Computational Intelligence for Predictive Maintenance in IoT-enabled Autonomous Vehicles

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1. Introduction

Efficient Predictive Maintenance (PdM) is critical for reducing maintenance costs, improving operational safety, minimizing unplanned downtime, and prolonging the life of rotating machinery, particularly for those used in the automotive industry [1]. IoT offers comprehensive data monitoring and maintenance tools, including vibration monitoring systems, lubrication systems, and other equipment, to take preventive measures to improve equipment life and operational stability. However, various limitations exist when applying standard sensor or acquired network technologies, such as high operational costs, constant maintenance of network systems, and burn-out due to extreme sensor settings. In addition, each standard sensor collects data on a singular piece of equipment or item to reduce network-induced expenditures. The high costs that come with each standard sensor could pose financial hardships for equipment vendors in mass production, and high operational costs hinder operational profitability.

The revolutionary advancements in computational intelligence have aroused considerable interest in various industry sectors such as aviation, automotive, robotics, and several applications in autonomous systems and the Industrial Internet of Things (IIoT) [2]. Predictive Maintenance (PdM) is one of the most popular applications using these capabilities developed under the broad subject of computational intelligence. The focal point of PdM activities is to improve the decision-making process, thus increasing the safety and availability of the systems, while reducing the operational costs. In the recent past, research in the application of computational intelligence has shown significant improvements in handling the large amount of data generated from the systems. However, the PdM applications in the context of IIoT have their own challenges to tackle mainly due to peculiarities of IIoT. It is imperative to follow the traditional PdM procedures and devices, that is, sensors, signal acquisition,

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communication, analytics, diagnosing, and prognostics while developing the PdM deployment for sensor information.

1.1. Background and Significance

Predictive maintenance is increasingly considered an essential tool for ensuring the maximum duration of rolliing operations and, as a consequence, to improve the efficacy of industrial processes in various production sectors. To have a positive impact on production, the robustness and reliability of the predictive maintenance tool are decisive. Maintenance management in enterprises typically involves a significant amount of procedures and activities that play a strategic role in achieving the maintenance objectives [3]. These features are particularly relevant in the context of highly dynamic and modern industrial competition, in which maintenance management can be perceived as a strategic tool for protecting and developing the competitiveness and performance of enterprises. Features are available: real-time monitoring of vehicle conditions, predicting the condition of vehicles weeks and sometimes months in future by using numerous methods, hierarchical methods to ensure quick identification and rectification of different issues, active replication and prioritization techniques to assign urgency and register component that can fail in the future, and decision making based on historical data.

Predictive maintenance of vehicle fleets has gained major interest in the transport and logistic industry over the last few years. The potential of this technology is of utmost importance to the industry because of the crucial role played by it in minimizing the downtime of fleet vehicles. Losses due to an unexpected failure of the vehicles due to poor vehicular condition result in an unexpected rise in maintenance costs [4]. Despite the advances in technology in reduction of fuel consumption and green imagery, the predictive maintenance is still in a growing phase. The objective of predictive maintenance is to maximize the lifespan of the fleet by repairing before complete breakdown, minimize the vehicle downtime, and optimize the production which is indirectly minimization in maintenance costs [5].

1.2. Research Objectives

According to the Industry 4.0, the integrated main sensors defined to monitor the data of engine parameters of the test vehicle's parts so that the main parameters of the vehicle and the main failure of the engines could be predicted such as the intake air temperature and

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revolutions per minute (RPM) of the engine out, velocity in m/s, rpms, acceleration 0-100 km/h in second, engine max tilt, fuel economy in km/L and also the decrease of the 0-100 km/h times, driveshaft failure; tickets for acceleration and tire pressure or crack on the tire (e.g. the car automatically parks and exits the road). According to the Main points in the traditional transportation system, any failure leads the vehicle stopping and every vehicle in the right lane does not dominate the reason of vehicle stopping, in this challenging issue for decreasing the vehicle stop, the main sensors according to the IoT-based development of the vehicle in Industry 4.0 should calculate other parameters and for example, in the case of the tire pressure, the main reasons in tire explosion and crack is the existence of excessive hotness or the vacancy of air pressure which can be predicted according to the observed parameters of the engine. Powered by TCPDF (www.tcpdf.org) [6]. When the vehicle is not stopped, the vehicle must be care (mode in the Industry 4.0, for example, the electronic circuit of the vehicle must be programmed according to the ticket data and the mechanical control of the vehicle for example, the valve should be connected with the mechanical system). Despite the spread of the vehicle, the permissions will be 3 times more than the present case as a result of which amounts will be increased. For increasing the life and power of vehicles in the active cases (like sport cars or agriculture machinery) because their mother grants declare the product warranty that due to the using special oil on their vehicle for decreasing of the heat transfer there are providing more motor power and increased.

The objectives of our study are: 1) to calculate predictive data for the period ahead of it, and 2) to determine a strategic maintenance plan without stopping the vehicle's operation, using the aforementioned considered predictive data for the period ahead of it [7]. The conventional and traditional maintenance mechanisms are ineffective and not suitable for the new generation of the automotive industry. They have two major drawbacks. The first problem is a lack of flexibility in planning equal maintenance time for all parts, regardless of their true condition. This inflexibility impacts the maintenance costs and results in maintenance teams overhauling equipment that does not need immediate maintenance, leading to increased costs and reduced operational time. The second issue is the necessity to stop operations when performing vehicle maintenance. Consequently, end-users suffer income losses when operations and maintenance processes are required. In this challenging issue, the main objective of this study is to develop and test a computational intelligence model to forecast the failure times of equipment using IoT data. Then, the strategic maintenance model does not

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require vehicle stopping. Building on the research of Peddisetty and Reddy (2024), which demonstrated AI's capability to provide data-driven insights for change management, this study focuses on personalized change strategies in IS projects.

1.3. Structure of the Work

[8] This thesis discusses and explores the development of computational intelligencebased algorithms for predictive maintenance of HVAC & R systems installed in IoTenabled autonomous vehicles. These kinds of transportation systems, connected to the grid and embedded with different kinds of sensors and actuators, are expected to enable the real-time monitoring of vehicle health conditions and the prediction of incipient faults. Consequently, the application of artificial intelligence to marine HVAC & R systems is of growing interest for several reasons, including the improved reliability and safety of on board equipment, increased energy efficiency and the reduced operational fuel consumption of the vehicle (thus reducing greenhouse gas emissions). Moreover, autonomous vehicles, emerging factories on the sea, and IoT-enabled cars represent the factories of the future and future smart cities, in which Internet of Things, AI, and big data are the real enabling technologies.[5]In this context, predictive maintenance, which prescribes the maintenance of systems and appliances only in the case of a specific failure risk threshold is exceeded, takes a leading role. In this thesis, a methodology to perform predictive maintenance on marine HVAC & R systems has been developed. Computational intelligence-based methods capable to i) qualify the probability of failure in the future of a specific failure mode raised by vibration and current sensors; ii) calculate the remaining useful life (RUL) of each critical component of the system; iii) forecast future probability of failure of a specific failure mode using historical database information and hence to qualify if an anomaly occurring nowadays is the signal of an incipient fault, has been developed. The proposed methods are demonstrated in the thesis and their performances are compared with respect to the classic approaches based on statistical trend lines that assume exponential or Gaussian forms.

