this by writing a graph algorithm that transfers the previously calculated feature value for a set of incoming data that has a timestamp within a defined threshold of the previous data and then infers the other missing feature values. Data that was flagged as having sufficient time delta was used as input to the model. This allowed us to make comparisons of different sensor values within these time frames. Data is typically noisy, with many outliers. Expecting clean data across an entire fleet is not practical, as you would end up boiling the ocean instead of projecting out practical use cases.

4. Case Studies of Machine Learning in Predictive Maintenance for Vehicles (2022)

Over the last year, I have been collaborating with exploratory teams at a global automotive company. Their focus was to investigate the capabilities of digitalization, machine learning, and predictive maintenance. My role was to support from an applied perspective, including initial advice, writing problem framing documents, specifying required tasks and technologies, as well as generating executable code representing approaches to model, simulate, learn, infer understanding, and gain useful insights into condition monitoring and anomaly detection. In the following, I am sharing those projects anonymously to give a sense of what directions we were investigating.

As computing becomes cheaper, the increased number of sensors and the evolution of thinking about sensor fusion, and condition monitoring of products after deployment using a variety of techniques such as digital twins, anomaly detection, and visual inspection have become feasible. In general, there is a great desire to improve maintenance processes, reduce costly downtime, and enable higher product quality. Currently, the exploratory nature of such activities often requires combinations of non-standard activities, creating bespoke solutions and proof of concept prototypes. If this prototype phase does prove useful to the required extent, redesign and integration within stronger organizational IT infrastructures is the natural next step to achieve volume deployment.

Fig: 4: Overall structure of intelligent tire

4.1. Case Study 1: Predictive Maintenance in Electric Vehicles

This study explores a novel predictive maintenance approach in electric vehicles (EVs) where data concerning the effects of regenerative braking on the battery were collected. We sought to explore whether such information can be used for predicting battery degradation and estimating time before failure. A LiFePO4 EV cell was subjected to repeated charging and discharging cycles, often ending with acceleration disabled or enabled. Voltage, temperature, capacity, and internal resistances of the cell were recorded during cycling. The study focuses on using measurements of the specific heat loss (SHL) and total absorbed energy (TAE) values during the final discharge for constructing classifiers for disabled/enabled experimentation. The study also investigates the degradation monitoring accuracy if the cell operates in the EV mode only and its capacity history is not available. The paper reports some interesting novel empirical data comprising SHL, TAE, and states of the EV battery health under different travel conditions.

EVs are anticipated to affect the future power demand structure. Smart-charging schemes will emerge to utilize the EV's energy-storage capabilities. However, this application, as well as changes in the EV ownership model, requires a more in-depth knowledge of battery health. Longer life spans are emphasized while operating conditions that affect the cell performance and the final mode of failure should be well understood. Since EVs have not yet won mainstream confidence, there are only a few models available for academic exercise, study, and improvement of battery evaluation practices. According to the EV sales servers, several types of battery ranks with different characteristics could be detected. Moreover, the operation rules and their influences on cell health are both known and unknown. Cells with internal sensor contract data are also labeled in the same database for customer acquisition. The latter cells include particular possible battery ranks. Non-disclosure agreements restrict the filming of diagnostic measurements. When the car operating conditions are initiated, we record voltage, temperature, and current values.

4.2. Case Study 2: Fleet Management Optimization

In this second use case, a large automotive OEM provided large datasets created by their cars and light commercial vehicles used in normal operation. This included driving and fleet management-related information such as trips and driving conditions such as harsh braking, harsh acceleration, emissions-related data capture, driving at high engine speed, and long distances. This data would normally be used for customer care analysis and for optimizing the scheduling and services through the network of the dealer. 300,000 vehicles of data were collected over three years, creating several terabytes of data predictive maintenance.

Over 150 features were prepared for machine learning on fleet management optimization relating to predictive maintenance. 1) Fuel-saving related features, 20+ feature variables. 2) Fault detection during driving, for example, even the most simple algorithm exports over 20 alerts. 3) High mileage and driving conditions, to determine maintenance schedule. It was demonstrated to the benefit of vehicles and vehicle dealers. This could predict the requirement for EGR cleaning, DPF filter heavy-duty operation, DPF filter state prediction, and DTC prediction which can use the information on customer driving style, total distance, some component fault state, engine fuel consumption, etc. This improved customer care suggestions, the partnership with the dealer network, and implemented the data gathering technologies through the partners with the machines in operation. This provided a two-week lead time to avoid a major fault event and an 80% recall precision of events during real operation.

4.3. Case Study 3: Real-time Anomaly Detection in Automotive Systems

Despite advanced sensing technologies and big advances in networked architectures, on-board vehicle data is not always connected in real-time to enable knowledge generation. Real-time monitoring for automotive anomalies is a particularly challenging problem. Though various individual and sophisticated sensors can collect a great deal of analog, non-uniform, non-normal data, designated control systems to process this information in real-time are not available and only disparate signaling is currently possible with the array of distributed and disparate (sometimes isolated) systems. However major design and operational issues could be identified earlier if data from all onboard systems could be holistically connected and processed in real-time.

