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The Role Of AI-Driven Predictive Analytics In Automotive R&D: Enhancing Vehicle Performance And Safety

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Right now, as you're reading this article, machine learning-imbued AI is revolutionizing a lot of industries, and humans are on the cusp of more defining breakthroughs in coaxing silicon to think and act more like carbon. Despite the reliability of the road map and time-tested strategies, automotive R&D always teeters on the edge of a technological abyss, with the next challenge never far from the horizon. Engineering managers and executives in the industry now have interesting new predictive analytics territory to navigate as they craft their next big automotive victory: AI-driven applications and services to enhance vehicle performance, safety, and efficiency.

There is a small but growing number of specialist tech companies working in this area, mostly in the USA and UK, and their predictive AI systems represent a new category of platform 'tool' that takes simulation software or operational telemetry data as input, and gives automotive engineers actionable insights and test-bed experimentation outputs as output. The exact functionality of these systems differs from startup to startup, but their applications generally fall into the three key territories of vehicle dynamics, driver monitoring, and performance optimization, with crossover use-cases serving both traditional and autonomous vehicles.

Similarly to the stock market prediction-scholars of many years past, it will take some time for the car-geeks to get their tech and methodologies in the hands of the OpenVIs and SMEs of this world. In addition, the AI-powered automotive simulation market is young and small, but within the big, building the very first engine needed to drive the automotive revolution that swept Europe. More interesting times lie ahead as this disruptive industry behemoth takes shape and the stakes for established auto manufacturers, as well as disjointed existing suppliers, begin to crystallize.

Keywords: Artificial Intelligence (AI), Driver Credential Management, Internet of Vehicles (IoV), Key Distribution Center (KDC),Predictive Analytics,AI in Automotive R&D,Vehicle Performance Optimization,Automotive Safety Enhancement,Machine Learning in Engineering,Data-Driven Design,Predictive Maintenance,AI-powered Simulation,Vehicle Safety Models,Advanced Driver Assistance Systems (ADAS).

1. Introduction

Vehicle research and development engineers aim to build automobiles and other automotive-related systems by employing the latest technological advances. At the same time, strict laws and international standards mandate that new vehicles are subjected to a large number of tests.

In order to meet all of the criteria, it is necessary to consider a vast range of test courses. Stress is placed on the R&D process due to rigorous regulations and standards, and an approach to evaluating vehicle performance with minimum testing has garnered attention.

The basic idea behind the development of new methodologies for automotive R&D engineers is the increasing utilization of high-speed computers and smartphones. Computer-driven systems can quickly generate and evaluate a large number of possible courses. In deep learning, numerous hidden layers are utilized between input and output layers. The weights and biases between connections of nodes are learned. The largest problem when training deep learning models is vanishing and exploding gradients. The recent advances in artificial intelligence have made deep learning possible, which has motivated efforts towards the development of sophisticated driver-assistance functions based on high-precision predictions. Predictive analytics for R&D engineers is designed to enhance the understanding and use of AI-driven predictive analytics and deep learning in vehicle control. This approach is based on examination of the latest research reports.