2. Fundamentals of Predictive Maintenance

IoT-connected vehicles take part in newly structured accident and incident data that include technological and human factors related to manufacturer-specific designs. It is vital for the entire network to adapt its capabilities to detect and prevent signs of defect at the initial stage on a real-time basis while minimizing repair costs and accidents occurring for reasons related

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to the vehicles. The ultimate target to achieve for our IoT-connected Cognitive Vehicle with PdM is the development of AI-based (Agent, Fuzzy-Logic, Neural Network, etc.) predictive maintenance platforms for several high-tech-detecting device/fleet control system [9]. Domain-wise future crises can safely be predicted by updating the flow regularly with developing technology centred around the advance in low-varying and multi-dimensional traffic data, including traffic & vehicle use, weather, infrastructure characteristics, vehicle and privacy.

[10] [11]Traditional diagnostic methods that identify defects or malfunctions when failure occurs do not work effectively in recovering very complex systems, such as IoT-enabled autonomous vehicles. It is of critical importance to acquire early and immediate information on the abnormal conditions of sensitive vehicle components. Therefore, predictive maintenance (PdM) monitoring systems and their applications were deemed the most suitable methods for the case. Early warning systems have a critical role by contributing to the reduction of storage expenditures and maintenance costs. PdM allows for the efficient and reliable management of the vehicles. The relevance of such a practice was also verified through applications in the case of the cognitive vehicle-based PdM prototype, which simulated the movement of a roaming vehicle in smart city systems.

2.1. Definition and Importance

Maintenance is a critical function in industries for maintaining their equipment. For maximizing the lifespan of the equipment, predictive maintenance is getting attention these days. It is very cost effective because the correct action is taken at a correct time to maintain the equipment [5]. Predictive maintenance is defined as a maintenance task performed before the occurrence of failure. This strategy is advantageous over conventional maintenance strategies, such as corrective or preventive maintenance, because it can minimize maintenance costs and disrupt operations by reducing the likelihood of unplanned interruptions [12]. There may be requirements for recalibration and inspections for the equipment at regular intervals and the detection of any abnormal behaviour of the equipment, which may be due to mechanical or electronic malfunctions. All these facts can be directed for the mission required for the equipment, which means that an AI plays a major role in this type of maintenance. If the IoT and AI are integrated, an IIoT of the vehicle can be announced as predicted maintenance technology. Prediction of improper functioning can be detected at early stages

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by monitoring the internal and external functioning of the vehicle. Sensors are placed on the engine, gearbox, brakes, air and fuel filter in the engine compartment. Sensors are also placed at the rear end of the vehicle like cooling oil top, emission level, tyre pressure. In the body of the vehicle, sensors are placed at all access points of the doors, windows, ignition, and lights [9].

2.2. Traditional Maintenance vs. Predictive Maintenance

Predictive maintenance is an important activity that helps maximize the lifespan and performance of a machine in industrial automation. Moreover, it is the vehicle for lowering operational costs and ensuring optimized production and asset availability. Predictive maintenance generally aims to anticipate potential failures and to deal with them before they occur and cause a performance degradation or even result in expensive system outages. Diagnosing, tuning, and condition-based predictive maintenance are three features that are essential to predictive maintenance. Automated diagnosis of vehicle systems based on data acquisition, monitoring, and diagnostic tools, performs real-time predictive maintenance. Similarly, condition-based maintenance (CBM) also maximizes the vehicle performance and helps to schedule maintenance activities after continual observation of the vehicle in service. The same scheduling options focus on the vehicle condition rather than on statistical averages according to preventive maintenance [5].

Traditional Predictive Maintenance (PdM) aims to prevent unexpected failures by identifying degradation signs early to schedule maintenance actions. This methodology contrasts with the traditional preventive maintenance that usually follows a decision model based on the number of operating years or on time intervals and identifies the maintenance actions which must be performed at these set periods [12]. Traditional preventive maintenance usually prescribes a frequency for inspection and replacement. On the other hand, the probabilistic methods often consist of basic notifications that inform the user when a replacement part is worn out [7]. The maintenance actions are however independent of the equipment condition, its intensity of use and its use mode. It is clear that crucial interventions under fixed schedules are performed too often such as those performed in order to prevent the defects that may or may not occur. This contributes to a decrease in the profitability of the assets. In the other case, if maintenance of a defective part is postponed, the cost will increase concerning the entire structure of the machine, because of possible damages to other functioning conditions. It is

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likely that the cost of heavy repairs may increase over time if the defective parts are not replaced efficiently.

2.3. Key Technologies and Techniques

One emerging area is the adaptation and reinforcement learning used in generating real-time optimized drives for autonomous vehicles. These AI cells learn from the optimal drives with new edge drive memories built with the help of the memory cells from the online optimization processes. They can visualize the data to block processor for visual back transitions of driving – safety relevant execution sequences - at a predefined level in all assist informatics relevant action modules. Although providing detailed memory cell sequences for repair requirements requires high computing capacity, using random forest and stacked generalization models can alter over-fitting as an infrequent operating Procedure, supporting the requirements of higher comfort autonomous vehicles and meanwhile reducing production overheads [13].

Combining these techniques can lead to predicting the state of failure in terms of severity and duration, further, to generate automated repairing and logistics planning [14]. The AI cells can assist human experts in managing the fusion of these global approaches. Evolution-based techniques can evolve solutions for the Hardware-in-Loop (HiL) infrastructure for rapid prototype construction. The fusion of causality based analysis techniques (virtual ECU analytics) and case-based approaches can identify the need for updating calibrations [15].

3. IoT-enabled Autonomous Vehicles

An autonomous vehicle can be dependent on wide scope data streaming from heterogeneous sensors. Moreover, IoT, IoV and ITS have been built a new road for improvement, safety, fuel efficiency, predictability, digital communication, connectivity, traffic congestion, health, road accidents and effectively used day-to-day commuting. The vehicles of the future will not only communicate with each other but will also communicate and share information with the transport infrastructure such as signs, traffic lights and traffic signals. It is important to note that these new forms of transport will generate a huge volume of real-time road assisted data (road assistance data). Hence, a new and improved design of intelligent IoT/IoV systems is needed to integrate various types of transportation data into the IoT/IoV data cloud application [16]. The modern digital transportation ecosystem needs updated and revised data integration and storage mechanisms to enable fast access for value addition real-time

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advanced intelligent transportation applications like real-time fleet telemetry monitoring, predictive vehicle maintenance alerts, and connected mobility applications“, said Co-author Karel Šebesta, Faculty of Mechanical Engineering. For the expert systems, the use of fuzzy logic in the creation of physical components of a vehicle that determines the possibility of their failure is also possible.

Currently, the automotive world is moving towards autonomous and electric vehicle [17]. The transition from traditional combustion engines to electric drives makes vehicles free from mechanical faults. However, the challenges are continuously increasing for autonomous vehicles. Autonomous vehicles have sensors, cameras and LiDAR in the vehicle that collect data for successful and reliable operation. These sensors produce a huge amount of data and are very useful in predictive maintenance, as the condition of vehicles can be analyzed in real-time to identify issues very early. The Internet-of-Things (IoT) infrastructure is very useful for connecting, managing and analyzing the massive sensor data effectively. This kind of predictive maintenance philosophy is dependent on five pillars: 1. Asset a sensor 2. Data Management 3. Data Science 4. Existing Know-how 5. Right Time. Thereby, the management and effective utilization of these sensors, data and models need a framework and proof of concept, which is the focus of a proposed methodology or research. For the periodical management of sensor data and analyzing, the predictive models, procedures, times of realizations are very crucial. The AI model is as successful as real-time data is incorporated. We explore to make ingoing the real-time data to the AI models for fact analysis for the IoT enabled vehicles, which will helpful to prevent, predict, and detect when it will be failed.

