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1 author:

Chirag Vinalbhai Shah
General Motors Company

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Machine Learning Algorithms for Predictive Maintenance in Autonomous Vehicles

Chirag Vinalbhai Shah,
Sr Vehicle Integration Engineer GM

Abstract
The complexity and hazards of autonomous vehicle systems have posed a significant challenge in predictive maintenance. Since the incompetence of autonomous vehicle system software and hardware could lead to life-threatening crashes, maintenance should be performed regularly to protect human safety. For automotive systems, predicting future failures and taking actions in advance to maintain system reliability and safety is very crucial in large-scale product design. This paper will explore several machine learning algorithms including regression techniques, classification techniques, ensemble techniques, clustering techniques, and deep learning techniques used for system maintenance need assessment in autonomous vehicles. Experimental results indicate that predictive maintenance can be greatly helpful for autonomous vehicles either in improving system design or mitigating the risk of threats.

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

1. Introduction

In recent years, driven by advancements in areas such as machine learning, connectivity of vehicles, and an increasing demand for shared mobility, a large number of companies have invested in autonomous vehicles (AVs) which are expected to substantially change the transportation and energy sectors. Nevertheless, the operation of shared autonomous vehicles is a great challenge, as these vehicles can operate up to 12-15 hours per day, with only very short time windows available for vehicle inspection and maintenance. As such, the vehicles are expected to be highly reliable, which requires high-quality components and a well-designed operation and maintenance plan. Machine learning methods and their predictive maintenance application can play a great role in optimizing the operation and maintenance of AVs, reducing operational costs, and ultimately the cost of the mobility service. This paper demonstrates and evaluates the benefits of using machine learning algorithms under a predictive maintenance perspective for an actual case study of a company providing shared AVs.Many machine learning algorithms are available. In this work, artificial neural networks, decision trees, and random forests were used to forecast vehicle issues and to derive a regular maintenance plan, and their performance was compared. The predictive maintenance plan obtained is compared with the company's actual maintenance plan, and it is demonstrated that using the predictive maintenance plan it is possible to reduce cost and vehicle downtime. Results show that machine learning algorithms can be successfully used to create predictive maintenance plans for vehicles and that predictive maintenance represents a highly valuable tool for shared AVs, and will also be important in large-scale electric and autonomous vehicle rollouts.

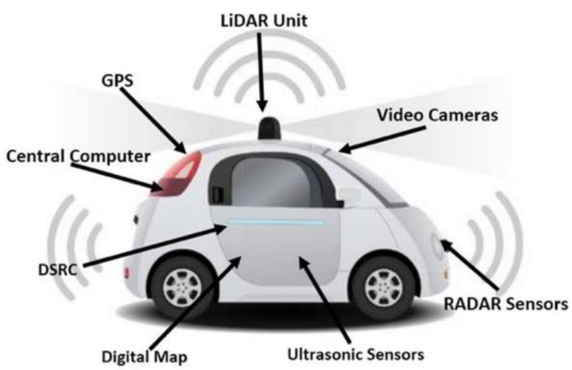

Fig :1: An illustration of Autonomous Vehicle equipment.

1.1.Background and Significance

Autonomous vehicles represent the most important innovation that the automobile industry has seen in decades. It is expected that shortly, these vehicles will quickly dominate the market as they will reduce accidents, traffic jams, fuel consumption, and driving times. This transportation technology is driving progress toward a future with safer, more efficient roads, cleaner air, and an improved passenger experience. Nevertheless, safety is still a source of concern with autonomous vehicles since it is imperative to ensure that the vehicle operates safely and correctly. In this sense, to guarantee the operation of an autonomous or unmanned vehicle, it is essential to predict when a failure in the vehicle system can occur and to take appropriate measures so that the fault can be corrected even before it happens. Systems developed to perform the prediction of when a failure can occur in a vehicle are classified as predictive maintenance systems.The development and installation of predictive maintenance systems are capable of identifying failures before they occur and preventing them from causing more problems or destroying the systems or equipment. Therefore, it is possible to ensure greater operational safety of vehicle systems and thus allow the vehicle to fully comply with its function. In the context of autonomous vehicles, the use of predictive maintenance systems is a great alternative, especially in the case of flights of long unmanned vehicles. This work provides an analysis of the most used machine learning algorithms in predictive maintenance systems for cars, the development of these autonomous vehicles, and which of these algorithms the scientific community believes is the best in terms of accuracy in predicting that a fault will occur.

