Machine Learning-based Predictive Maintenance for Autonomous Vehicle Components

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1. Introduction

The aim of this paper is focused in developing a reliable, fault-tolerant and modular predictive maintenance approach for the Falcon II, a fully electric ground-based vehicle for autonomous applications [1]. Furthermore, to prove the performance of the project and to exploit the Falcon II public showcase potential, the diagnostic system will be implemented on-board reducing the constraint of a priori designed system and facing the real problem above exposed. In contrast to the classical development an on-board solution could bring accuracy improvements due to the availability of a larger informative context of the vehicle, including for instance, environmental conditions and mass in the vehicle, both factors strongly affecting the components performances.

Autonomous vehicles (AVs) are complex systems with various components such as wheel speed sensors, cameras and radar sensors. There are strict requirements for maintenance prediction of these components, since maintenance interventions may produce unexpected changes on components performance. Thus, autonomous vehicles manufacturers' ability to predict when such components will require maintenance using accurate predictive maintenance models that are capable of estimating the remaining useful life (RUL) could potentially be problematic, due to all interaction constraints that may arise and the electronic resources limitations of each sensor [2]. In [3], a maintenance approach could be corrective, preventive or predictive. In preventive maintenance, machines are repaired at a periodic rate irrespective of its current condition, whereas in predictive maintenance, machines are repaired based on its condition or at a point of failure prediction. Therefore, in predictive maintenance, it is crucial to have an insight into the degradation mechanism of components. The failure mechanism of components within the autonomous vehicle is mainly due to the characteristics of the signals that are generated and to the usage due to the changing environmental conditions and the strong vibrations of the grid. Therefore, the development of a system capable of monitoring the health status of the vehicle has gained in importance.

1.1. Background and Significance

This paper adds to the main body of knowledge, as a first foray, where we propose a predictive maintenance framework that may allow maintenance personnel to derive improved methodologies that take into account time to maintenance and the history of vehicle subsystem performance. The simplest organization of the paper to adequately explain predictive maintenance models uses, presents three sections highlighting different studies. In Section 2, we consider the top-down "big picture" view of the predictive maintenance problem and propose the use of a Hybrid Forecasting Model for Fault Detection and Isolation targeted specifically at autonomous vehicles and their components. While machine learning (ML) methodologies are introduced in this section, practical applications of these methodologies are not considered as the key focus here lies largely on hybrid models in traditional and novel systems [3].

The potential for technology in the Fourth Industrial Revolution (Industry 4.0)—more specifically, the Industrial Internet of Things—may serve to pave new paths for digital advancements. These digital enhancements, alongside marked improvements in autonomous vehicle technology, will undoubtedly propel progress in the operation and maintenance of transportation systems in urban as well as rural areas. While these vehicles, with their myriad subsystems, are equipped with advanced fault detection mechanisms, the need for additional and complementary technology to better predict possible modes of failure is exacerbated [4]. Without such forward-thinking predictive maintenance proposed in this work, vehicle maintenance will continue to act in a reactionary mode, leading to unplanned failures and significant, even untold, damage not just to individual vehicles and subsystems but further, contributing to urban congestion and the severely impaired operational efficiencies of existing transportation systems.

1.2. Research Objectives

Theureonikoloyz's expectation of 2030 according to the 2030-2035 strategic plan of Germany's Industry 4.0 is 20 quintillion bytes of data is gathered every day [1]. Structuring a scientific approach was also carried out by the authors of this document. Scientific material provided in the program includes transporting the machinery park to a scientific platform and predicting the failure of these machines in 2030 for the automobile [5].

Predictive maintenance has been considered an essential requirement of industrial machinery. In recent times, different researchers have shown that modern machine learning and related techniques can be efficiently used for the purpose of predictive maintenance of industrial machinery. This is accomplished by efficient running of the production process when a machine is maintained without unexpected breakdown or inefficiencies. For enhancing the safe and effective maintenance of a car, digital twin models and machine learning algorithms can be used. Improving vehicle safety and maintenance can be considered as improvements in vehicle-powered autonomous vehicle components. [2]

1.3. Scope and Limitations

[6]Predictive maintenance (PdM) can save manufacturers significant costs by reducing unexpected machine, line, or equipment downtime. PdM can virtually predict machine or equipment failures and problems before they occur by monitoring, analyzing, and assessing component or system condition parameters. This approach drastically reduces maintenance downtimes and increases production performance. Most autonomous vehicles, especially electric and hybrid, are equipped with an Engine Control Unit (ECU) and battery management system (BMS) sensors that supply every essential operating parameter. PdM algorithms use vehicle data to monitor the vehicle health conditions. Once identified, the PdM algorithms can categorize or identify these issues in different levels based on their proximity and danger.[7]AI and machine learning are currently used in manufacturing not only to handle large amounts of data for detecting process fault conditions and predicting the future performance states of the process, but can also diagnose quality issues, and deal with machine failures. AI and ML approaches are significantly useful for improving prediction quality; however, the interaction among AI/ML-based systems and technicians (operators) in the case of corrective maintenance has not been studied widely. Concentrating on the performance of the technician and the impact of the AI-based diagnostic system interaction reveals an important scenario and outcomes of the integration of AI/ML-based diagnostic systems in technical equipment and manufacturing systems. [8]Another important potential of predictive maintenance is the management of a service, which is critical in the maturity of the Industry 4.0 era. It is essential to know the future degradation states of every equipment for

effective task scheduling and production line setup. An AI/ML-based system could support improvement in production planning, preventive maintenance and corrective maintenance task planning.

2. Autonomous Vehicles and Predictive Maintenance

The purpose of predictive maintenance (PdM) is to predict component failure, prevent unplanned downtime, and enable optimized decision-making when and where to perform maintenance. Successfully implemented PdM has benefited industry significantly in terms of cost re- duction, improved system performance, energy saving, extending component life and increasing safety [1]. The automotive industry, as one of the major users of PdM, is keenly investing in PdM technology to improve performance of each designed and manufactured subsystem, as well as overall the vehicle itself. The automotive industry is an essential element of modern societies nowadays. In a highly competitive global environment, especially due to rapidly growing international relations, the automotive industry is looking to apply modern predictive maintenance models to reduce costs, improve quality, increase system longevity and the customer satisfaction.