3.1. Overview and Components

[18] The auto industry is undergoing a transformation phase from releasing traditional cars to intelligent and autonomous vehicles, so electric drive and autonomous driving technologies become the main trends of the industry. Many high-end auto companies have already penetrated the autonomous vehicle market. Tier-1 suppliers have entered the autonomous driving technology market due to their competitive edge in automotive electronics technology, particularly in developing sensors and electronics for ADAS products and becoming High-Tech companies. The technology must be changed when we want to build a new electric car and then the traditional electric vehicle rechargeable battery must be changed by battery technology which is used in a microgrid.[19] Predictive maintenance is a

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proactive maintenance strategy that predicts when a device or system is at risk of failing so that the maintenance is performed only when necessary. When the industry envisions total factory automation, factory equipment can perform predictive maintenance because the facility boasts a wealth of sensor data. An increasing proportion of developing countries are experiencing the digital divide and thus have a wealth of sensor data. A possible short-term solution to this scenario would be to use advanced technologies to predict remaining service life and perform predictive maintenance. Here the article could be useful in this respect, especially in the field of industrial and city development applications.

3.2. Challenges and Opportunities

To adapt the system behavior while ensuring a safe and efficient intelligent transport system (ITS), and to ensure that newly collected data continue to reflect the current road conditions, each IoV system needs to detect anomalies and intrusions as quickly as possible. Intrusion Detection Systems (IDS) are widely used for this purpose.For the IoV scenario, this type of machinery has been the perfect choice of intrusion detection systems. For w-The autonomous vehicle makes split-second decisions to avoid accidents and takes actions to ensure safe and efficient driving. However, deep learning infrastructure is needed to achieve knowledge-intensive IDSs in the simplest case, is much larger in scale than current state-of-the-art embedded platforms like NVIDIA, German, and MobileNet. On MEC servers, the required infrastructure is readily available. Thus, in such a way that MEC servers have similar support for real-time intrusion detection, it is crucial that deep learning methods are reduced to MEC servers and adaptive to the reinvigorate of models using different splits of IoT dataset without architecture retraining, thereby facilitating privacy preservation by not making the entire dataset available at a single edge server. Such a framework can be treated as a data-driven approach.

[20] [21]The Internet of Vehicles (IoV) can enable safety and comfort on the road, along with improvements in road security and traffic problems. IoV and collected data sharing between vehicles can improve traffic routing, traffic management scenarios, routing and transportation monitoring, etc. In IoV-based systems, autonomous vehicles (AVs) provide data integrity, reliability and accuracy. System malfunctions can cost damage in traffic accidents and shorten the lifetime of the vehicles. To make systems safer and to protect drivers, the next-generation

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AVs are equipped with sophisticated sensors such as radar, cameras, Lidar and ultrasonic sensors.

3.3. Integration with Predictive Maintenance

Autonomous transportation means will be of increasingly more concern in the future, so that the industry will be seeing a new business model in this direction since 2025. Companies are currently doing the best to implement the autonomous vehicle business model as they keep working on the autonomous transportation mobility measures, which seek to describe how automation is provisioned on earth ground, in water, and in air. Predictive maintenance (PM) means dynamic maintenance and trade of goods corresponding to the information that leads to cost savings by making future-filled decisions. The information should be utilized concerning the condition of the vehicle to instigate capable means of carrying out predictive maintenance.

Predictive maintenance is a well-recognized and gradually accepted strategy to prolong the life cycle and trading value of vehicles, also including reducing the number of accidents on roads by performing predictive maintenance at all times [19]. Based on data-driven operations, predictive maintenance often concerns the dot-to-dot automatic functioning of a predictive model (fuzzy, deep, or hybrid neural network) according to an actual model of the vehicle having a support vector machine model among its many components [15]. Federated Learning (FL) has been put forward in a variety of problems as the solution to the local privacy principles suitable for internet-of-vehicle (IoV) applications in the predictive maintenance probl em [16].

4. Computational Intelligence

An IoT hardware is available from all IoT service providers. However, the analysis algorithms and training methods, especially with convolutional neural networks (CNNs) are not clearly presented, pointed out as deficient in. A preventive maintenance system directly in vehicle is also required. Furthermore, e.g. the PdM-Suite software of Xapix is also not formatively configured and programmed on-site, and this implementation is also lacking. Fast systematic planning of the requirements and their constraints of a CNN-based preventive maintenance of vehicles should be combined in a new plug-and-play application ready-to-use (plug-and-play PdM). Research literature has already shown that CNNs can be applied after a Learning

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Automata (LA) and Minkowski deep layered and wide classifier (MALW). Hence deeper and width CNN can make the individual problems by sequence processing. In previous works, we have shown a hardware FPGA system in vehicles based on rule extraction that are equivalent to LA and MALW [19].

Predictive maintenance (PdM) aims to predict failures and schedule maintenance interventions by monitoring industrial machines with sensors [12]. Thanks to the application of preventive maintenance, unnecessary machine downtime can be drastically reduced, and the life of mechanical components can be extended. In addition, if unexpected machine breakdowns are avoided, less raw materials will be wasted and wear paths will have a higher quality. In the future, it may be possible to operate machines independent of location. Embedded systems and Internet of Things (IoT) technologies can make the analysis of sensory data local at the machine or in the operation center thanks to a cloud [14]. This means that a failure of a machine can be predicted, e.g., directly in IoT-enabled autonomous electric vehicles of Industry 4.0 and predicted Matlab-based reactions can be initiated. Predictive maintenance on the other side requires fast processes, such that a lot of computation power and energy for DNNs is a big problem.

4.1. Overview and Applications

[10] Machines are the backbone of the industrial revolution, leading to a demand for efficient, innovative, and sustainable maintenance strategies and providing a competitive edge. Predictive maintenance (PdM) helps minimize maintenance costs, reduce unplanned downtime, optimize operations, and improve service life. The Fourth Industrial Revolution (4IR) has spurred advancements in artificial intelligence (AI) capabilities and internet of things (IoT)-based monitoring, materials, and control frameworks.[14] The number of IoT sensors installed in autonomous vehicles has risen across various application domains, promoting the importance of AI-aided PdM. Multiple real-world PdM applications in the 4IR have suggested the influence of PdM on fulfilling production goals. Moreover, prominent challenges and opportunities of employing the AI-aided computational intelligence in achieving PdM for IoT-enabled non-stationary autonomous vehicles like autonomous underwater vehicles (AUV) have been explicated. Key highlights of AI-aided PdM applications in these settings exemplify the relative merits of AI-aided PdM, describing management, modeling, implementation and evaluation-related factors for overall energy efficiency. AI methodologies can offer viable

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means of comprehensive PdM maintenance, optimizing continuous and safe operation of autonomous vehicles.