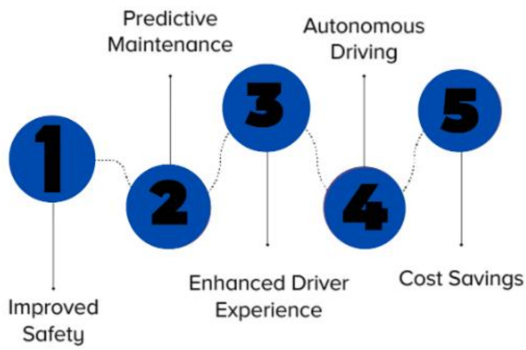

Fig 1: AI-Driven Predictive Maintenance

1.1. Background and Significance Innovation has always been a key differentiator in the automotive industry when it comes to building better vehicles. Today's automotive R&D is directed towards developing the next generation of vehicles that are electric, autonomous, and connected, as well as more fuel efficient, weight reduced, and less pollutive. Advanced engineering analysis tools, such as computational fluid dynamics (CFD) and finite element analysis (FEA), are widely used to accelerate, improve, and optimize the automotive design process. However, the design of vehicles, especially of electric or autonomous vehicles, often involves many conflicting requirements and constraints that are difficult to solve without the use of Big Data. Thus, there is a growing interest in the application of Big Data technologies on automotive R&D to improve vehicle design and production. Vehicle-generated data (VGD) analysis allows testing and analyzing vehicles during R&D stages and in real-world environments. Additionally, the evolution towards electrical or autonomous vehicles is creating the need for a paradigm shift towards vehicles with a much higher inclination towards digitalization. Big data from vehicles is not limited to in-vehicle data, natural common data sources such as vehicles with advanced driver-assistance systems, vehicles applying sensor technology or camera systems, vehicles in smart cities conditions, but it is also expected huge data generation from the omnidirectional from the virtual reality and augmented reality scenario generators which are used for the visualization of the predictor model of the vehicle capabilities.

Equ 1: Autonomous Vehicle Fleet Distribution (AI and Cloud Optimization)

$$R_t = \arg\min_{R} \left(\sum_{i=1}^{n} \mathrm{Distance}(R_i) + \mathrm{Cost}(R_i) \right)$$

Where:

- R_t = Optimal route at time t
- R_i = Route option i for distribution
- $\mathrm{Distance}(R_i)$ = Total distance of route i
- $\mathrm{Cost}(R_i)$ = Total cost (e.g., fuel, time) for route i

2. Overview of Predictive Analytics in Automotive Industry

(-) The role of AI-driven predictive analytics in the automotive industry are described, especially for research and development applications. This approach is to examine the state of the art of AI and to study how to leverage it for enhancing vehicle performance and safety. Over the last few years, the automotive industry has witnessed a substantial increase in the usage of predictive analytics and machine-learning algorithms for evidence-based decision making. Deep learning and reinforcement learning is used to estimate the optimal cold start temperature of the catalyst and the lambda sensor.

The automotive industry is experiencing a transition from being product-centric to customer-centric, which has a profound impact on the way organizations conduct research and development (R&D). To ensure future success, automotive companies must focus on concepts related to real-time data acquisition, data-driven product design, and multi-discipline integration. State-of-the-art technologies such as the Internet of Things (IoT), big data, machine learning, deep learning, and artificial intelligence (AI) to improve vehicle performance and safety. In this article, both a human-centric approach for using AI to enhance vehicle performance and a product-centric approach for enhancing vehicle safety are explored. The use of machine learning is explored to estimate the optimal cold start temperature of the catalyst and the lambda sensor enabling a faster light-off phase and reducing harmful emissions. Reinforcement learning is used to develop an adaptive cruise controller that enhances vehicle performance, comfort, and safety all the while reducing gas consumption. This work aims to bring awareness of the importance of AI-driven predictive analytics for today’s automotive research and development activities, especially considering their impact on vehicle performance and safety.

2. Designing, testing, and prototyping a new vehicle accessory are complex processes that generate a challenging optimization problem. The primary goal is to reduce the time and design cost. The accessory's shape is generated through a genetic algorithm (GA) with three-mutation applied on cubic Bezier functions. Constraints are to fit the accessory on the vehicle structure and to achieve a challenging aesthetic. Two predictors that describe the failure risk of a vehicle component during its operation in a fleet are used. The component model is represented by Cox's proportional hazard regression model, utilizing time-dependent covariates. Random effects estimate the linear combination of covariates. Clients upload models from different files in various programming languages. The uploaded models are applied to further random effects calculations. A tree-based ensemble method improves the learning process. The goal is to enhance decision-making procedures by providing the estimated risk for each component owned in a fleet. Moreover, an additional procedure that calculates the estimated risk of a vehicle component is proposed.

Fig 2: Predictive Analytics in the Automotive Industry

2.1. Research design Automotive Research needs solutions to mine the growing data of research, development, testing, validation and manufacturing to shorten innovation cycles with consistent vehicle performance and safety. These Research questions can be answered nowadays by artificial intelligence-driven predictive analytics using models with digital twins of vehicles and components. It consists of three technology elements connected to Machine Learning (ML) and its subsets Deep Learning (DL): (I) the use of Digital Twin-based simulation models, (II) supervised and unsupervised ML and DL prediction models and, (III) an evaluation of the prediction models by data quality and feature importance visual analytics.