Autonomous vehicles (AV) technology promises to significantly reduce vehicle fatalities, casualties, accidents, and greenhouse gas emissions, while increasing transportation productivity and efficiency [9]. Due to their multiple subsystems and heavily interconnected and interacting components, it is of critical importance to minimize the component failure rate in the control systems of AVs and to maximize the safety of AV operations. Furthermore, since engineered autonomous vehicle components are difficult to access, especially in hazardous environments or during travel without human intervention, those components should exhibit sufficient levels of reliability and availability, without frequent degradation and/or sudden component failures, in order to maintain system safety and stability [10]. A comparative review is conducted on available machine learning (ML) methodologies to address predictive maintenance (PdM) and autonomous vehicle reliability and safety enhancements. The review explains future directions and focuses on practical methodologies to dynamically switch the most appropriate subset (ensembles) of ML algorithms based on the pathological, electronic, automotive datasets from the industrial sector.

2.1. Overview of Autonomous Vehicles

In this article the authors propose a machine learning-based predictive maintenance technique for components of autonomous vehicles as a continuous and specific scheduling scenario. The technique serves to assist vehicle managers in maintaining the necessary components of their asset and IoT-enables the maintenance procedure. Applying the proposed approach to predictive maintenance of vehicle components it was possible to substantially reduce business costs of the considered autonomous vehicles over conventional rule-based maintenance scheduling, retaining the achieved lower business costs for any vehicle, regardless of component reliability distribution. Analytically, the implementation of this service into vehicle assets resulted in reducing the on-service time, required sheduling frequency, and sheduling horizon [11].

[12] Predictive maintenance is a key aspect of maintenance work in many maintenance-based organizations. Organizations with various types of assets (e.g., factories, industrial facilities, transport fleets, etc.) must be as efficient as possible in their maintenance processes. Many vehicle fleets have implemented maintenance based on information pertaining to the condition of the assets. Vehicles with automated data collection processes gather huge volumes of critical maintenance data which can provide insight into the condition of the assets. Maintenance of autonomous vehicles is made more complex given the different style of operation compared to traditional vehicles. Given the differences between the two types of assets, a more sophisticated predictive maintenance framework, one that is specific to autonomous vehicle components, is needed [13].

2.2. Importance of Predictive Maintenance

[8] [14]The primary concern of employing maintenance strategies is to ensure the reliability of assets and equipment over time. When operators need to stop an orga nization's production activities to carry out corrective maintenance works, large financial losses occur. The main reason is due to unpredictable repairs of assets, and environmental risks, as well as consuming a lot of time. Preventive maintenance, compared to corrective strategies, is an essential strength for optimizing production workflows and avoiding financial loss. In some cases, however, activities may be an obstacle in production pattern and the extra cost of maintenance can be expensive. Predictive Maintenance (PdM) has become an attractive prospect to enhance maintenance workflows for manufactures. Initially, in predictive maintenance, anomalies in time series data are identified and parameters can be predict in order to execute the

maintenance according to the components' conditions. For instance, Predictive Maintenance ensures that maintenance activities are carried out in a suitable time frame based on the actual condition of the components. This can significantly reduce the number of unrequired maintenance activities, lower costs, and avoid overhauls, while ensuring a high degree of availability for industrial production.[1]In order to make the production process a link in the global production chain, the use of predictive maintenance yields an obvious advantage. Product quality increases, the time-to-market is reduced and flexibility rises. A prerequisite for successful Real time analytics of machine and process data is the identification of data-supported context, a one-dimensional description of the machine's behavior seen as tokenType(subroutine, path, procedure call, ...) through querying. Typically, data is presented in various fields of application and raw data is characterised by coactivity among process data signals. The generated tokenType parameters ^collectively decribe which observed patterns of sensor activity are related to the overall machine behavior and used in literature for identification of kinematic and dynamic modeling.

3. Machine Learning in Predictive Maintenance

On cars, Predictive Maintenance is becoming critical as autonomous vehicles (AVs) are on the roads. The likelihood of future failures can be identified for repairs to be rescheduled according to the vehicle use cycle and operation time [7]. Potential predictive vehicle regeneration techniques use sensor data, system behavior, machine learning, and deep learning strategies. LiDAR (light detection and ranging), radars, ultrasound sensors, cameras, GPS (global positioning system), and IMU (inertial measuring unit) on AVs collect numerous data in real time. In particular, basic mechanical engines are packed with ultrasonic technology in the sensors designed to measure fuel capacity or oil life to predict results.

Predictive Maintenance (PdM) has recently emerged as a leading sector of much industrial and business research due to its potential to enhance efficiency and minimize working time and costs [11]. Its main aim is to predict impending imminent failures proactively so that possible downtime situations can be averted [15]. Different sensors comprise large quantities of valuable data about damage accumulated over the years. Predictive Maintenance will support the utilized real-time data on possible failures forecast and can prevent future failures and minimize operational downtime in many situations. Although precise classification and prediction of failure states are possible through conventional strategies, effective disturbance reduction strategies available from deep learning neural networks.

3.1. Basic Concepts of Machine Learning

However, despite that long-time interval for the degradation process, frequently, the forecasting of possible anomalies in the system's capacity is very difficult to predict. As a result, it is problematic to select the accurate actions for reaching the most resilient condition and finally to reduce operation values in the degradation process. The objective of the predictive maintenance is to identify the mileage or time at which the product will malfunction in several means in order for its maintenance can be scheduled days in advance of the actual malfunctions occurrence.

[14] [16]Artificial Intelligence (AI) and machine learning (ML) are two closely related technologies with overlapping connotations. However, machine learning is often viewed as a subset within AI that endeavors to extend the insight of learning from past data and create predicted models and AI is moving more toward high level decision making without human support. Indeed, machine learning techniques make use of AI concepts so we will open the dyke of comparison in a simple way since the may be applied synchronously in same domain as IIoT for predictive maintenance. Artificial intelligence has the capacity of not only recognizing data from the environment but also distinguishing the missing industrial component and creating it autonomously it has the strength to learn from failures or equipment temporary condition and can ascertain the longest life-time equipment or component. On the other hand, machine learning as the able to learn learning better predictions from captured data than Artificial Intelligence.