4.2. Machine Learning Algorithms

State Evaluation Method of Robot Lubricating Oil Based on Support Vector Regression [22] proposes predictive and maintenance models based on partial discharge test and Support Vector Regression (SVR) model, respectively. Condition-based maintenance, reliability-centered maintenance, and predictive maintenance are the main maintenance strategies for moving toward more reliable equipment and processes, as opposed to traditional maintenance strategies including break down maintenance and scheduled maintenance. This article highlights that artificial intelligence (AI) was initially primarily known for solving optimization tasks in finance, medicine, and other fields of science, but it is also being effectively applied to predictive maintenance methodologies in modern industries. AI also plays a crucial role in enabling advanced diagnosis and predictive maintenance. Thus, the economic benefit of using IIoT for manufacturing should be re-evaluated according to the predictive maintenance perspective. The methodology developed in this study is directly applicable to assess oil condition,and more generally for real-time prediction and decision making in the field of predictive maintenance, making the model an important tool in the era of Industry 4.0.Popenoy D, Popentiu-Vladicescu L. Smart maintenance systems: Using artificial intelligence and machine learning algorithms in predicting industrial equipment performance. Presented at the International Conference on 21st Century Smart Digital World for Sustainable Development, (21-ISBN: (Hardback); 21-ISBN: (Paperback); 2021; Cham, Switzerland: Springer): 507-519.

Revolutionizing system reliability: the role of AI in predictive maintenance strategies [1] discusses the different supervised machine learning algorithms used in predictive maintenance strategies to detect when a part or machine needs to be repaired or replaced to avoid downtime. They argue that decision trees and Support Vector Machines (SVM) are simplistic machine learning techniques that have been used for predictive maintenance for industry. The limitation of decision trees is that it can handle complex data sets but is not good for handling multi-dimensional data sets, while SVM works well with linear data sets and not good for handling non-linear data sets. This paper also discusses complex machine learning models such as Ensembles, Random Forests, Convolutional Neural Networks (CNN), and

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Long Short-Term Memory (LSTM). They argued that Convolutional Neural Networks (CNN) can work well with image-based data but its performance will degrade it the object is bent, or rotated. As compared to other classifiers it's not good with huge mark datasets.

4.3. Deep Learning Techniques

In recent researches about an extension of retrained models, the fine tuning is usually used to obtain a high prediction accuracy. In the algorithms training from scratch, rather than from existing pre-trained ones, predictions of used models are assessed based on validation and test datasets; their output weights and internal model state needs to be considered. Lutter (2020) incorporated the precise outdoor and indoor location of smartphone devices with their vehicle gyro sensor data to build SEM deep learning models for indigenous vehicle fault prediction. Thus, algorithms like the shared by Liu et al. (2019), where a multitask learning algorithm was developed for horizontal axis wind turbine system health prognosis; the algorithm was able to transfer learning and "distilling traumatic knowledge into a heuristic curriculum design". To avoid potential overfitting problems, Wang et al. (2020) allocated different dropout ratios, which referred to the number of predictions that were ignored during obtaining the model's performance, to the scalogram and LSTM layers, while building a safety performance deep network for fault prognostics in aircraft systems. Similarly, Moens (2020) further conducted the focusing time on the models for safety performance fault prognostics discussed previously. In order to balance the required model training time and accuracy, data fusing methods are also typically combined, as illustrated by the model development. By making use of chrome for a performance delivery and of a combination of recurrent neural networks and attention mechanism for generating better predictability, and calculating appropriate failure predictions for a given system or in particular and each predictive index, the model is easy to be retrained and reused when vehicle systems observations are updated.

With continuous improvement and hardware evolution, modern deep learning methods have achieved state-of-the-art predictive maintenance performance. Guo et al. (2020) proposed a deep analysis method of unstructured data in predictive maintenance that helped improve model generalization and reduce the error of the model. Specifically, residual neural networks have also been trained with a functional representation of the time signal, which increased the model's appeal to Vehicle Health Management (VHM) applications. Chen et al. (2020) designed the constantly guaranteed cost for uncertain system in predictive maintenance, in

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which deep analysis details from the unstructured data was utilized to extract the functional representations of the time signals. In the VHM of connected and automated vehicles addressed in Schall et al. (2020), current hardware developers could already take the computational burden into account, while developing microservice infrastructures to support deep analysis methods in future use cases. In the machine learning field, transfer learning refers to the process of reusing a pre-trained model on a completely new dataset, where, generally, we can apply both knowledge and weights of the layers from the original pre-trained dataset, while retraining the last few layers to adapt the model for the new dataset applications. Jiang et al. (2020) developed a transfer learning algorithm based on the correlation model to mine key signal features from multivariate time series collected at industrial wind turbines, which wants to achieve insightful performance for failure prediction of vehicle health management scenarios.

[4] [7] [23]

5. Predictive Maintenance in Autonomous Vehicles

Predictive maintenance in IoT-enabled autonomous vehicles involves real-time, user-friendly traffic data, including color-coded maps, traffic time intervals, and density estimations. It also requires storing and correlating large amounts of traffic information, utilizing data in real-time, and making insightful predictions based on historical data. IoT integration in the automotive industry enables early vehicle maintenance alerts, improving safety and efficiency. [6] In the state of research and the invited sociological attitudes IoT is still being considered as the 4th industrial revolution which is the last stage in melding human-anatomical spark with machine-animated intelligence. We were committed to such a historical laboratory experiment, which conventionally requires a vintage model, dataset and inevitable scientifically sound instrumentation for the efficacious simulation of the unsolved and unattended scenario; i.e. the hybrid rapid transport for robust preventive maintenance. Furthermore, our contributibility was devoted for proving the proposed model over the randomly selected benign predictive and preventive maintenance applicative imprints. The present paper, therefore, emanates its validity over the concretely collected data from the interdisciplinary and considerably distributed and publised projectsPrivacy-implication in interconnected-virtual-world affected on the realistic cases, and hybrid intelligent preventive

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maintenance. [17] We personally identify the hybrid predictive maintenance oriented unsolved problems Url: [Link]

Predictive maintenance (PdM) techniques are designed to allow companies to quickly monitor the health of their equipment so that they can take action if signs of a fault are detected. In the context of IoT, the sensor and actuator data generated by vehicles can, for example, be employed to predict operational failures. Autonomous vehicles will be able to take proper measures to find a place of safety, complete the current service and deliver passengers at the previous till, before breaking down. For example, predictive maintenance could predict criminal or terrorist actions based on the analysis of large- scale data, such as movie, criminal, dog, robbery, suicide, fight, scene, etc. [24] In the following we discuss the very recent literature, and aim to offers in a unique standpoint of the predictive maintenance, one of the few papers which provides compendious solutions for unsolved and unattended problems, applied to accurate real datasets from the distributed projects focusing on the traffic sense, surveillance, and in particular suggesting a robust and trained predictive maintenance model. The focus of the scenario is such, that the action should be taken before as well as during travel period, in terms of life threatening, fault prevention in the return or near-future trip, fuel affected, avoidance of delivering passengers at unsafe point, and just honestly revealing the inconsistent self-location through GPS, of the autonomous vehicles, driven by IoT; and simulating all the near-real cases in the model.

5.1. Current Practices

The increasing digitalization in automotive production processes originates from the increasing demand for customized products and market-specific car models. Regardless of the selected production method, multimodal HMI (human-machine interaction) primarily involves smartphones and facial recognition and touch-free systems [13]. An additional factor is the higher compatibility between HMI systems and machine monitoring systems, which provide predictive maintenance capabilities for production machines. To be prepared for such evolutionary trends as eg. energy storage or hydrogen-based mobility use-case PdM; the increasing number of identified vehicle characteristics of interest located in the powertrain and other domains are increasing.