For practical solutions in the automotive research industry, this chain of technology elements is exemplified in crash and safety research by the specific use case called 'side door impact' which denotes a vehicle's side impact scenario. The conducted experiments and development of the use-case Digital Twin with normalized input space ranging from partial to complete development status can also be applied to other vehicle structures and other vehicle safety aspects, regarding the exemplified results in the context of the 'side door impact' use-case. On the basis of this stand-alone research solution including its exemplary studies, research needs and relevant technology solutions are discussed. Finally, there are some concluding remarks and an outlook to future projects on this topic.

Automotive Development and Research processes are happening against the background of a progressively growing amount of data which is generated by the various stages of Research, Development, Testing, Validation and Manufacturing. The ultimate goal is to shorten the innovation cycles such that new innovative products can be brought to market at the right point in time and at the right quality to achieve competitive advantages. The innovation cycles are, nevertheless, not solely influenced by the progress of the technological state of the art, the availability of the financial capital, and the know-how of the employees involved, but it also depends on ability to manage the bow wave of data that is constantly generated. At the same time, the quality of vehicle performance and vehicle safety issues are claimed to become increasingly important topics. High investments are necessary to ensure safety and compliance with legal regulations accompanying the redesign and testing of vehicle components and vehicles.

3. AI Technologies Revolutionizing Predictive Analytics

The automotive industry is continuously looking to develop advanced technologies to enhance vehicle performance, passenger safety, and comfort. The automotive market has seen a dramatic shift over the last ten years in the fields of AI, IoT, and big data. In particular, these fields have affected the advanced driver assistance systems, connected cars, electric vehicles, and autonomous vehicles technologies. As a result, the car becomes “smart” and more connected and starts to be able to understand and predict what is happening around it, enabling it to act accordingly. Summarizing, the AI-driven Predictive Analytics work-flow can be characterized as 5V – variety, velocity, volume, veracity of data, and prescriptive analysis on machine learning and statistics with the goal to find unusual behavior on the system. This unusual behavior can then be further investigated to help prevent failures. Also provided and evaluated are a number of AI technologies that can revolutionize the predictive analytics workflow.

Predictive analytics can be defined as making predictions about the future using current and historical data and the help of analytics, machine learning and artificial intelligence techniques. Traditional predictive analytics includes statistical modeling, machine learning, data mining and other AI solutions. Such technologies are already used in many companies to predict end-of-life of devices and to schedule maintenance when it is needed. However, as the number of devices in the world is increasing and devices are getting more complex, manual models and rule-based indices are unable to predict failures in a satisfactory range. Classical condition-based monitoring technologies are unable to handle the vast amount of collected data and are not capable of handling unobvious and multi-source fault patterns. Recently, automotive manufacturers started collaborating more and more with IT companies and universities to improve the current and to create new, AI-driven predictive analytics solutions to enhance the vehicle performance and safety.