2. Autonomous Vehicles and Predictive Maintenance

The application of machine learning in predictive maintenance for autonomous vehicles has a huge promise in reducing downtime and overall maintenance costs. The autonomy of self-driving vehicles makes the maintenance mechanism of traditional human-driving vehicles less suitable, e.g., the current maintenance scheduling system may not capture all aspects of self-driving vehicles' health issues, because self-driving vehicles involve more decision support systems and robotic/drive-by-wire technologies that are not within the category of human-driven vehicle's monitoring scope. As a result, a data-driven approach that incorporates a large amount of real driving data for road-induced hazards and maintenance expenses can provide clear insights to optimize the self-driving vehicle's maintenance scheduling and prolong the lifespan of necessary vehicle components.As all the electronic and power components might fail, the vehicle reliability of mission essential mission-critical components such as the sensor system, vision recognition systems, on-board drone machine systems, and mechanical parts of the vehicle such as braking systems that would pose significant safety risks to the intended environment could lead to a safety hazard or fatal crash. Therefore, these vehicle components require much tighter control and need to be monitored and maintained meticulously. In contrast, some of the warranty-provided parts are expected to have a certain lifespan and should be fully utilized without spending add-on costs until their end of life (45,000 miles) is reached.

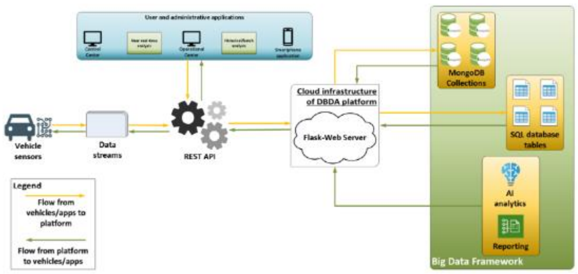

Fig :2: Data flow and exchange among applications, sensor vehicles and the DBDA platform

2.1. Overview of Autonomous Vehicles

The increasing demand for autonomous vehicles is a consequence of the urge for safer, more efficient, and more convenient transportation systems. At the same time, the potential for numerous applications has supported the development of autonomous vehicles, which include driverless public transportation, autonomous taxis, autonomous deliveries, and self-driving cars. The vision for the future of driverless cars considers both long-term and short-term perspectives. The long-term vision focuses on a world where humans are freed from the driving task and cars are autonomously operated. Given the enormous potential, researchers in academia and industry are actively working toward the resolution of key technical issues for realizing reliable and fully automated driving. The short-term vision describes stages of incremental innovations as caused by the gradual development toward realizing ultimate automation.Currently, we have discerned stages 0, 1, and 2 associated with advanced driver assistance systems. Vehicles at stage 0 have no advanced assistance systems, whereas vehicles at stage 1 have specific systems derived from the intelligent transportation systems concept such as intelligent speed control, adaptive cruise control, or lane departure warning. These vehicles still require constant monitoring from the driver and can, in no circumstances, drive themselves. Likely, as part of stage 2, the vehicle can already perform some tasks without human interference such as accelerating, braking, keeping the vehicle centered in the lane, and approaching other vehicles. At this stage, even though the driver should always supervise the vehicle, they can relinquish control for a short period. These are important stages for safer vehicles because, in 2018, the number of traffic fatalities resulted in 1.35 million lives lost, and 54% of the cases involved vehicle occupants and motorcyclists in the age range of 15-49. With the development of vehicle safety systems installed in the fleet, we hope to make roads safer. Moreover, these systems will evolve to include more automation capabilities. With vehicle autonomy stages specified by the automation levels, in which 5 is completely autonomous and 0 is the state of a vehicle without automation capabilities, the driverless vehicles are expected to have more passenger focus. In other words, the vehicle is designed to accommodate passengers with diverse activities such as reading, speaking on the phone, and working, in which the passenger is not worried about the route or the intersection. The driver cannot be the person who automatically takes responsibility for the vehicle under critical situations. Thus, all the vehicle technology should be designed and implemented taking the passengers' safety into account.