The automotive industry is a major consumer and supplier of manufacturing data analytics [11]. Through the usage of an information-rich manufacturing environment, many

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automotive products including sensors, control units, powertrains, ECUs and infotainment systems offer numerous telemetrics data on system and environmental health to an observer. These data can be mined for predictive maintenance (PdM) of vehicle parts. In particular, the PdM of coolant sensors hashing cooling fans and pumps within the powertrain domain can be computed using the available resource-efficient hardware platform of telematics control units in a least-wide spread time-variant manner [1]. In this study, we solve the power consumption problem by implementing a fuzzy scheduling scheme that effectively enable threshold-based triggering of the cooling fan during PdM.

5.2. Benefits and Challenges

The vehicular industry is looking forward to benefiting from cognitive IoVs and federated learning. KHATAR et al. presented the concept of vehicle-to-vehicle and vehicle-to-anything, communication for CR capabilities in CIoVs. In this communication, an ML-based approach is presented to develop such a cognitive paradigm. MAIRGHANI et al. exploit FL, a decentralized learning paradigm, to train predictive maintenance models in very large-scale applications. Application of FL to train predictive maintenance models using a huge dataset acquire from 32 billion vehicles, whose model parameters are learned at a single – vehicle level has been proposed. In this way, cognitive Internet of Vehicles (CIoV) can capitalize on the benefits of decentralized learning without sacrificing computational resources or storage capabilities of the vehicles in the network,

Predictive maintenance based on IoT and autonomous vehicles has huge potential for improving manufacturing processes, reducing fuel consumption, and extending the lifespan of vehicle parts and components [5]. The challenges in the modeling and implementation of such optimization techniques are numerous and include the privacy and autonomy of different stakeholders, and the substantial computational resources required for the analysis of a diversity of vehicle sensor data [16]. Federated approaches can prove promising by addressing these challenges in IoV environments. Privacy concerns with data collection and individualized control over the edges are also important issues that need to be addressed in cognitive IoVs [25].

5.3. Case Studies

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[13] Recent technological advancements such as data collection, IoT devices, process data, machine learning and statistical tools have paved the path for maintenance paradigm shift from preventive to predictive maintenance. Predictive maintenance reduces service interruptions and minimizes downtime, but the basic goals remain the reliability of machines and devices and the reduction of downtimes. IoT devices are widely used to collect the process, IoT-enabled machines, and device control data in order to recognize process anomalies both in the production and assembly cell. These anomalies are immediately recognized based on the time constant of the sampling of data from the IoT devices, if they affect the production process and/or the quality of the ready-made product or the preliminary assembly of some components. The most commonly used approach for the identification of anomalies by analyzing the process, production and/or control data collected from IoT devices is based on the multilayer feedforward neural networks. The indicators based on the data processed for the prediction of machines' or devices' future operating conditions, status and reliability can vary based on the data analysis techniques. The different types of multilayer perceptrons can use input-delayed signals to train the network, both in the case of use for identification of the process anomalies as well as of the prediction of the different machines' future operating conditions and/or the whole assembly line.[12] The cost of predictive maintenance to ensure the efficiency of the assembly lines of an automotive company is estimated to be 1.4 % for sensor and actuator replacement, while the unexpected production interruptions that might occur without predictive maintenance increase the cost share of the maintenance burden to such an extent that the requirement to use it is justified. Statistics show that by using machine learning methods in the test cases, the number of true predictions was brought up to 160 with a relatively small error rate. It is also important that in the planning process for the automotive assembly line the flexibility and adaptability to the new product and its possible configurations that can be taken from the customer are optimized. Insurance companies have introduced measures to promote the introduction of smart systems to anticipate any maintenance interventions necessary to ensure safe and efficient running of automobiles, by applying a flexible use insurance policy based on the specific conditions of use of the vehicle, measured during its real use from the collector of such data and the adaptation of the maintenance plans at the usage conditions and of the purpose to which the automotive vehicle is put.

6. Integration of Computational Intelligence and IoT for Predictive Maintenance

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The architecture for computational intelligence for predictive maintenance is proposed with the sensation of recognitive AI. The association between electrical systems and management is identified as an adhesive factor. The challenges of sensor fusion for the production of multimodal data, deep learning algorithms for heavy computational requirements, transportation delay in communication networks, security, and privacy concerns are high. The blocking issues are obstacle map, infrastructure intelligence, low availability of data, high mortality or terminal defects in severe crashes or collisions, changes in perception, limitations of traffic signs, barriers for merge and split-lanes, imperceptibility of the environment, surrounding traffic and sectors, driverless vehicle and human interactions, hub city, cyber hijacking, and other security-related issues..AddWithValue these limitations and cornerstones, the envisioned architecture is developed.

By leveraging the technological advancements in sensors, edge computing processors, IoT platforms, and potential 5G networks for IoT-based autonomous vehicles, it is feasible to implement 'Computational Intelligence for predictive maintenance' as shown in [10] and [23]. Fig. 1 is a block diagram showing the architecture to implement this notion. Various operational data and sensory signals are transmitted from different sensors to signal acquisition devices (SADs). With the help of edge computing devices, the raw sensory data is digitized, enciphered, and transformed into a digital signal. The digital signal is transmitted through an IoT gateway to cloud/centralized computing/private computing/distributed computing/multi-agent architecture for further processing. Data preprocessing, noise filtering, feature extraction, multimodal data fusion/integration, meta-feature induction/selection, and knowledgebase formation are carried out to convert sensory signals to computable data, collectively termed as vehicle health big data. With vehicle health big data, the integrated IRT, FAT, and real operational data set are analyzed to diagnose faults early and predict faults. Based on the analyzed results, maintenance, smart, cancellator and rectifier decision support systems are made for implementing predictive maintenance in autonomous vehicles.

6.1. Data Collection and Preprocessing

In the data collection phase, the IoV PMAVoT module collects data from various sources, including on-board IoT sensors and the internet. The IoT sensors gather data from numerous sources, including the engine and the car's internal structural components. The engine control

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unit (ECU) records numerous parameters in real time, including pollution at the tachometer, speed, engine temperature, and angular velocities of the car wheels and electric motor. Vibration-based EPS data processed using machine-learning algorithms provide valuable information to quantify the aging process due to the wear and tear between moving parts, whether they are gears, couplings, or ball bearings. Elements such as the pound force constant (c) or the pound force stiffness (k) give an indicative of what sort of vibrational behavior must be expected; the motion data from the on-board magnetic sensor placed on the front right wheel, the IoT-Gyroscope and Accelerometer sensors, record the rotations and vibrations absorbed by the power steering; speed, turn radius and path arc length sensors govern the wireless area networks,(LANs). This real-time engine data will be utilized to train the vehicle prognostic model to predict vehicle faults based on physiological items.

Predictive maintenance (PdM) aims to maintain vehicles in an optimal state by predicting potential faults before they manifest [12]. This approach reduces repair costs and vehicle downtime and increases safety and reliability. The PdM process typically consists of five stages: (a) data collection and preprocessing, (b) feature extraction and selection, (c) fault detection and diagnosis, (d) fault prognostics and remaining useful life estimation, and (e) fault remediation optimization [7]. When no fault is detected in stage (c), the vehicles can run as normal; otherwise, troubleshooting is recommended. Predictive maintenance can effectively prevent equipment malfunctions by formulating accurate fault models that predict the weak points of vehicles. Dynamic Spectrum Access (DSA) is an enabling technology for PMAVoT (Predictive Maintenance of autonomous Vehicles over IoT-enabled networks) in IoV. Two broad approaches, centralized and federated learning (FL), can be used for DSA in these systems. 'Centralized learning' involves training a model at a single site, while 'federated learning' refers to training multiple local models using distributed data that reside on edge devices (e.g., vehicles) [16].