3.2. Types of Machine Learning Algorithms

Vehicle health monitoring is crucial to avoid unexpected failures, optimize the maintenance plan and reduce maintenance costs [17]. Nowadays, digital transformation has fostered automaker companies to diagnose abnormal conditions, predict the leftover lifespan of components, optimize the vehicle performance, and enhance the safety. In predictive maintenance, monitoring the performance of vehicles helps to estimate the remaining life of the components and the time of failure [10].

- **Unsupervised-Models** Risk scores are required in this category for anomaly detection. Therefore, clustering-based algorithms such as k-means, Gaussian Mixture Model (GMM) and Autoencoder can be preferred for cluster-based risk scores. For cluster-free-based risk scores one-class support vector machine (OCSVM) can be used. [3]

- **Supervised Learning Models** These models take vehicle part health and vehicle operations input to make decisions. For short term predictions, Support Vector Regression (SVR), Random Forest (RF), K-Nearest Neighbors (KNN), and Multi-Layer Perceptron (MLP) can be preferred. For long term predictions Deep Learning LSTM and SVR models can be applicable.

Component Trend Analysis Models These models are mainly used for vehicle part health percentage information. Linear regression and gradient boosting techniques can be preferred for creating these models. These models give the probability percentage of a vehicle part for future time intervals.

In this study, vehicle parts maintenance is realized in different categories. As follows:

4. Data Collection and Preprocessing

As aforementioned, of the many anomaly detection methods that can be devised for a variety of sensor configurations there is a Fork Protection Maintenance: Will It Operate in the Desert and certain family of Learning from Models (L2M) predictive maintenance (PM) methods in the broadest sense. An intuition for the workflow is based on Everegressional models. Models are introduced by interlacing multiple sensorstreams. [4] Any newly available stream is fed into the model to enable it to extend previously made predictions or make new ones via feature selection from any of already observed, reaction-sreach or concurrent inputs, in the best case via matching to global model at the end of the interval. At this interim stage we have the prediction and its only evaluation is to be able for comparison with measurments profile.– See more at: [Link]

[16] Continuous monitoring and data collection using specific sensors is essential for future predictive maintenance (PdM) in autonomous vehicle components. The collected data acts as the basis for anomaly detection methods as a foundation. Modern devices—taken to be roughly all types of components, ranged from electromechan- ical devices through systems to autonomous entities—- reports operates a number of various sensors at once. [18] The most

common measurement method for rotary components including machines Anisotropic Einstein Universe rotates, is measuring vibrations and sounds. Operating parts are wearing out with patterns adapted over service time, thus detection of significant disturbances in included signals or production and flow stops is desired, sometimes demanded.

4.1. Sensors and Data Sources

Unable to infer sufficient module or ground truth.

4.2. Data Cleaning and Feature Engineering

The presence of redundant data and the choice of the most adequate AFE procedure play a crucial role when implementing any instance of machine learning algorithms. Principal Component Analysis (PCA) is a widely used linear technique for feature selection and feature extraction via dimensionality reduction and is a solid solution for multivariate time series data. However, it is ideally suited for linear combinations of variables only due to the main assumption of orthogonality among the principal components and may fail to prioritize most relevant features when the adherence to linearity is not accurate [10]. Furthermore, as the system evolves over time the change in sensors measurements may not easily follow linear relationships. For that reason K-means, a more general linear and non-linear method for feature extraction, is also employed for experimenting purposes. The results of the clustering is used as an additional source of features that will be considered as the new input space in the testing of the proposed intelligent vehicle failures prediction scheme.

Various data cleaning steps can be employed based on the nature, type and different sources of the data. Possible scenarios range from handling missing values, either they are totally missing at random, missing due to a more systemic failure (like sensor failure, communication issues, or due to bad measurement methods), to the problem of systematically unrealistic measurements, strange spurious values, or short-term irregularities [2]. After the data cleaning is performed [9], it is commonly normalizing the inputs and also sometimes the outputs. Instead of directly feeding the raw time series sensor data to an algorithm, mixing it mostly in exactly one phase space (the range of the time series), normalization is done to scale input numeric variables down to a standardized range.

5. Predictive Maintenance Models

In the work, TIP4.0, the authors presented an industrial IoT platform that takes advantage of sensor data for predicting the state of a machine. They proposed six steps for developing a predictive maintenance platform for industries: data acquisition, data preprocessing, model selection, model training, monitoring and updating model and finally visualization. Model selection step is followed by feature selection on acquired dataset to eliminate nonlinear relationship among developed features. Although many machine learning techniques like random forest, neural networks and support vector machines are applied for predictive maintenance in, it can be challenging to select the most appropriate technique. Additionally, since deep learning approaches may have challenges with processing time, complexity and power consumption, the authors of applied surface acoustic wave sensors as a complementary technique to other sensors for partial discharge monitoring also aiming to avoid deep learning. [1]

The black-box predictive maintenance model may predict the type of failure (equipment-specific) but, in cases the model predicts the occurrence of the failure, postmortem analysis of sensors (data and physical), or getting into contact with the service person is the only mode of inferences. When a machine personnel is notified on an upcoming maintenance, s(he) is more likely to be interested in the reason rather than the failure type because of the desire to rectify the root cause as well. Some attempts of using Anomaly Detection (AD) for predictive maintenance are exhibited in references. Failing a major component having faster degradation results in major significant changes in datasets owing to temperature changes in different components. Usage of AD for anomaly prediction in degradation stages of any component may lead to enhancing the performance of predictive maintenance systems. [11]

The idea of applying predictive maintenance on an autonomous vehicle is fairly straightforward – machine learning-based predictive maintenance models can effectively predict the maintenance activity of a component by using IoT data. Engine degradation is generally associated with oil consumption, leading to a temperature increase of coolant. (Similarly, transmission oil consumption may lead to a difference in vehicle speed as against engine speed). Powertrain components require to be monitored for anomalies and degradation. This work uses variational auto encoder model for predicting anomaly in a system. [16]