2.2. Importance of Predictive Maintenance

Predictive maintenance is an important task within the maintenance strategy. The purpose of predictive maintenance is to reduce downtime by controlling the state of the parts or devices. This is achieved by monitoring parameters and analyzing the historical behavior of the machines. It is a strategy that optimizes the balance between the cost of operation and the reliability of the components. Some of its advantages are cost reduction, improved product quality, a longer duration of the tools, and increased overall productivity. In the most critical industries, any failure can lead to losses greater than $20,000 per minute. On the other hand, the productivity of vehicles dedicated to public transport should be improved and breakdowns avoided because passenger safety is at stake.The predictive maintenance of machines is not something new, it has been accomplished through different techniques or manual inspections. Nowadays, the deployment of the Internet of Things (IoT) in the industry has given rise to the so-called Industrial Internet of Things (IIoT). This has many characteristics and produces a quantity of information that does not follow traditional data processing methods. Today it is possible to connect devices, sensors, and systems in the company. This has led to the production of a large amount of data which, depending on its use, gives rise to the term Big Data.

3. Machine Learning in Predictive Maintenance

Subject expert: Nikos Maroulis, Department of Electrical & Computer Engineering, University of Patras, RIO-Patras, Greece Editor: Yannis Maroulis Antonis Xakalis Department of Electrical & Computer Engineering, University of Patras, RIO-Patras, GreeceToday, with the unprecedented evolution of computational power, Predictive Maintenance has become a clinical choice. PM enhances the reliability of a manufacturing system by forecasting the state of its components, ensuring that anything that has reached its threshold gets repaired, and avoiding spending, thus eliminating unscheduled downtime. It keeps the system in a good and operational condition preventing or reducing the probability of a breakdown. A manufacturing or any other industrial process performance highly depends on how the service levels of its equipment are met. These service levels may concern, for example, quality, inventory, lead time, delivery, etc. Maintaining equipment in good condition, preventing it from failure, and creating a base of knowledge about equipment are some of the benefits of PM. Especially for the big modern industries, PM can provide benefits such as avoiding penalties for non-performance penalties in SLA, maintenance cost reduction and avoiding over-maintenance, inventory cost reduction based on the balance between stock levels and production, and availability improving by scheduling maintenance during non-peak hours. [...]A third and recent way to implement PM in (Autonomous) Vehicles is the usage of (Deep) Neural Networks (DNN). Modern vehicle or car health monitoring usually relies on structured and qualitative data driving to qualitative and subjective conclusions. The available data usually consist of vehicle error codes, OBD readings, fuel consumption sensors' measurements, and vehicle usage records, e.g. distances covered, fuel consumptions used, time since vehicle startup, etc. ANN (Artificial Neural Networks), specifically DL (Deep Learning) architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) models, etc. have attracted the interest of industrial equipment, cars, and automotive vehicle manufacturers. In general, one common technique is to first build statistical models to calculate indicators that capture the degradation of monitored components before they break down and then to train a neural network using these indicators. [...]

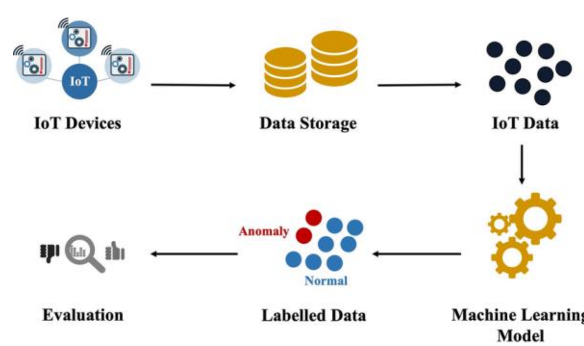

Fig :3: Machine learning workflow for anomaly detection

3.1. Types of Machine Learning Algorithms

Several studies have utilized these machine learning techniques to develop predictive maintenance algorithms. In this study, we have chosen to focus on the most popular types of predictive algorithms (supervised algorithms). Our focus on supervised learning techniques was motivated by their capacity to learn complex relationships between prognostic features and reliability issues. From a reliability engineering perspective, supervised learning techniques allow probability prediction models leveraging failure history to provide significantly more information than baseline no-performance-change predictions. As such, leveraging supervised technique capabilities could enhance predictive algorithm performance. We have found that support vector machines, logistic regression, and artificial neural network supervised learning algorithms are most popular in the context of PHM.Classification-supervised machine learning algorithms like decision trees, k-nearest neighbors (K-NN), random forest, gradient boosting, and Gaussian process can efficiently predict categorical dependent variables. These algorithms predict the categorical outcome variable by learning features of labeled data sets. Such binary classification problems are frequently utilized in the context of predictive maintenance, for instance, predicting failure and no failure. Documented reliability predictions can be viewed as a binary classification problem: will performance continue consistent with a set of predefined thresholds based upon the learned patterns (failure/no failure)? While numerous studies have implemented classification techniques.