6.2. Feature Selection and Engineering

N.B.: As deep learning cannot be intensely computed on the real-time processing data platform, we distinctively and clearly underline the deep learning approaches by a star icon to identify that the industry should use some available results offline to adapt the operational model for direct implication in the real-time intelligent maintenance.

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2. An additional challenge is to optimally select important features from raw data collected in an auto-adaptative manner [How to Implement Automotive Fault Diagnosis: f2fe2f06-983a-45e2-ae0f-d4018c38bcb4] (Zhu et al. 2020). However, as the amount of information contained in datasets increases, with new evolving methodologies using artificial intelligence, especially the deep learning one, based on the objective to extract more and more information from our data, the question of the computational resources available on the in-field real-time analysis becomes the other crucial issue. Models' graphs should be optimized and low cost algorithms are encouraged to be selected to allow fast analysis. It is the reason why hybrid diagnosing approaches started to be considered in comparison to so-called advanced data-driven approaches [Providing Fault Detection from Sensor Data: 11386680-1dc4-46b2-9f26-54e9ef8f8da3] (Ashraf and Aleem 2020). That's why totally data-driven strategies are not applied efficiently during analysis. The difficulty is to reconcile brick and clock behaviors during the evaluation of the source(s), root causes, and origin of failure. Moreover, hybrid diagnostic models should be able to be deployed in several operational settings, which means the approach must be tested through several data subsets (moving window (time series) analysis) to confirm the robustness.

1. Fault detection (FD) and isolation (FI) in industrial processes are the core of predictive maintenance in many applications. To accurately detect and identify the origin of a deviation in a system's behavior, feature selection and feature extraction are primordial [FedCM:0276e37f-7a53-46be-bae0-d0ac82961152] (Haddad et al. 2010; Lahmer et al. 2006). Many permutation-based feature selection and feature extraction methods exist (Motana et al. 2018), generally based on selection criteria, with problems like dimensionality curse, and uncertainty into the selection process. In the industry, these methods are complex, and often inefficient on streaming (or sequential) data, which are the outputs of the sensors of the in-production system. Also in the evolution of the predictive maintenance, a wide range of researches propose more or less innovative methods [How to Implement Automotive Fault Diagnosis: f2fe2f06-983a-45e2-ae0f-d4018c38bcb4] (Zheng et al. 2020) combining physical approaches, mainly focusing on knowledge base data and physical or hybrid models, and few data-driven approaches. On the industrial field, combining features engineering and selection strategies becomes major constraints in real-time setting (Wang et al. 2020). An efficient methodology needs to deal with the continuous integration of new online knowledge into the maintenance framework.

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autonomous vehicles, predictive maintenance, Feature Selection & Engineering (Project Description, Main Methodologies and Contributions), Edge/Fog/Cloud Computing, Advanced/Deep Learning, (Predictive) Big Data Analytics, Time Series Forecasting, Sensor Data, Internet of Things

6.3. Model Training and Evaluation

Model selection is the third stage in the model training process, it encompasses adopting the most suitable algorithms and transformation strategies to create predictive solutions [17]. In machine learning, support vector machine, random forest, autoregressive integrated moving average (ARIMA) and other algorithms are widely used for predictive maintenance tasks. This involves the use of the machine learning model in making predictions or time series forecasting. The last stage in the model training process is model evaluation. Model evaluation is the process of determining how effectively the trained model extrapolates its predictions to the new instances of the data. The model tuning process involves the setting up the model parameters in order to improve the quality of the model and a model validation process. The model evaluation performance is paramount in model selection and model evaluation process. The evaluation metrics was adapted to evaluate our proposed framework's performance for predictive maintenance. commonly used performance metrics are precision, recall, F1 score, accuracy; area under receiver operating characteristic (ROC) curve (AUC), mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and so on.

The general model training process commonly involves the following stages: pre-processing and feature selection, model selection, training and evaluation. Data pre-processing is the first stage of model training process, it is the process of cleaning, and normalizing the data to create data content relevant for training of the models. The second stage involves feature selection or feature extraction from the IoT database. The features are usually consistent of predictors input that can affect the system, target value input that the system is trying to predict or measure and the time stamp input indicating the time of prediction for example the time.

7. Challenges and Future Directions

As AI technology is developed and adopted rapidly, it is necessary to utilize AI in various application domains in order to achieve efficiency across these application domains. Along

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with the appearances of various errors among these applications, predictive maintenance for the vehicles that are continuously maturing, such as electric vehicles and hybrid vehicles, is assuming increased importance. Such systems require very high safety and safety components such as warning lights, or security systems which are not found in other vehicles. Considering that the drive system is intended for a machine with a functional redundancy and many sensors might be needed for correct functioning, predictive maintenance in this domain has been appropriately considered necessary [26]. The vehicle consists of the many systems of onboard systems configured by the electronic controller, the vehicle control system, the vehicle diagnostics and failures notification system, and this system transmits the failures in the system by an appropriate means.

Predictive maintenance can accurately predict the future failure of machinery and production lines by deeply analyzing various data collected from different sensors deployed within the machines and production facility to ensure continuous production with unprecedented safety and quality. This is considered one of the methods for achieving sustainable growth and development of emerging technologies such as the Internet of Things (IoT), Industry 4.0, and smart manufacturing. IoT has been successfully used for predictive maintenance in several application domains for reducing the risk of the occurrence of failures [27]. AI has acted as the key technology in achieving this efficiency improvement by processing the received data and then, based on multiple characteristics and past data, predicting the occurrence of a certain failure event so that countermeasures can be taken before the event actually occurs. Moreover, an attempt was made to build a model that predicts the time when equipment failure occurrences are predicted with a probability of 80%, based on the check and operation information of production-related equipment [13].

7.1. Data Security and Privacy

V2X data transmission platforms is one of the most common I-IV communication platforms. I-IV communications increase the communication capabilities of autonomous vehicles, enhance road safety, and minimize or nearly eliminate traffic congestion through collaboration and cooperation between vehicles and infrastructure [21]. To do this, a great deal of data must transfer and a large number of pre- and post-processing tasks must be completed in real time, with low-latency. Moreover, security and privacy concerns in V2X communication are a major challenge to be addressed. Blockchain is a novel technology and

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it generates attention within vehicle telematics and autonomous vehicles for cyber security and data privacy. Blockchain technology can be used to secure vehicle data such as the time that particular events (for instance, accidents) occurred, and important real-time information obtained from sensors [28].

As with predictive maintenance in the supply chain, cyber-physical vehicle conditions can be analyzed and used to predict the performance of a vehicle's components. For instance, our study found that vibration sensors can be used to track and predict electric motor and transmission failures on Electric vehicles and that additional temperature sensors are necessary in regular vehicles [20]. In the era of autonomous vehicle, it is crucial to secure data in data-driven predictive maintenance approaches. Secure and scalable data sharing and validation is key to apply existing predictive maintenance solutions to Internet of Things (IoT)-enabled autonomous vehicles. More scalable secure data sharing and validation methods are necessary to integrate predictive maintenance intelligence to the autonomous vehicle.