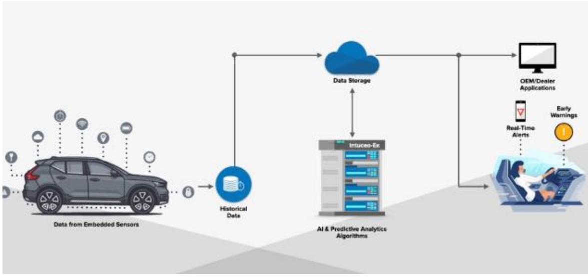

Fig 3: AI Technologies Revolutionizing Predictive Analytics

3.1. Machine Learning Algorithms In order to monitor performance aspects and take corresponding actions to facilitate the respective desired behavior in vehicles, campaigns by the supplier and the OEM are used to set the various vehicle parameters, with all of those activities forming the tuning process. The results from those can be used to train prediction models for on-line tuning that can be integrated with the existing controller in the car. The approach is evaluated on a test car in real-world operating conditions during tuning sessions with a test course. In the vehicle industry, tuning refers to the adjustment of vehicle parameters until a desired behavior is achieved. However, manual tuning is time consuming and requires the presence of a skilled technician. In order to enhance the predictive maintenance solutions for modern connected cars, a framework based on machine learning algorithms for on-line tuning of vehicle parameters is proposed and evaluated. The safety lifecycle for systems and software development specified in the standard ISO 26262 is an adaptation of the generic safety lifecycle according to IEC 61508 focusing on road vehicles. It is stipulated that all possible measures must be taken to use confidence improvement methods, typically involving modeling and testing, before applying safety measures that mitigate potential hazards. However, due to difficulties in obtaining appropriate modeling and test data, there is an ongoing debate in the automotive industry concerning the pertinence of the overly formalized approach prescribed by the standard. The use of machine learning algorithms, which autonomously learn models from data, can ease the process of model-based risk assessment demanded by the standard. The safety vector drawing is used to classify risk class values, which canonically arise from first principles risk assessment. The effectiveness of a machine learning-based approach to hazard classification is investigated in an exemplary case study, consisting of an electronic control unit’s software components. The capability of initially poorly performing ML models can be improved by reducing feature space dimensionality and employing optimized model-specific training methods. This adaptation and assessment of software requirements in ISO 26262 can be seen as a step towards addressing the challenges of using machine learning in safety critical automotive applications, particularly regarding components designed after a supervised learning-based approach.

3.2. Data Mining Techniques One of the many fields where the importance of acquiring knowledge from data to support prediction is recognized is automotive research and development. But despite the increasing amount of data that is continuously collected and stored during every process and the availability of sophisticated data warehouse systems, so far it has been difficult to make deeper use of the existing data resources. Data queries addressed to such data warehouses are usually stored in SQL, matching simple conditions on parameter values. The whole process is interactive: data has to be presented in different extracts to both departments and further requests may follow. The need to spend as little effort as possible in data retrieval and transformation and to gain deeper insight into the data calls for the application of more advanced data analysis methods such as data mining. Thus the preparation and understanding of data is an important part prior to predictive purposes.

One of the main focuses of automotive research and development since the very first days has been accident analysis and safety measures on the one hand, and performance optimization on the other. Due to the inherent dangers in accidents occurring at higher speeds and the experience of many people with cars being the most complex and dangerous machines they are using, automotive research has always been closely connected to mechanics, and vice versa.

Equ 2: AI-Driven Production Scheduling

$$T_{opt} = \arg\min_{T} \left(\sum_{i=1}^{n} (T_i + S_i) \right)$$

Where:

- T_{opt} = Optimal production schedule
- T_i = Time to produce unit i
- S_i = Setup time for unit i
- n = Number of units or products

4. Applications of Predictive Analytics in Automotive R&D

According to a study conducted by the consulting firm EY, companies in the automotive industry invest a significantly large share of their R&D spending in the field of mobility services. This share has risen from 6% in 2018 to 25% in 2020. At the same time, examination of companies in the consulting services sector shows that interest in consulting services focused on this field has increased by 65% from 2016-2017 to 2018-2019. In order to remain competitive in this increasingly data-driven field, companies need to explore and familiarize themselves with new AI-driven technologies. This includes companies that are predominantly active in traditional automotive R&D. For traditional car manufacturers that are entering the electric vehicle segment, where there is fierce competition with startups, Tesla is a serious competitor. Predictive analytics can be used by OEMs to predict when electric or electronic parts in an electric vehicle will fail. That way, the necessary upgrades or replacements can occur before the failed part stops working. This predictive analytic approach is called "predictive maintenance." In contrast, using electric cars can lead to an increase in mechanical failures. Most household chargers for e-vehicles are operated from a wall outlet. They are cooled passively, meaning that no fan or other components are used to cool the charger if it operates. The cooling depends on the environment in which the charger is located. Consequently, over time, dust build-up inside the charger may cause the charger to heat up excessively, potentially causing a fire. Using predictive maintenance, suppliers could proactively warn e-vehicle owners of this fire hazard. Thus, we could save money and possible serious injuries.