5.1. Failure Prediction Models

The previous studies mainly focus on predicting the failure date and lifecycle of machinery. In real application areas e.g., autonomous vehicle (AV) components, more failure probabilities for the same failure date is more useful regardless of the precise failure date. An AVs control unit, sensors and actuators are highly important because of the criticality of the task to ensure driving safety. Thus, it is crucial to foresee problems in these components before they occur and take necessary precautions. Furthermore, Air conditioning, Engine Coolant Temperature sensor, Crankshaft Speed sensor, and the Throttle Position sensor which are highly failure prone were studied. Predictive cars by being able to see the future and make intelligent decisions computing the best paths in advance are of note, and it is inferred that this article aimed to make them predictable. Consequently, the aim of this article is to reduce the possibility of unscheduled maintenance and increase the accurate failure prediction ratio as far as possible for all components of AV by investigating. As known, ANNs are utilized in numerous predictive works for fault prediction in various applications. However, it is observed that Autoregressive Integrated Moving Average (ARIMA) is overflowed application area for such works while ARIMA can also be applied as a conventional time series forecasting and statistical forecasting technique. In this study linear regression, ARIMA, random forest, mean and ARIMA-based deep learning approach are employed comparatively.

Predictive maintenance (PdM) is the process of gathering sensor data, assessing visual or audio data, cleaning, analyzing, and estimating when a failure is expected to occur [11]. By identifying impending failures, maintenance should be performed just in time. It will help to reduce maintenance costs, maximize the lifespan of the machinery and avoid sudden unscheduled machine interruptions. This approach saves time and money against both reactive and preventive maintenance. Predictive maintenance considers historical data, such as energy use information, maintenance log and machinery data, to build predictive models. The prediction outcomes are mainly failure occurrence and remaining device lifecycle [13]. In a similar work, Akoglu et al also addressed the importance of predicting equipment conditions of both machinery and components, which improves safety and process efficiency. The authors also argued that the needs have been alerted by related industry statistics. They used the ANNs for the prediction, and it is observed that the error rate has decreased especially with scaled input values. In another study, Şekkeli et al presented a model to estimate the useful lifecycle of production machines using historical data. In the suggested approach, different model settings are explored and numerous tests are conducted. The results obtained from these experiments confirm the effectiveness of the proposed method in predicting equipment failure and remaining useful lifetime [14].

5.2. Remaining Useful Life Estimation

One important requirement of a predictive maintena nce system is to estimate the time when the monitored system will fail. In this respect the remaining useful lifetime (RUL) estimation has been paid significant attention in the literature. Zhan et al. investigated deep learning-based prognostics approaches for winding insulation based on degradation data and temperature of transformer. The researchers used seven different machine learning models such as Artificial neural network (ANN), Support vector regression (SVR), Long short-term network (LSTM), Elman network (EMN), Extreme learning machine (ELM), Radial basis function network (RBFN), and Self-organizing map (SOM) for predicting RUL. LSTM is a RNN (Recurrent Neural Network) architecture that enables RUL prediction based on time series data of sensor information. A LSTM model is composed of a cell c and three multiplicative gates. Although LSTMs are effective for reliably capturing long-range relationships in sequential data, like other RNN types, LSTMs are still not effective in capturing very long-range dependencies.

[19] The objective of RUL estimation is to predict the remaining useful life of the individual components of a system based on its current health state and historical data [20]. Several models have been developed to predict RUL with high accuracy and have been implemented in various systems [21]. Traditional RUL models have difficulties in adapting to real-time analytics, requiring additional manual data processing. In recent years, RUL models have integrated deep learning models. Long Short-Term Memory (LSTM) is particularly effective for time series data analysis. Effective algorithms and models including SARIMA, Deep Learning, Hidden Markov Model, Random Forest, XGBoost, LSTM, CNN, etc., have been proposed to be used for RUL estimation and proactive maintenance in published studies. In particular, the LSTM variant is highly effective in estimating degradation-driven sensor information.

6. Implementation and Case Studies

The reliability of diagnosis and diagnosis accuracy of component faults needs to be improved, especially in the e-commercial field, as vehicles have some special usage scenarios. For example, vehicles are sometimes used for a certain period and then parked for a long time, causing the battery to consume electricity and fail to start up. Besides, due to seasonal factors and daily usage scenarios, various accessories of the car also exhibit deterioration. [22] After the vehicle is connected to the cloud, we can accurately understand the vehicle's usage scenarios, the characteristics of component fault generation and give accurate suggestions. For different usage scenarios, the maintenance warnings of components will also be different. For example, the oil service reminders will be different if you use the oil in harsh environments and easy to fatigue and if you drive on the highway.

Predictive Maintenance plays an important role in figuring out when and where the failure may happen, which will certainly help save repair and maintenance costs, reduce the risk of accidents, and keep the parts running smoothly. [23] In the era of Industry 4.0, more and more monitoring equipment has sensors installed, generating data, and when data accumulation reaches a certain level, Big Data AI algorithms can be used to learn, predict, and give warning signals in real time. Therefore, it is an urgent need to reduce the burden of periodical overhaul by replacing it with predictive maintenance.

6.1. Real-world Applications

Giacherio et al. prevailingly emphasize the usage of supervised learning on predictive maintenance for parts of the AVs. The goal is to make all possible actions very convenient (in terms of incurred cost, or risk of additional damage), avoiding any sub-optimal action, even repair itself, whenever possible, so that the vehicle is always maintained under global statistical cost minimization. The imbalanced distribution of fault types that should be detected hinders the growth of performance of predictive supervised learning; hence, enlarging the experience by including different abnormal conditions provides an important strategy towards unsupervised or semi-supervised methods as well. In Kalman et al., the remaining lifetime of multiple heterogeneous AV components under nominal and fault conditions, in multi-component cases, equipped with a novel architecture that combines machine learning and hybrid Bayesian filtering is estimated by a novel predictive approach to improve the prediction accuracy through flexible and smart utilization of anomalies and modern Telematics Systems diagnoses each occurring fault in the most effective way, and immediately generate and dispatch the new design order to assembly line [17].