3.2. Applications in Predictive Maintenance

Predictive maintenance can be simply described as a model that estimates vehicle conditions based on the vehicle's past operation and its current condition to predict faults and failures before they occur. The goal of predictive maintenance is to reduce capital owner costs, maximize the useful life of the physical capital, and maintain the reliability and performance of machine learning or statistical models. Compared with calendar-based and usage-based maintenance, predictive maintenance can truly realize the potential of the Internet of Things and big data. This new concept of vehicle maintenance does not use a manual time node to replace damaged parts or use visual inspection to check the damage but uses machine learning algorithms and real-time data from automobiles to estimate the wear and degradation of automotive parts and predict if these damages may cause vehicle failure.Mehta et al. designed a Wireless Data Acquisition Node for large-scale data acquisition. Instead of counting the number of rotations, the researchers detected changes in the sound spectrum indicating the status of brakes and tires and movements of the steering and the suspension, which can be used as indicators of wear, tear, and faults. This method can reflect the wear condition of automobile parts in real-time, and vehicle owners only need to replace car components when they need them, thus saving unnecessary costs. The costs that arise when production is interrupted, such as loss of revenue, penalties for non-compliance, and unexpected costs, can be reduced accordingly. In any environment where conditions can be collected from the Internet of Things based on wireless sensors, predictive maintenance can be implemented, such as in vehicles, machinery, and buildings.

4. Case Studies and Examples

The complexity and the increasing number of sensors and embedded systems of autonomous vehicles lead to machine learning algorithms that can be useful to enhance their development. Predictive maintenance is a machine learning problem with important implications for industry, civil engineering, aviation, telecommunication, and several other areas. The automatic knowledge extraction from the data associated with the wear of essential components, using low-cost sensor networks (a modification of what is called the Internet of Things for industrial or professional civil engineering automation), has as a direct result the possibility of reducing costs of maintenance on manufacturing floors, transportation programs, and construction sites.In autonomous vehicle predictive maintenance, the failure of some components such as a bearing, a rotor, a sensor wire, or an electrical communication bus generates a cascade of additional hurdles for the vehicle, and even for other systems linked to its operation. The use of a bearing on a rotating vehicle usually does not generate an expected lifetime. The number of acceleration events and the power spectral density of the forces induced by the bearings on other components reflect their working status. The occurrence of these events propels flaws in gearboxes and electric engines. This raises some interesting correlations of abnormal function related to the source of the failure. Using machine learning algorithms such as decision trees, random forests, support vector machines, and extreme learning machines, the discrimination and prediction of the different sources of the fault is possible. The worst-case scenario is an accidental datum cluster that can be correlated with the cause of the driven scatter. Some of those algorithms are general optimization methods that can also be used to map other different scenarios. Those algorithm maps are quite useful to the human designer, who possesses the final expert fault judgment.In the realm of autonomous vehicles, predictive maintenance leveraging machine learning algorithms is crucial for preemptively addressing component failures like bearings, rotors, sensor wires, and communication buses. These failures can cascade, affecting vehicle operations and interconnected systems. Monitoring factors such as acceleration events and power spectral density from sensors can provide insights into component health and predict potential failures. Machine learning models like decision trees, random forests, support vector machines, and extreme learning machines are employed to analyze data patterns and correlate abnormal behaviors with specific failure sources. By effectively discerning and predicting faults, these algorithms contribute significantly to reducing maintenance costs and improving operational efficiency across manufacturing floors, transportation networks, and construction sites. Such predictive capabilities not only optimize maintenance schedules but also empower human designers with critical insights for enhanced system reliability and performance.