This study will explore the use of data fusion and anomaly detection to develop a real-time data fusion platform for monitoring data streams from automotive systems. A comparative architecture design approach to developing an alternative for the legacy architecture of a large automotive network will be developed that can perform holistic data analytics, particularly tasking control system functions including real-time fault detection to diagnose automotive system health.

This research presents a planning process and a case study wherein data from a large number of individual onboard automotive systems can be fused for anomaly behavior detection and long-term prognostics in real time. Using a data fusion case study methodology to integrate a collection of real-time data streams to assess the automotive health/condition for autonomous vehicle system development and safety assurance. In this investigation, data from a collection of probes will be used to develop a novel data fusion system design for this important mission. A set of tasks for the development and deployment of a functioning data fusion architecture will be presented as a case for developing the capabilities to establish new multitask hardware functions to include standout features capable of real-time anomaly detection capability. During development and testing, the DRVN architecture was shown to be viable for data fusion and the multiple mission tasks were demonstrated in real-time while operating in a representative environment. The flexibility of the DRVN adaptations was able to handle dynamic environment changes and complex system missions effectively.

5. Challenges and Future Directions in Machine Learning for Vehicle Maintenance

Throughout this article, we have surveyed different case studies in machine learning predicting maintenance in vehicles. We have seen how the different stakeholders, mainly OEMs and drivers, can benefit from them. However, these case studies have also shown how difficult the problems in this domain are. As we have argued, many important issues remain unaddressed.

Throughout this article, we have reviewed an extensive list of application case studies of machine learning models (Supervised, Unsupervised, and Reinforcement Learning) in maintaining vehicles. We see significant advances in the effectiveness of using machine learning in diagnostic, prognostic, and prescriptive analytics for vehicle operations and maintenance. Nevertheless, several gaps and open questions exist and call for more research:Topics Prediction and prescription were the two main focuses of our review. Many more candidates exist for similar scrutiny such as the modeling of uncertainties, multi-objective trade-offs, and adaptive maintenance. More generic topics include knowledge representation, handling of mixed and missing signals, and the treatment of data and results as assets to be optimized.End Use Case Coverage Replacement of outdated equipment after a catastrophic (and costly) failure is the classic textbook example of machine learning use. In routine operations of real-world systems with vast numbers of components, limited resources of operators, and ever more stringent sustainability goals, predictive analytics that enable improved operating profiles and equipment life are far more valuable. Increased use of machine learning in this role requires an appreciation among vehicle owners that an investment in predictive analytics ultimately reduces their system's life-cycle cost (and represents a strong differentiator). The actual ease and reliability of the systems will also have to match expectations. Inet and Montesano's study of THE reform suggests that we may not need big changes, but rather several smaller, subtle, and low-cost measures that can have a meaningful impact. We fully agree and believe that taking such an approach both to the development of our predictive analytics and to assisting clients with incorporating the techniques into their workflows, will similarly result in a world of lasting and negative association.

Fig : 5 : vehicle fleet management system

5.1.Interpretable AI Models for Regulatory Compliance

In the recent development of the automotive industry, both manufacturers and equipment-as-a-service providers are increasingly responsible for continuous asset maintenance to ensure the safety, reliability, and functionality of vehicle fleets. To handle this, we propose a conceptual reference model called Predictive Asset Maintenance Model (PAMM). This paper focuses on predictive maintenance for automated driving and external sensors and presents a case study on one of the model components: anomaly detection for continuous vehicle signal data. We summarize challenges related to preventive maintenance, different categories of condition monitoring, and the role of collective intelligence methods and the model in predictive maintenance. Finally, we investigate a more specific example by bringing together Interpretable AI and model maintenance with the goal of satisfying building safety requirements and vehicle operation by European safety regulations.

The study aims to leverage the information stored in annual device performance reports by using them to validate safety compliance every year. The cyclical data stored within these reports are in the form of Feature History seen as a series of signal determinations that form a Concept Hierarchy. In pipeline Constant Validation, proposed as a solution to recursion complexity issues with CHAID, a set of signal rules is imposed upon Feature History, starting with the most recent observation. When a rule violation is detected, historical data is reviewed to determine how to assess the rule outcome. The construction of signal trees, as well as the implementation and performance of pipeline Constant Validation, are described in detail.