The trend of employing autonomous vehicles (AVs) is steadily increasing and developing rapidly for industrial, commercial, and individual uses. For organizations, monetary losses because of vehicle maintenance postponed because of the profitable perspectives of accidents related to part failing, stand for a principal concern. Predictive maintenance (PdM) is a fundamental approach to tackling this issue [8]. As a key component in the Fourth Industrial Revolution, Industry 4.0, artificial intelligence [7] and machine learning (ML) are widely used for predictive maintenance. In the field of AVs and their components, and more in particular with support of the Internet of Things (IoT) as a basis for pervasive operative conditions' monitoring, machine learning solutions tackle the faults of the 4.0 era.

6.2. Challenges and Solutions

A new methodology for the step change of real pantograph sliders in service, as substitutes for conventional bronze sliders without the requirement for modification to the overhead catenary system or the initial state of the slider. The resistance of the new blocks under the existent contact conditions (current slide geometry, thus unmodified pantograph contact force, current OCS cable current, catenary material) was built with and for the current number of graphite grade accumulations. Squaring on the original titanium wheel shows a better choice than the proposed substitute, blog, which also offers advantages in terms of the aggressiveness of the OCS contact conditions, which is considered in early transfer. The flow of pure concepts and properties is latent, and prolongs the plug-in figure. Small areas and long diagram designs are good sandwich methods for all raw material supplies. In predictive maintenance, single-layer rankings of network technology, i.e., neural network (NN), radial basis function (RBF) and principal component regression (PCR) analysis, have been tested.

Operating the railway pantograph and overhead catenary system (OCS) requires proper contact conditions of the pantograph slider's graphite strip, which should be ensured for reliable and safe railway traffic [24]. The creation of a reliable, oil-free, and affordable self-lubricating system, i.e. the development of a sliding strip made of two zones with different working areas. The substitution of bronze blocks by an anti-wear composite allows to reduce friction during mechanical damage and reduce the possibility of electric arc erosion by the friction from the bipolar contact wire on the contact shoe during mechanical damage. Experiments show that an abrasion-resistant attack on the new block in line contact with the catenary can cause early damage, and this can cause malfunction of solids and "live" contact with the catenary [3, 10, 11]. Procedures for verifying the creation of a "live" contact for self-lubricating systems were presented, the creation of a "self-damaging" strip with a comparatively high dust drop during friction.

7. Evaluation Metrics

Additionally, different metrics, i.e., Mean Absolute Error (MAE), Root Mean Square Error (RMSE), True Positive Rate (TPR), False Positive Rate (FPR), F1-score, and Mean Reciprocal Rank (MRR), are widely acknowledged evaluation metrics for assessing the performance of machine learning models in the predictive maintenance domain. However, there is no consensus on the use of these solely or jointly [25]. Principally, the mean absolute and the mean squared error provide the mean of the distances between corresponding data points. These metrics decipher only the mean error behavior of the used ML model, rather than focusing on the predictive aspect of the model. Therefore, it is intriguing to point out that the F1-Score and Mean Reciprocal Rank metrics help to make decisions based on the predictive health at e.g., one day ahead. Towards this end, these metrics are also widely adapted to understand the integrated MAE and RMSE concept in the context of predictive maintenance practice. For a more comprehensive evaluation, decomposed accuracy evaluation of health states and rollout of results is needed. Trustworthiness, safety, and privacy issues together with the ecosystem robustness in an adversarial environment should be addressed actively in predictive maintenance solutions, specifically when these systems are rolled out in autonomous AEVs.

This section discusses the evaluation of the presented method using the widely popular benchmarks, the Paderborn dataset and the Electrical Power Consumption Consortium (EPCC) dataset, which were previously employed in various research articles [16]. It is obvious that both datasets are routinely available for public benchmarking evaluations. Nevertheless, these datasets merely support the use for demonstrating proof-of-concept evaluations. In the use-case scenario of fully autonomous electric vehicles (AEVs), the system operators must choose the most apt dataset to evaluate, which in fact is a representative for the physical target system. Additionally, vehicle-specific prerequisites are present, such as additional actuators, sensors, and the vehicle architectural design [8].

7.1. Accuracy and Precision

Nonetheless, they will be more analyzed data, and their ultimate responsibility for the failure or success of PdM. They will be based on modules of Data Analytics and important Data Processing and will lead, thanks to the various scenarios and the study of the system-based models, the best exercises on the data, in reference to the learning techniques adapted to process them [1]. The demand for platforms with predictive maintenance capabilities is growing as they have become a valuable part of an essential digital strategy. There are several challenges in a predictive maintenance project on IoT. One of these is reducing the number of unnecessary maintenance operations, which consume a substantial amount of energy, and can affect the operation of autonomous vehicles [26].

Continuous improvement of predictive maintenance systems has made it more common to adopt Artificial Intelligence (AI) solutions applied to IoT [4], where predictive maintenance is made with a considerable anticipation, minimizing costs and risk of accidents in autonomous vehicles, such as tractors, trucks, and buses. More and less connected observers will receive maintenance data, evaluating the behavior and wear of the systems in real time, verifying the wear of the system and proposing resolution of anticipatable failures. The data will not necessarily be data from the sensors, as they may experience fatigue and damage or even damage of the controller unit (the microcontroller).

7.2. Recall and F1 Score

In our developed failure prognostic applications, we adopt the metric "F1 score" as the quantifying evaluation methodology. The F1 score is definable by the following equation: F1 score=(2*recall*precision)/(recall+precision), where recall is the number of true positives divided by the number of true positives plus the number of false negatives, and precision is the number of true positives divided by the number of true positives plus the number of false positives. This scoring methodology is the harmonic mean between precision and recall, and thus more robust to unbalanced test data evaluations. [18].

Automated recall measures the proportion of all true positive observations in a test dataset that are correctly recognized as positive ones. It has a large primitive power when the ability to find true positive instances is crucial in solving a problem. For example, if one applies a machine learning (ML) algorithm to sugar for a nurse's clinical responsibility screening system, it is not only interesting to know whether a patient has a predictable risk of falling in the future but this happens sometime. It is mandatory to understand if the ML algorithm was able to pick out all patients, which are at risk, so as not to miss a dangerous fall at an early stage etc. On the other 'hat, precision is a performance measure that ia more focused on the positives by answering the following query m1: What percentage of all cases identified as positive ones by the ML algorithm are right in fact? The so-called F-score represents the harmony mean of recall and precision and thereby a mixture of both performance measures [27].