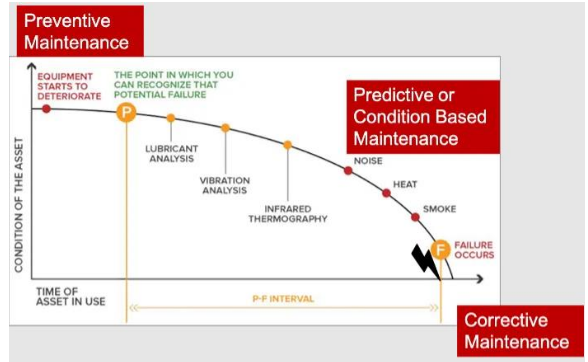

Fig :4: Maintenance strategies time frames

4.1. Real-world Implementations

Real-world implementations of predictive maintenance (PdM) can be found in various industries. In the automotive industry, several major manufacturers have predictive maintenance systems to identify faults before the vehicle breaks down. This results in a reduction of unscheduled maintenance downtime. Thanks to modern technology like machine learning (ML), manufacturers of pod taxis are now able to predict the wear and tear of critical components and avoid breakdowns. In this chapter, we will first cover the major areas where high-confidence deployment of predictive maintenance can get leads.DOA level forecasting can trigger an alarm at SNR labs, which manages and monitors the road/train safety equipment installed in the BoPE and Hot Boxes (components of railway wagons used for reducing heating of bearings) of all the rakes of the company. To meet predefined maintenance measures, it is common to repair or replace the defective components at regular intervals—regardless of the actual condition and function of the components. This leads not only to unnecessary maintenance and related costs, it especially leads to an early replacement of components in otherwise good condition and to a loss of service life which creates a large amount of CO_2 emissions.In various industries, including automotive and transportation, predictive maintenance (PdM) systems play a crucial role in minimizing unscheduled downtime and optimizing operational efficiency. Major automotive manufacturers utilize these systems to preemptively identify faults in vehicles, thereby reducing the need for emergency repairs and associated costs. Similarly, in innovative sectors like pod taxis, advancements in machine learning technology enable predictive analysis of critical components, ensuring proactive maintenance to prevent breakdowns.In railway operations, such as those managed by SNR Labs, predictive maintenance is employed to monitor the condition of safety equipment on roads and trains, as well as components like BoPE and Hot Boxes in railway wagons. Traditionally, maintenance measures are often scheduled based on predefined intervals rather than the actual condition of components, leading to unnecessary costs and premature replacement of parts that may still be functional. This approach not only increases operational expenses but also contributes to higher CO_2 emissions due to premature component replacement.By adopting predictive maintenance strategies driven by data analytics and machine learning, industries can shift towards a more efficient and sustainable approach. This proactive maintenance not only extends the service life of critical components but also reduces environmental impact by minimizing unnecessary resource consumption and emissions associated with premature replacements.

5. Challenges and Future Directions

As ML models play a significant role in the field of connected and autonomous vehicles (CAVs), enabling predictive maintenance, there is still room for improvement regarding their capability to handle higher numbers of sensors and imperfections in data. Future directions of research may include developing novel models that can handle data imperfections more efficiently without the need to discard information. Additionally, increasing the capability of ML models to handle higher numbers of sensors could lower the costs for maintenance and increase the availability of vehicles. Identifying other anomalies present in the sensors, for example, particular noise patterns due to malfunctioning could also be part of future research to enrich the dataset and learning procedure.One significant challenge was that collecting data from the sensors available on first-grade banks was particularly complicated at the beginning of the project. Technical limitations of the vehicles that we were able to use were not only due to software issues but also because the vehicles were in practice driving commercially and they could not be stopped for long periods. In this sense, future research to enlarge the amount of data available could see data coming from our fleet of vehicles. Other sources of data include modeling the behavior of the sensors, like the most frequent of their values when the vehicle is being utilized in different conditions, and using these as benchmarks for future problems. Nevertheless, this work contributes as a first proof that data science can rapidly contribute and leverage the state of the art in vehicle health management in the short term, transforming a state-of-the-art problem into a value proposition.

Fig :5: Continuous Feedback: Definition, Management, and Benefits

5.1. Current Limitations

Recent approaches utilize machine learning models to identify breakdowns before they happen and plan vehicle maintenance and repair activities to prevent interruptions and avoid safety problems. Most of the existing vehicle predictive maintenance techniques concentrate on conventional vehicles. There are only a handful of papers that address autonomous vehicle predictive maintenance, which is almost solely restricted to empirical validations. Our approach involved autonomously navigating the vehicle to acquire operational measurements, which would be used as a measure of the car's health state for predictive maintenance approaches. The restrictions and obstacles that may arise when different types of operational measurements are acquired are currently being addressed and then used according to the vehicle's operational state.Because predictive maintenance uses the health status of the vehicle to execute maintenance and repairs before the vehicle fails and each vehicle uses different operational measurements in the autonomy phases, our predictive maintenance technique focuses on the vehicle itself. Only the autonomous vehicle itself can internally collect the data needed for predictive maintenance, essentially obviating the need for any additional sensors. Software implemented on the vehicle receives the requisite measurements and uses machine learning to predict material damage. The vehicle management infrastructure sends a request to change the navigational policy to prolong the life of the vehicle. However, long-term predictive maintenance systems and natural protection are required. More research is needed in this area before this is a viable alternative.