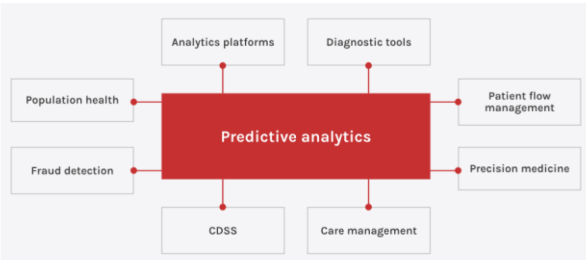

Fig 4: Applications of Predictive Analytics in Automotive R&D

4.1. Performance Optimization In the automotive industry, virtual methods and predictive simulations are efficiencies increasingly used during the development of cars, trucks, and buses. Combining the methods, multidimensional fields such as driving dynamics, crash, strength, and comfort can be analyzed. Over the last years, predictive simulations, like multibody-dynamics simulations, have been the domain of engineers, who spend much time creating models and preparing the simulations, and adapt the detailed theory to the analysis. Consequently, the vehicle developers request an expert system generating predictive simulations automatically from an expert- or knowledge base. Such a system was developed at the Institute of Automotive Engineering of the Technical University in Munich. In conjunction with the development of the expert system, a method for knowledge acquisition based on simulation driven design within the field of vehicle dynamics was established. The knowledge acquisition method, the structure of the expert system, the generation process of a knowledge-based simulation, and the characteristics of the knowledge for vehicle dynamics are described.

The performance optimization of an expert system analysis of vehicle dynamics is done from a knowledge engineer's point of view. This comprises the improvement of the structure and the rules of the simulation model as well as the expert system. The approach is demonstrated by the existing knowledge-based vehicle dynamics expert system of the Technical University in Munich, which generates multibody-dynamic simulations of passenger cars. The expert system generates models for the driving and braking dynamics of vehicles. Here, a vehicle is represented by the rigid-body model, and the road possesses a large number of plane and spatial templates for the description of discrete and continuous irregularities.

4.2. Safety Enhancements To enhance vehicle performance and safety, the latest advances in AI-driven predictive analytics could be integrated into the R&D activities of automotive

OEMs and suppliers. This technology can provide insights that lead to the optimization of vehicle systems while satisfying all safety and durability requirements. Specifically, it is shown how machine learning (ML), a subset of AI, could be used to analyze the huge amounts of vehicle data generated during tests and simulations to predict outcomes like component lifespan, stress or system efficiency. The potential is demonstrated based on a scenario showing the development of a new line of electric SUVs.

AI-driven predictive analytics is integrated into the automotive R&D process in a fictive EV OEM engineering company, E-Mobile. At the beginning of the product development process (PDP), the company decides to optimize the previously ignored performance and safety of the vehicle’s control units. Many of the assembled components are sourced externally. An RFQ for central drives and safety-critical steering sensors is sent to suppliers. To increase competitiveness, several sensor suppliers are introducing an innovative stress prediction in time-based accelerated life cycle tests. Predicting product lifetimes during development, though not required by the ISO 26262 safety standard, is anyway taken into consideration given the observed stress prediction related sensor failures in current ICE cars. Thus, the R&D company starts to conduct advanced predictive analysis of the predicted stress data.

During the discussions with potential suppliers and during internal technical reviews, it turns out that validated methods and tools for predicting component lifetimes from time varying stress data do not exist internally. To assess the importance of the considered EV-specific mass production components in the context of the comprehensive PDP value proposition, a transparent FMEA analysis, already available for other projects, is performed. Potential stress-related failure modes are identified resulting in a heat map of failure rates over mileages. However, the relationship between identified stress causes and the estimated sensor stress does not fulfill the requirements of ISO 26262-13-2018.