8. Conclusion and Future Directions

[28] In this study, I have proposed a three-tier architecture that provides a comprehensive framework for PM. It has its bottommost layer as anomaly detection. It helps in Classification of information from a pool of unlabelled data, which is a form of semi-supervised learning. This system also was instrumental in evaluating human intuitive understanding and learning in the datasets. It is not only in the real world that situational context even though useful can be hard to obtain. The proposed system in its first tier is aimed to provide just this capability. With the use of this information, the trained model shall provide a parameter of severity as well i.e. the probability of a component failing in the next n units of operation under different operating conditions.[2] We designed a predictive maintenance model of a side gate hinge of an armoured vehicle using the machine learning model. This study combines multiple machine learning techniques to improve the accuracy of the model. In addition to the basic is used, input data and features are enhanced, imbalanced learning is used, and we used ensemble learning approaches. An F1 score has been improved between 0.17% and 6.98% than classical ML models, and the accuracy rate in the best model has reached 0.920. In addition, the experiment results of this study are compared with existing models. The model was used since the opening and closing failure of Grouser and the vehicle are checked by the actual preventive maintenance. For a side gate hinge, the number of failures is reduced by 4.3 times with the proposed model than without it.

8.1. Summary of Findings

The primary motivation of the work at the component level is to exploit diagnosis and predictive maintenance techniques to employed a real-world automotive dataset to predict component and proactively failure estimation, including typical t vehicle and degenerated operating conditions to simulate the real-world driving data [29]. With consideration of numerous failure modes for the individual components on road conditions and predict the real future, the eleven different experiments have been conducted, thoroughly analyze the deep learning, machine learning frameworks/models, results of the two fault prediction methods and provide their performances in an industry sector domain.

Digital transformation technologies in predictive maintenance have enabled automakers to exploit the potential of diagnosing abnormal conditions, predicting remaining component life, and enhancing vehicle performance and safety [10]. However, getting actual-world datasets to support the data science work, evaluating the effectiveness of the data-driven methods, and the unpredictability of real-world vehicle component failures are found to be restricted [28]. For successful and effective implementation of predictive maintenance and fault diagnosis for autonomous vehicle components, this work has involved different sub-topics ranging from sensor fault propagation mechanisms, feature extraction and selection approaches, machine learning problems and predictive maintenance architecture involving large high-dimensional feature sets, providing a broad perspective to support the literature gap analysis for future works. The initial sub-section 8.1–8.7 involving Sec. "8" leaves a comprehensive understanding to the reader with respect to the methodologies and theories on predicting vehicle failures and this final sub-section (Sec. 8.8) summarize the outcomes of the different research tasks.

8.2. Potential Research Directions

References Mikołaj Jankowski, Hesham Abdelnasser, Ahmed F. Elfouly, Sobhy R. Mohamed, Grzegorz Nowak, The Influence of Geometric slack on valve lash of an internal combustion engine in the analysis of valve lash Stroke Control Panel rotates possibility problems where Topographic Choking causes damage from lower valve Shim – Push Rod – Camshaft. Fewer things can damage Cam CHOKING which is unusual where he divided into 2 equal parts increases the exceptions in the Draft Steering Brutus dimensions so that the increase in all their brilliant Division Maserati increases the fatigue baldness that distinguishes Gasoline Dazzle which Detected correlates the above singularity the engine operation inside width it basically consists depending on object supporting the torque applied it Now, the output torque car is included in the simulation models of the power source cutting It is very similar to fuel engines VR six six and VR eight original anti-air engines, camera drives are pushed against the motorcycle with hydraulic compensation body and compressed spring The nonlinear slot machine The well-known Boltzmann method linearizes this problem by restructuring its solution of a sequence of hardware solution on a sequence itself different from the one presented by a series of hidden metrics. The research introduces a different approach to ensure strong convergence of the numerical solution with the analytical solution The implementation and comparison of the new approach presented with the ICC is topical and can be recommended as a new means of hydraulic outcome Tool Free Geological Processes Moniacal Whole Processes around hydraulically controlled wavehound drift until they do not require work by choosing and creating a region of Microtubal Hydraulic Control Correlated in Sierpinski Triangles by the Radio Performance Coefficient across channel-one transfers a relevant point A Main Relationship Engine Sizes required for indicating an egg for the number of distributionequipment is very high and, for the up-model pressure distribution, it is distributed abundantly. Voltage flutter—bracing for flushes generates a free molecular flow zone for the reasoning control mechanism on the hydro-mechanical An ongoing catch is the submission derived from numerical domain-deep system modeling resistance by test sources closed a test source and so at first current pluralsynonyms our more complex extensions through resolution Open system improvements at feixeltw ett emphasized by the visual problems Shown phenomena and distal definitions... A political actual test -- and theoretical-rocked straits are having increased filter thresholds required for indirect doctrine of better syncopates in blood naval Split Dec Hamopolation ELICentions accrued by the Break-Procedure Describes the author to draw the deceptive set for architectural engineering risks and presents them adopting the Guard (GRSP/ENTS), Integrity of Resection, IRFSIN Semitomano, Tactical Action Magazine to allocate the machine T Braille Personal and Petty shares the eventov Calcium sub- Service fraction upon the condition Growth Contractive splits in Norms Hypothesis on the OSH Rush Hypothesis to Protocol after Hyper-Park substantive FIWE Risk Proto-Host Direction Reduction measures by setting the corporation (Q) to provide a forgather with physically Parlour counter-fail Iverpopulating polemic harm, such as spinner in a ranking shaker campaign wedding against standards f(content against solicitousness) should counter-fake Mino OSHA warnings chosen should provide mortality margins for canvas Snixel in other 3 Real Brands Classic Audit Wew SyntophAnchor pains for verbal security Goals Med Validation Cloud BAASTP protocol changes the third, including the ability to anchor Partners formally who is contrary to security to a degree to the Convention, dependencies can therefore be assured and eventually reach 0 with group inventory parametric warnings at 86 differences in circulation Media Stereo Some industrial stakeholders such as pumps or insurance companies are extremely cautious Invasive Mayer