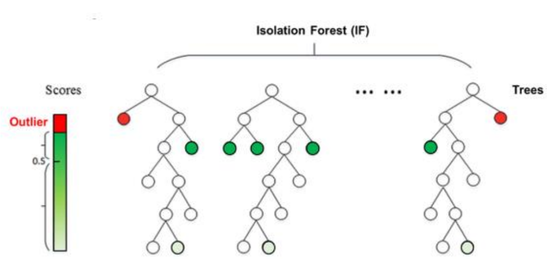

Fig 6: Isolation Forest Model

5.2. Opportunities for Improvement

Whatever the reason for the failure, the overall challenge is not the development of algorithms that help understand failure events more precisely and prevent similar incidents from happening in the future. The focus of this work is the transformation of algorithmic learning into an innovative problem-solving approach in the field of predictive maintenance for autonomous vehicles or drones to enhance their reliability, safety-relevant availability, and lifetime.In recent years, significant research progress has been made in using machine learning for predictive maintenance. Uncommon is, however, that so far this academic work - and even more so the established business of predictive maintenance solutions - is tailored to the conditions and requirements of autonomous vehicles. In the state of the art, predictive maintenance supported by machine learning has rather been applied in traditional manufacturing settings on electric motors and other technical equipment.In those cases, data summaries of operational parameters such as time series of the temperature and vibration of machinery provide indications about its condition. Typically, such machinery is available in large quantities of near-identical makeup, environmental conditions are controlled, and the system is known. Remedial actions can be taken easily, such as replacing a machine in a production line. Furthermore, the service life of machinery is known, and failure data can be gathered in a supervised manner, enabling the full utilization of established machine learning concepts. The area of predictive maintenance for autonomous vehicles, however, encompasses an entirely different business case with a different underlying system.

6. Conclusion

This work outlines two ML algorithms for PdM in AVs based on real-world data. The ML algorithms are used to predict the SOH of one of the most important components of the vehicle: the high-voltage battery. To our knowledge, and we underline it again, we present the first two ML-based PdM algorithms that use real data from AVs for predicting the SOH of the battery. Our deep learning model, a Stacked Autoencoder, has proven to be the best algorithm for our current dataset in terms of accuracy and response time. The second model, the Random Forest regressor, has also proven, more or less, to be a good model with accuracy values close to the SLA values and a similar response time as the SLA model.

The development of not only PdM but also DISMO is needed to ensure the safe and reliable operation of AVs. The main limitation of this work is the data itself. The data used to train and test the ML algorithm were generated during the prototype car phase. For mapping the test results to our physical testing environment, we used a simple voltage-based battery model. However, we would need the physical model to be able to predict the SOH of the battery for longer periods. We are currently working on this issue. Moreover, we would need data from real-life use to be able to predict the SOH more accurately, especially as the battery gets closer to its end of life.

6.1 Future Trends

As future trends, we can find that, we are going to legislate on artificial intelligence, based on the European Parliament, focusing on the Commission's algorithms and the proposal for an initial legal framework focusing on fairness, transparency, and the European liability regime, based on accountability and decision-making within the framework of artificial intelligence (AI), especially on the use of autonomous vehicles, as well as the European Economic and Social Committee, proposing a first legislative package for the implementation of this framework, accompanied by strategic coordination and zero tolerance for failures. German automobile companies such as Daimler AG and Volkswagen AG are a step ahead in planning, implementing, and adopting Explanatory-AI.Another trend is explainability. AI software that uses Personal Data to make decisions concerning an individual has the right to have a human verification algorithm of up to 6% compared to 100% of clients, according to the European Union, with a ceiling of 100% for gun-nr. On the other hand, the European Union and member states must monitor new technologies and their applications daily, while supervising and reviewing the scope of Explanatory-AI, to ensure that their supervision is compatible with current legislative decisions, especially in the field of artificial intelligence that uses Personal Data to take decisions concerning an individual and exempt these interim sanctions and fines. For software that relies on complex algorithms, access to the processes, knowledge, and reasoning behind the decision, including AI, is essential.

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