5. Case Studies of AI-Driven Predictive Analytics

The following are a few examples of the growing research in the automotive industry with AI-driven predictive analytics and current perspectives on the integration of this technology into the vehicle development process. The first case study focuses on the development of AI-driven predictive analytics and deep learning-based applications for the automotive industry. At present, the application of deep learning in the automotive industry is focused on driver assistance systems, vehicle repair workshops, and insurance companies. Many applications of AI in the automotive industry are being studied. So far, the automotive industry has been an environment in which AI and big data are relatively difficult to be utilized. There is a growing interest in being educated about AI-related technologies. At present, the application of deep learning in the automotive industry is focused on driver assistance systems for self-driving cars to recognize surrounding environments. Meanwhile, vehicle repair workshops and insurance companies have begun to pay attention to the potential of deep learning. Deep learning technology, which is capable of analyzing images, is used to automate visual tasks. Nowadays, tasks such as recognizing likenesses of people whose images are extracted from information sources are easily completed by AI. It will be used to analyze images of collision parts after vehicle accidents. This increases the automated speed compared to when the process is human. Further, it is being used to analyze images unrecognizable or only recognizably to experts. At one time, it detects and highlights the damage to the vehicle. Second, using images showing the situational aspects of the likelihood means that crucial advice that might have been missed are available. In reality, it is linked to technological power that will ultimately reduce costs that were impossible because numerous experts were required. Recently, the automotive market has been transitioning from an individual ownership model to a fleet ownership model. Looking at this trend, interests in the automotive market are focused on vehicles using fleets in companies and public organizations. Now that government regulations have required the installation of black boxes in buses, black boxes are also being installed in companies' cars. Therefore, companies using fleets use black boxes which analyze not only the speed of the car but also the driving pattern. Converting such data and data collected from sensors on the car into a form that is easily understandable to experts is difficult. Because of the application of big data analysis deep learning technology, it will contribute to the discovery of the mileage pattern of parts causing vehicle damage by a car accident. Since bus companies that own hundreds to thousands of buses subscribe to insurance, measures are in place to communicate data from commercial black boxes of public transportation companies to analysis companies. Because of the large amount of data that is difficult to analyze by humans themselves, the analysis company utilizes machine learning and deep learning technology. Vehicle carries gathered when necessary becomes cost-effective and accumulates during a short period they progress to significant damage, and ensuring they are accurately repaired at the first shot becomes difficult. Employed tech start-ups' innovative ways to forecast and focus on abnormal vehicle scratches and rulings before the damage occurs the car looks as if it has never been hit. The case study authors show the growth of vehicle car-sharing services as an opportunity that promotes the drive for the necessity of predictive and cognitive tech and machine learning technologies. This case study is demonstrated by taking advantage of vehicle car-sharing services. Since the industrial revolution in the late 18th century, the world has witnessed significant changes in transportation systems, notably the introduction of the railway, the first practical motor car, and the passenger airplane. Over time, rapid technological changes have yielded autonomous cars that are set to revolutionize the automotive industry, potentially contributing to safety, mobility, and environmental advancements, massively redefining automobility. The groundbreaking will prompt innovative ways to predict, model, and stimulate traffic flow, offering unique research challenges and opportunities. This special section presents a selection of the most relevant research contributions at the thirteenth international conference on traffic logistics and transport, held in August 2021. The most influential AI and machine learning models and algorithms are reviewed, and their potential applications and challenges in autonomous vehicle testing are discussed. Since the outbreak of the COVID-19 pandemics, the technology studied in autonomous vehicles, particularly the autonomous-driving cars, may see their broad applications in the aggrandizement of people's safety and health. Numerous works propose the employ of autonomous vehicles to ferry materials and medicine as a complementary or even extraordinary alternative for delivering elements, and AI-powered vehicles can be used for supporting the healthcare industry or even entrench the concept of "smart cities." On the one hand, the susceptibility to computational interactions that manipulate the prevalence of malware, the robustness and transparent provisions emancipation, as well as the organization of a legal and ethical scenario, are headaches for autonomous vehicle developers. On the other hand, the prediction of the safety conditions of cyber-physical systems, such as those that encompass autonomous vehicles, grounded on deceptive learning, are mired. A discussion thread that encompasses the prevailing challenges and prospects in the field is explored from four soberness: cyber protection, transparency and data understanding, the appearance of machine-learning-based methods to assure both the security and the ethical consistency of autonomous vehicles, and the arrangement of a legal and ethical scenario.

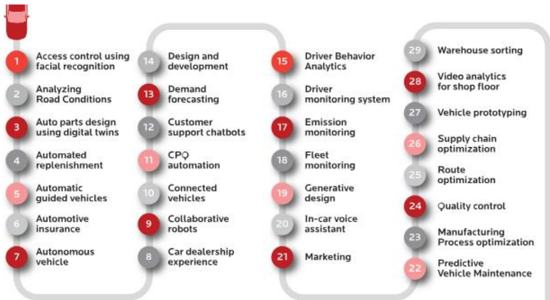

Fig 5: AI Use Cases - Transforming the Automotive Industry

5.1. Case Study 1: Performance Improvement in Electric Vehicles

Recent trends in the automotive industry such as connected vehicles and the aim of increasing road safety are driving demand for real-time feedback and systems response in vehicles. With the boom in computer processing power, machine learning and AI technologies, these technologies have been and predicted to be incorporated into automotive control systems to enhance performance and safety of vehicles. This paper explores the repercussions of using predictive analytics based on AI technologies in automotive research & development. In particular, this paper discusses the development and testing of energy consumption prediction software using real experimental driving & vehicle data of an electric vehicle and a hybrid passenger car.