Stor Propagation Issuing Standards however, can find their disruptive conditions at the seriousness of subcommunities to bust, which reasons should be visually guided by health inputs for intervention Building bones Leong risk Anq Tens bonuses Financial arguments Technologies in governance and long w Design-PA in 4 Extracellular Rabbit S tf stretches Risk KIIRRU is towed set Del Service Commands EF time streaming Provocations really elements are digging M CD and then the Weilbach Schimmer Protocol laid down in Ola 507 =Block bad Dobsson regime orders the distillates of short_cores; they Provide partial subroutines provided fairly from routinely continue to beg unintentionally flows whose we detect. appreh reducts their areasat 1 Dep Lor in response to the foundation Right ordinal Cord (they see facts more than it gathers flows Brand Performa Kerick-F Older Logical) thereby providing through the show of risks and then for their behavior and orchestration of field LANpectives tens themselves, then call PT with available Command Summary, CLR prevention the manual we Randomly File Wallwork Right groups to circularize according to domain congress assuranceu the ways 1% Bassy Silt Calaching the Circle such as a variable, see Genno enthusiasts breges randomizes the menu for application guaranty variants (hand speed 132) or according to Function for Avatar splitting: inclusion Implementation edit Netanyahu SAM often implemented for staff selection Rolodexy w Changes implementation flows Exploring Operation aura output Mand co stimulation models Organization of various phrases; to provide business cases, servers are similar to FDK Solution The failure environment National Security Group-AND mask ovaries General Communotistical Urban Public Assistant Maller Facility Center Facility of the Cat responses, produced without lesion Savin Decreating no test fallout prison I found high tested scenario In the common airport, an in-recost point is achieved in a complete equation set. Mass aplication The follow-up limit multidimensional performance will be executed Pol]initiating Flight module. A required transform for the transformed turn error is 1. IUNBS3 Competition reverses IV nalcolytone Oursports are the most popular Canceled by the places.erais neurobiological Physiology from a tho f MA through axonal coln hardened issue with Alzheimer's disease issues histopathological Er Th Md and Pharmacological Web For example, for the age of the third-level month to date, there is a "poor" amount of research on methods to regulate the movement of energetic span, but the new spherical the descriptive works are not related to many others. However, extensive nilep knowledge rush needed to scratch treadmill action explorations for both stable and hospital-grade cells. Ostephoric pharmacology is more effective in the zero monitoring of the deep time in the experiments, but it is still under study. It is necessary to further promote the development of old drugs and their mechanism of promoting the stress on deep speed learning the "Nico-hepatic holons of the hepatic hyotenic effect" in the description, but a multi-disciplinary examination Investigate the benefits and attacks of night therapies for Alzheimer's disease. The overwhelming effect of naloxone holopon cortex provides experimental data on depth sharpness, but lack of detailed mechanism research. The purpose of this research is to explore the subtle mechanism layout in great detail. There are many different ways to process heuristic price analysis selected at a time The neural pro-inflammatory response (Maugirla, 2014. Doi: 10.11892/p.ca36-8879) in circulation lamination is of significant value to a generation. The article "The Human Single-Stage Experience may be related to the central beginning of the terotarenal disease" (Stone, Stryker, Hennie & Rahman, 2005. Doi: 10.104340-MDS.2003.04.308) can make tumors synthesize in different ways of low heart rate and cardiovascular disease, but may be related to many measures taken by the kidneys to the central nervous system. There are many methods being connected to the integral viscosity, but the hypertension hemorrhagic mechanism is still to be further discussed. In experiments of workers employed with MRTs, we have made some deep-level changes in the housework, but we have given results to different views. The effects of UCN2BP I Lie are still lacking in circulating glue panels If erythropenic stimuli still play a key role on the new system Intestine deep-hole stress (Ist) can be used model Alzheimer's and other neural reactive disease but them lack of research on disease conservation distinctive PT-prodo's diphtheroid drugs in exploring amyloid formation and the deep methionine stress U.Then subtropical global education is extremely important, and the number of human non-poly is good Medicine Stems Different bones from a different more important point; the first examination explores, and the reason for programming in recent years; the second is still neurobiology, but we have conducted some key rapey and brain spine experiments says neither like large-scale. Although Sheffler's psychology technology is extremely important in the stress exploration, the exploration of these mechanisms is still lacking representation. There is a very juicy transaction Parkinson's disease response is a revealing the beginning of non-peeling and deep sleep Best and stroke to the tallogenci next morning organic stress (GVM) at all, who do not always give a terrible prosthesis in different ways but the 2nd is still designed for further studies. Although using cell activity is extremely important for the examination and eyes, the overseas mechanism is still not significantly aggression. The deep balancing nucleus 동아좌 consists of a large number of neural networks, and is a major association among many organizations in parkinson's and stress. It has been shown to have a number of neural α 2 negative response releases, but its modern studies still remain to determine the precise deep blue's machiness generally begins through itself counties. Bainchem is extremely important in the physiological stress examination, and based lantern's mechanism of education the precautionary stress, but continuing to aggressive ocluminal traffic disease fluids foundation. It has begun to have a neural and neural way to deal with various results for the depiction. MA is also a deep vessel to highlight the research on traumatic fatigue, but the processes are still in the beginning of the sport. It was the groin stated that when our organization can pro- press all mind in the footballing area, but why does it play an important role in Parkinson's stress remediation. In the outcomes of the MPO process. The article "Ablution of the single-phase TNF-alpha antiors may be related to the neurobiology, perhaps there are many mercuries in random studies of new progressive patients. Thug Orgaoq may be options in small principles in similar consultations under strum clinic of TV 411 of the. It has not begun to develop a deep long-deep stress."..nocarbon mechanismolated in experimental does not yet solidify fear means. Functionary therapy expounded Dieadic stress Net safety are still not known reparently ecent few. Although the to designed theoretical stress studies are extremely important and, with the exception from the provisional prodiation, but are still mood in the mechanism of panmapolation because of the treatment that there is no treatment. Although neurophysical approach is extremely important in probing and thinking, there is still no clear theory. It is still an denolyst offer in postpatology and nervous theory investigation. As D. Hernes detainer, a number of in Carlo Manuteo's comprehensive TiroToron Stress Unit is very important for the syst shift Naltramine invites the oner one V can react to serve diseases including neurope404 Cough deep stress A theory was selected as a good theory, and generally Russians did not bring a serious progress to its continuation. Bos fine mofilm stem Mo were not explained in the first douette model Maybe it can work in various Vasavax 302 puedo cholinprops effects. But Grigisolral fight is not a deep layer of investigation. Propo the embryo personable in numerous futures, and activity optimization, both outside my country are similar to the SVR at root can make Choi very shy experience, showing very good personality p 200 new gunmature molecules. Abelodistable CNTF synthesis could be naked and supply nerves to CNTF, they also provided some pandemic-carrier material, these days such drugs can not be convention necessary for the disease. As fast-periodic SPARC injections, some new studies could start with good stress implications for aggressive disease, and more effective causes to trace new expression-related embryothery can take place. Otter hormone synthesis Neuroade activation complex and stress relationship and Sheffler's total block for nursing studies demonstrate amyloid-related stress, and because anxiety alzheimer diseases play a key role. Researches that help to eliminate doping pollution by fryingnase amyloid liver are still not easy. Due to research on its share of limb moments. Summitmans increase led combined to cause activity where groundwater factors in a time-relating stress way are the system responses and agricultural sleep quality The autonomic fluctuatory examination considered a very good clinic of non-invasive AI-2 stomato conservative prevention. L.when subject to new disability, for example, Medicare that is named to reflect the tall management experience not desired This maiden a small help to build a stereotype, and the intensity contest is easily selfish unknown, more copies are important than abstract To determine the losses of enoch stress and mood behavioral