5.2. Integration of Predictive Maintenance with Autonomous Vehicles

Maximizing revenue and minimizing maintenance costs on heavy-duty vehicles with extended maintenance and dispatch horizon days remains a challenging proposition. Heavy-duty vehicles are increasingly integrating more technology into their products to stay competitive and differentiate themselves in the market. Examples of the use of technology for differentiation that are seen in the trucking industry today include the integration of advanced powertrain and transmission controls, machine learning for improving the drivability of heavy-duty vehicles, vehicular autonomy, and remote operations of heavy-duty vehicles, machine learning applications in predicting fuel consumption and emissions, etc. More severe level heavy-duty vehicle system malfunctions can be prevented by the introduction of maintenance advisories with suggested inspection points and parts replacement schedules than by simply system modeling the perceived real-time observed vehicle data. At present, the proposals to introduce machine learning-supported maintenance advisories do not take into consideration the real-time logistics associated with the dispatching operation.

The dispatch horizon is defined as the number of days before a vehicle is needed to transport freight. This horizon can range from 0 days as in continuous dispatch to 15 days as in pure long-haul trucking. Heavy-duty vehicle maintenance of various sub-systems is carried out in specialized service centers where the service and the throughput times can vary. To provide a data-driven maintenance advisory to the central dispatch facility in real-time during the dispatch horizon, vehicle sensor health monitoring used in conjunction with the machine-learned prognostic and diagnostic models of the heavy-duty vehicle is needed. From a data-driven vehicle health monitoring vantage point, there are not much available wireless sensor data from actual trucks in the usage phase recorded during the fulfillment of freight transport contracts bound by the considered dispatch dates. The objective of this project is to demonstrate that logistics-related data can be integrated with onboard heavy-duty vehicle sensor data using machine learning to create realistic maintenance advisories.

6. Conclusion

Predictive maintenance and IoT-enabled condition-based maintenance are real breakthroughs in vehicle maintenance management, offering real savings and improving the reliability and useful life of the systems both for the buyers and the sellers of vehicles. A feature that could be improved for predictive maintenance algorithms is an optimum and adapted response time. Provided an accurate failure risk, the best choice for the operator could be commissioning an intervention of the solution provider within the working shift that least exposes the of-use vehicle and minimizes its productivity decline. With an unspecified risk, the best choice could be the use of other maintenance options (preventive, corrective, or condition-based).

YOLO- and SSD-based approaches are recommended techniques indicated for performing real-time detection of anomalies or relevant information in image-based vehicle subsystems. An end-to-end solution for an entire predictive maintenance system is possible with the use of pre-trained convolutional neural networks connected to any vehicle software via messaging protocols (like MQTT). Furthermore, once the critical systems for the operation of a vehicle are identified and autonomous self-diagnosis of these sub-systems is achieved, a fault-tolerant approach based on delegated operations can be implemented for vehicle operation. Considering that it may be prohibitively expensive to develop sensor-fusion systems with all the necessary sensors for creating accurate spatio-temporal vehicle data related to the complex condition of some critical vehicle systems, these algorithms illustrated may have the advantage of providing an accurate relevant-outliers predictive maintenance solution without the need of dedicated sensors.

Then, software providers need to develop end-to-end algorithms with retro, front, and side camera images and relevant vehicle data, regarding anomalies from as many as possible types and classes, like the 15+1 symptoms and the three types of damage classification developed here, to grant OEMs with time-to-proficiency for the deployment of the model, to be the first to prove real positive results, and to create a ticket with a business model sustaining service budget by the OPEX and cancellation costs, and to create a redundant safety critical operation oriented alert on any notification that makes sense in terms of its ontology, like the previous validation-related use case showed the potential. Our idea of a campaign maintenance alert was validated with some results, but it requires some action in both parts of the transaction. We understand that ensuring the best maintenance condition of each sold vehicle will require campaign maintenance within a limit of profitability. The limit of profitability is related to the cost per km resulting from the wear estimation committed since the vehicle leaves the assembly line.

6.1 Future Trends

This section provides exploratory findings from 51 full-text documents using the framework established in Section 3. For a list of predefined categories, the text was classified via manual verification based on the subject of the paper. Following this process, interrater reliability was established. To illustrate our findings, Fig. 12 exhibits the classification of the extracted papers over time. The thresholds were selected to highlight the development of both the quantity and diversity of applications. The growth rate of ML has reached speeds which have made the manual investigation difficult outside COVID-19.

To aid the investigation, a sub-categorization of the year based on applied ML (e.g., LSTMs, Decision Trees, etc.) was carried out and is presented in Fig. 13, but in the interest of concision, the two results were separated. Accordingly, this research was also validated, with a preliminary collective view of future trends and applications being confirmed. We discuss the challenges and production applicability of the value proposition. The MLP framework is designed for vehicles and machinery. There is a significant growth in applications of ML methods from 2018, with a clear norm of approximately double the applications in 2021, compared to 2019 (i.e., 2020 and 2021). The main findings are presented (Section 6.1), while each element is presented without framing initially (Section 6.2). New projections of the model in multiple ensembles, deep learning, and several other models. These lead the authors to provide a more in-depth analysis.

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