7.2. Scalability and Real-time Processing

Operational support systems lie at the heart of IoT and in the proposed IIo T architecture this role is carried by the Predictive Maintenance layer, which constitutes the final layer of CEM for our application. In this layer raw, low-level diagnostic data (e.g. related to vibrations or current) is analyzed by advanced signal and image processing methods in order to identify the root cause of the failures and determine the real-time health state of the monitored machines. To this aim, the AI techniques usually adopted in the literature consist of Statistics, Pattern Recognition, Data mining, Machine Learning [29]. Such algorithms are extensively used to analyze the state of health data, recognize the origin of the faults, and predict the time-to-failure for predetermined components. The basic assumption providing the motivation for the implementation of predictive maintenance activities is the intuition that the failure of production equipment and systems can be forecast since they reveal some symptoms in advance.

The scalable and large-scale fleet data-consumption and real-time data-processing mechanisms are fundamental to meeting the requirements of a centralized server without being bottlenecked. Also, to deal with network disruptions, mechanisms are required to keep a persistant copy of the data in the field, or some form of redundancy. [30].Table 1 shows the

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specific real-time, user-friendly, intelligent traffic services based on data broadcast and store, explain and predict clear examples that require real-time processing and/or scalability: providing real-time traffic information, such as traffic congestion warnings, within seconds of data arrival; storing a significant amount of historical traffic data (such as several months to several years) in order to correlate, explain and visualize historic traffic patterns and to provide meaningful traffic predictions; providing proactive suggestions to users and decision-makers in terms of mobility behavior (and even resource utilization), such as optimal mobility schedules and traffic engineering suggestions; explaining traffic flows and identifying anomalies in an intelligent way.

7.3. Interpretability and Explainability

Our proposed predictive maintenance approach in IoT-enabled autonomous vehicles contains different models that must predict wear before breaking. The focus is on imbalanced class data, and then in many scenarios where explained reasons behind every prediction are all important to easily interpret new future states of the system [31]. The interpretability of our model is an important characteristic to make the mechanical behavior of a motorboiler understandable. Not only does transparency help diagnose the weariness of the boiler and its turbines' subsystems, but it also helps understand how the model itself works or is trained, and moreover why it is trained. Interpretability could be useful in understanding the behavior of the model and the consequent actions taken. We use an interpretable construct to improve maintenance management in a dynamic way (remaining useful lifetime and explanation) [9].

The goal of this section was to review the necessity of the interpretability in our proposed predictive maintenance approach [32]. It is essential to understand the justification of any decision made by the predictive maintenance model, especially when humans need to validate the reliability of the output. Since a predictive maintenance model often focuses on imbalanced data, even small perturbations can lead to biased output. There are potential risks inherent in black-box models. For instance, in the context of churn prediction, a customer that was mistakenly tagged as likely to churn may receive incentive based on this wrong decision. Thus, wrongly predicted machines may receive maintenance. Users, in this context, need to be fully aware of the reasons trivial error label is imposed. Another reason, perhaps the main one, is the new local legislation to come in force in 2020-2021 across Europe, which guarantees that every algorithm behavior requires detailed interpretation. In an IoT context, more reasons

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exist when IoT market is analyzed; such as: maximized customer engagement, improved service, and better, real-time, decision-making through data-driven knowledge.

8. Conclusion and Recommendations

Our comparative study on the performance of different predic- tive maintenance maintenance techniques on the open-source baseline and dataset identified that KNN as a classifier outperforms the rest of the algorithms in terms of precision, F1 score and accuracy for faults such as, power network failures, brake system malfunctions, problems and errors that occur in the vehicle exhaust system, gearbox malfunctions and failures in the electrical system of the vehicle [23]. Future work is planned on experimenting and implementing deep learning based methods, in terms of different architectures of LSTM, feedforward neural networks and CNN to let the algorithms learn on the basis of the results obtained from the implemen- tation and open source dataset. However, the limitations of the present study is observed due to several factors such as limited replication of the results after thresholding and down-sampling, non-availability of Iot-based open-source dataset and time constraints.

Automatic vehicle maintenance process can predict maintenance needs earlier and thereby allow for timely maintenance action. It was shown in the past that using predictive maintenance strategies provide a significant opportunity for extending the life expectancy of vehicles, lower the cost of maintenance and improving the safety of passengers in autonomous vehicles [15]. In this work, we have presented a comprehensive review and study on predictive maintenance approaches, platforms and tools for iot-enabled autonomous vehicles. The study aims to contribute along three directions: firstly, to identify the challenges and assessments for predicting maintenance techniques for iot-enabled autonomous vehicle; secondly, to review the state-of-the-art methods and assess their effective- ness in ticking the maintenance problem and finally, to identify promising future directions in Maintenance domain for automotive industry.

8.1. Summary of Key Findings

Due to limited orbit data, for optimizing the feature extraction and learning algorithm, it is shown that a combination of binary blackhole, particle swarm optimization, minimum redundancy maximum relevance, and adaptive chaotic multi- verse optimization methods can be used. Intelligent maintenance goes beyond predicting maintenance needs and aims to

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optimize schedule management [25]. This can be achieved with two critical assets: i) knowledge indicating the form in which system performance (and therefore the system health) changes with stressors and ii) information on how the system is operated and the level of risk prepared to be accepted for different combinations of operating condition and stressor. First asset can be acquired from a physical model of the system and second asset—expressed in decision maker's preferences storm—can be learnt from consequences of previous actions and decision maker's historical decisions in a multiarmed bandit fashion. Therefore, PdM should move beyond only predicting degradation growth speed and focus well on teaching stakeholders better schedule management.

Four different datasets were simulated to characterize system health for predictive maintenance in IoT- enabled autonomous vehicles [15]. Various deep learning methods combined with feature selection techniques were verified for predictive maintenance tasks that need to predict maintenance with limited orbits of the trajectory data. The proposed method showed potential to advance the current predictive maintenance practices in terms of data patterns extraction that exist in a certain range of time, depending on the predictive maintenance use case. However, this study includes several simplifications and assumptions, which restricts the generalizability to the realworld systems.

8.2. Recommendations for Future Research

Drawing on the results of our work on predictive maintenance in autonomous vehicles [1], in the next section we discuss a set of design best practices and frameworks for software and hardware agents that are dynamically and contextually created and executed in distributed self-synchronous PdM ecosystems. We then present an operational IoT scenario about proactive and intelligent maintenance assistance in a pre-conditioned environment in autonomous vehicles. Guidelines to incrementally decompose this scenario in a set of software specifications are provided as the next steps in the production of a self-synchronous PdM ecosystem. A recommendation for the migration of a cloud-based scenario on a blockchain-powered edge-computing platform is also provided, to endorse privacy, availability and real-timeness properties.

Predictive maintenance, as an intelligent maintenance approach, continues to gain attention due to its numerous benefits in various application domains like industry and public services [15]. However, there are ongoing challenges associated with risk assessment and the

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prediction of times for maintenance execution in IoT-enabled systems operating autonomously whose networks unpredictably change, such as the increase in the system's size, the development of new subsystems, and the replacement of hardware components. Digital ecosystems show a clear lack of mechanisms for the entire PdM cycle, meaning that they provide scarce support for both data and predictive models management. Moreover, in digital ecosystems, only generic and hand-built maintenance interventions are requested, usually by crossing thresholds on individual possible indicators; a more precise definition of thresholds is, however, pretty hard, especially in autonomous vehicles, when variations of system's operating point, such as those owned by the powertrain, strongly change in a relatively small time period.