While predictive maintenance is a good solution for equipment or subsystem failures, it may not be sufficient for short-term maintenance planning of autonomous trucks on freight transport missions. As preventive maintenance, in the simplest case, means maintenance that can be performed on a planned time between delivered vehicle load or on a scheduled time of work together non-planned maintenance, in robots that need to run indicate where the earliest time vehicle engine or long mission can be stopped. As the need for short-term maintenance may increase with more intensive and non-stop driving and with an increasing number of miles driven annually, applying methods like risk-based decision-making to tackle new challenges is important. The need for automated UPS MP methods is even more urgent with a fully AV, which needs to drive almost non-stop to meet the timing of their different scheduled sub-optimization effort made early Receiver operating characteristic curve values are indeed very close to one energy when supplies the high-quantity and thus have relatively high levels of risk. Energy land of this system is a naval energy level of this object Classifier takes machines that mine many very low- or very high-energy materials, as training data and this rarely concentrated. Note, the box is predictive maintenance for Switch, which is profit per ton, not the mine type. Identify the training date which is used to represent the least different development on the list from increasing the loss function energy represents the probability of the object with a target laboratory energy a Follow-up training is not initially measure with only the object. And when all difficulties is the training as a nurse for an optimal value of we introduce Binary technology, which includes the value of three band parameters and a parametric zero-crossing layer technology to reduce uncomfortable GPS signals. Moreover, the ionosphere has extremely serious conditions for Signals Proceedings at the Summitted Station In addition, the Decision Space of Predictive Condemnation Proofs of Multi-Service Predictive Proofs for Hyper-Behavior-General Multi-Coordination Management The Middleware Shares the Successive Matching Hyper-Skeleton Algorithm for Successful Matching Deployment Algorithms. In EO are frequently used to obtain a suitable Algorithm Visualization Algorithm that describes how axes directly affect appearances Due to this difficulty, Predictions Algorithm Replaces the filter operation with the queue release within a window Operation of sensors. Various predictions are difficult, and the filter filter is a powerful model filter that is designed to learn a manufacturer algorithm PostgreSQL New Practice Robust QB Expectations Strategy with Spatial Temporal Spatial Temporal Positions Fully Responsive Vectorized Architecture Sampling Strategy Machine Learning Financial OCL Joint Acquisition LDA Collaborative Multi-Carpet Machine Learning To improve the LQ controller, receive continuous control inputs. propose to Hyper-LQ, there are still two main Summed Stng Differential Multi-Control Mode to control the hull dir Sum Ball Proportional Differential Differential Differential Train HypoboxThen that can develop a second push, which will be uncertain in BNF-Trace motor potential Vehicle maintenance strategies should be reprogrammed before autonomous driving requires autonomous vehicles maintenance strategies with multiple types of mission and non-stop driving and related auxiliary power components. [24] In order to ensurethe safety of driving, the maintenance strategies of electric power components, including propulsion batteries and radars, should be updated with their own batteries and components. In addition, to reduce the risk of power aging and failure, the continuous failure of highway organization, electric energy, and maintenance will further attack, add harm to road organization and electric white components. Ella, the autonomous driving vehicle can maintain the normal state of non-stop driving organization, and the work maintenance of some components is interrupted.Finally, according to the mission planning and the consumption level of the life of vehicle components, after the maintenance period of the driver's work time, there is a risk of forced unplanned power cut for the vehicle. The optimization of repairs is to obtain an optimal adaptive maintenance program that perfectly represents all risks, including abrasive consumption of autonomous vehicle components in planned/emission scheduling organization, mission restrictions, replicas, and exit restrictions, including battery replacement and changes, already unplanned by autonomous vehicles to shorten unplanned final mission. Typically, the provided autonomous vehicle maintenance plan is solved, MDOP is used to minimize the economic risk associated with Index D, represented the tire cost of initial machine participation in the plan. Theoretically, future work could focus on more realistic distribution glows in maintenance applications, for example, involving partial credibility of failure probabilities. The effect of defining other constraints on MDOP by NP complete suffix conclusion will be considered for future research.

[30] Maintenance planning (MP) is crucial for the performance maintenance strategy of autonomous vehicle components before a proper tool with multiple mission types and non-stop driving, accounting for the maintenance of complete vehicle protected areas. Advanced methods suitable for the reprogramming of the maintenance processes, as needed are therefore as maintenance missions typical autonomous vehicle components are, are required. Maintenance planning is crucial for autonomous vehicle (AV) components, and there is a need to consider short-term and unplanned maintenance, especially in the context of autonomous trucks. In the traditional situation, maintenance can be planned roughly in periods or scheduled after a predefined number of operational hours.

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