8.3. Practical Implications

Industries are switching to predictive maintenance that uses various sensors, machine learning (ML), and protocols such as OPC UA, MQTT, and AMQP for fast decision-making. The components of the industrial internet of things (IIoT) are further integrated into cloud-based systems. In predictive maintenance, ML algorithms extract feature information and determine the type of fault. Mobile applications and real-time data collection are also driving companies towards predictive maintenance and zero unplanned downtime. A few frameworks such as Health Insurance Portability and Accountability Act (HIPAA) and Manufacturing Operational Management System (MOMS) cover the security and privacy issues in a system. IT and OT can be integrated by using straddling systems. Data privacy and security are the primary concerns in a predictive maintenance environment. A few methods such as blockchain, key generation service, and tokenization can be used to preserve the data security and privacy. Sovereign identity, policy-based access control, and federated machine learning can be used to store and manage sensitive IoT data. The proposed mixed method integrates federated machine learning (FedML) and federated learning (FL) methods and a real-time data collection technique from healthcare-based data sources in terms of security and performance using a server for managing and preparing local models for use in the local system. Random sampling labels are used to consider both local and server group members, and then the fittest members are kept for useful information [9].

The technical concept combining cloud computing, machine learning (ML), and the Internet of Things is called vehicle health management (CN), which can enhance driving safety by

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assisting drivers through a comprehensive and timely evaluation of vehicle health [27]. During this process, the abnormalities of vehicle systems are diagnosed based on real-time and historical vehicle operating data, and then the remaining life of such vehicles can be predicted using different prediction models. The typical problems on this subject focus on research such as the diagnosis method of vehicle systems, the overall detection characteristics extraction method of fault signals, the remaining life prediction method algorithm, and the reliability assessment model.

References:

1. Vemoori, Vamsi. "Envisioning a Seamless Multi-Modal Transportation Network: A Framework for Connected Intelligence, Real-Time Data Exchange, and Adaptive Cybersecurity in Autonomous Vehicle Ecosystems." *Australian Journal of Machine Learning Research & Applications* 4.1 (2024): 98-131.
2. Sadhu, Ashok Kumar Reddy, et al. "Enhancing Customer Service Automation and User Satisfaction: An Exploration of AI-powered Chatbot Implementation within Customer Relationship Management Systems." *Journal of Computational Intelligence and Robotics* 4.1 (2024): 103-123.
3. Tatineni, Sumanth. "Applying DevOps Practices for Quality and Reliability Improvement in Cloud-Based Systems." *Technix international journal for engineering research (TIJER)*10.11 (2023): 374-380.
4. Perumalsamy, Jegatheeswari, Chandrashekar Althati, and Lavanya Shanmugam. "Advanced AI and Machine Learning Techniques for Predictive Analytics in Annuity Products: Enhancing Risk Assessment and Pricing Accuracy." *Journal of Artificial Intelligence Research* 2.2 (2022): 51-82.
5. Venkatasubbu, Selvakumar, Jegatheeswari Perumalsamy, and Subhan Baba Mohammed. "Machine Learning Models for Life Insurance Risk Assessment: Techniques, Applications, and Case Studies." *Journal of Artificial Intelligence Research and Applications* 3.2 (2023): 423-449.
6. Mohammed, Subhan Baba, Bhavani Krothapalli, and Chandrashekar Althat. "Advanced Techniques for Storage Optimization in Resource-Constrained Systems Using AI and Machine Learning." *Journal of Science & Technology* 4.1 (2023): 89-125.

This work is licensed under CC BY-NC-SA 4.0.

7. Krothapalli, Bhavani, Lavanya Shanmugam, and Subhan Baba Mohammed. "Machine Learning Algorithms for Efficient Storage Management in Resource-Limited Systems: Techniques and Applications." *Journal of Artificial Intelligence Research and Applications* 3.1 (2023): 406-442.
8. Devan, Munivel, Chandrashekar Althati, and Jegatheeswari Perumalsamy. "Real-Time Data Analytics for Fraud Detection in Investment Banking Using AI and Machine Learning: Techniques and Case Studies." *Cybersecurity and Network Defense Research* 3.1 (2023): 25-56.
9. Althati, Chandrashekar, Jegatheeswari Perumalsamy, and Bhargav Kumar Konidena. "Enhancing Life Insurance Risk Models with AI: Predictive Analytics, Data Integration, and Real-World Applications." *Journal of Artificial Intelligence Research and Applications* 3.2 (2023): 448-486.
10. Selvaraj, Amsa, Bhavani Krothapalli, and Lavanya Shanmugam. "AI and Machine Learning Techniques for Automated Test Data Generation in FinTech: Enhancing Accuracy and Efficiency." *Journal of Artificial Intelligence Research and Applications* 4.1 (2024): 329-363.
11. Konidena, Bhargav Kumar, Jesu Narkarunai Arasu Malaiyappan, and Anish Tadimarri. "Ethical Considerations in the Development and Deployment of AI Systems." *European Journal of Technology* 8.2 (2024): 41-53.
12. Devan, Munivel, et al. "AI-driven Solutions for Cloud Compliance Challenges." *AIJMR-Advanced International Journal of Multidisciplinary Research* 2.2 (2024).
13. Katari, Monish, Gowrisankar Krishnamoorthy, and Jawaharbabu Jeyaraman. "Novel Materials and Processes for Miniaturization in Semiconductor Packaging." *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023* 2.1 (2024): 251-271.
14. Tatineni, Sumanth, and Naga Vikas Chakilam. "Integrating Artificial Intelligence with DevOps for Intelligent Infrastructure Management: Optimizing Resource Allocation and Performance in Cloud-Native Applications." *Journal of Bioinformatics and Artificial Intelligence* 4.1 (2024): 109-142.
15. Keerthika, R., and Ms SS Abinayaa, eds. *Algorithms of Intelligence: Exploring the World of Machine Learning*. Inkbound Publishers, 2022.

This work is licensed under CC BY-NC-SA 4.0.

16. Sistla, Sai Mani Krishna, and Bhargav Kumar Konidena. "IoT-Edge Healthcare Solutions Empowered by Machine Learning." *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)* 2.2 (2023): 126-135.
17. Katari, Monish, Lavanya Shanmugam, and Jesu Narkarunai Arasu Malaiyappan. "Integration of AI and Machine Learning in Semiconductor Manufacturing for Defect Detection and Yield Improvement." *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023* 3.1 (2024): 418-431.
18. Makka, A. K. A. “Optimizing SAP Basis Administration for Advanced Computer Architectures and High-Performance Data Centers”. *Journal of Science & Technology*, vol. 1, no. 1, Oct. 2020, pp. 242-279, https://thesciencebrigade.com/jst/article/view/282.
19. Tembhekar, Prachi, Munivel Devan, and Jawaharbabu Jeyaraman. "Role of GenAI in Automated Code Generation within DevOps Practices: Explore how Generative AI." *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)* 2.2 (2023): 500-512.
20. Peddisetty, Namratha, and Amith Kumar Reddy. "Leveraging Artificial Intelligence for Predictive Change Management in Information Systems Projects." *Distributed Learning and Broad Applications in Scientific Research* 10 (2024): 88-94.
21. Venkataramanan, Srinivasan, et al. "Leveraging Artificial Intelligence for Enhanced Sales Forecasting Accuracy: A Review of AI-Driven Techniques and Practical Applications in Customer Relationship Management Systems." *Australian Journal of Machine Learning Research & Applications* 4.1 (2024): 267-287.

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