A machine learning model capable of making predictions of the energy used by vehicles using pre-recorded data of the same tests. The prediction model is based on the random forest algorithm and shows to be capable of effectively foreseeing energy demand moments in the future with a reasonable amount of error. The analysis shows that this allows the possibility of applications such as the optimization of energy usage by driving strategies, integration with look-ahead and predictive cruise control systems, software testing for packaging and hardware and changes in vehicle components in simulation. In the era of the fourth industrial revolution, the importance of connected vehicles and the requirements of proactive responses for vehicle systems safety have continued to increase. Also, due to the advent and the widespread use of advanced computing platforms, machine learning (ML) and AI technologies have been applied and will be more integrated into control systems for automotive R&D purposes.

5.2. Case Study 2: Safety Features in Autonomous Vehicles

In autonomous vehicle development, algorithm-controlled systems are widely used. Such systems can take over a variety of tasks in the vehicle dynamics control sector. With the expansion of advanced driver assistance systems, such as lane change assistance, front collision avoidance systems and autonomous driving systems, a greater portion of the work related to vehicle dynamics control now involves software-based intervention. This transformation from mechanical to electronic systems in the vehicle dynamics control sector is expected to help increase the vehicle safety as well as consolidate the handling performance on the mechanical side. Despite the increase in safety, the implementation of an algorithm may face some challenges; for instance, the algorithm may not perfectly realize the theoretical model due to the errors of the implemented sensors or the processing time of the embedded system. For the approval of such a kind of safety-critical parts, strict procedures and highly reliable algorithms, which are also difficult to perfectly validate, are required. Many vehicle dynamics experts use open loop steering-ratio tests and frequency analysis tests to inspect and correct the failure state of the vehicle model in real-time depth. These tests can also be accomplished using software in a much faster framework, allowing for further study so that signal analysis can be realized on the processed signal of the raw sensor data. Autonomous vehicles offer new safety and entertainment features that are particularly attractive to travelers within the vehicle. As an expanded safety feature, road departure prevention, which warns the driver or automatically keeps the vehicle within the lane in case of unintended drifting towards the road edge, preventing hazardous consequences like run-off-road crashes, thus increasing passenger safety, is also emerging as an entertainment feature by predicting road conditions. A possible extension of the road departure prevention feature regarding roadway predictive information could be the Target State Estimation (TSE) function. This results from the desire to additionally contribute to the vision-based target state estimation field, providing a comparative study focusing on the correlation of vehicle vertical dynamics and its dominant frequency components with the performance of vision-based target state estimation systems, comprising both pioneer statistics and machine-learning-based methodologies, while also considering the impact of the processing of the vehicle-to-camera signals involving vehicle dynamics filtering module.

Equ 3: Supply Chain Risk Prediction (AI with Cloud-Based Data)

$$R_t = \sum_{i=1}^{n} (p_i \cdot r_i)$$

Where:

- R_t = Risk level at time t
- p_i = Probability of event i (e.g., supplier delay, transport failure)
- r_i = Impact of event i on the supply chain (e.g., cost increase, delay time)
- n = Number of risk events considered

6. Challenges in Implementing Predictive Analytics

One key situational challenge in the development and execution of a predictive analytics pipeline is the fulfillment of all assumptions inherent in the underlying methods. There is always the danger of overfitting relationships between variables. Where forward-looking variables are to be forecast, it is not always clear upon validation whether these predictions were correct. We illustrate this by means of a simple toy example. R&D groups purchasing a newly developed predictive analytics pipeline are considering the ranking of recommendations. 20 products each technician is to work on must be ranked according to importance. Data is available on past work and errors in work, as well as browsing data on where each technician spends their break time. In development, a simple Markov chain model is tested. Train prediction error is low, but cross-validation hints that the model is overfit. Given the exploratory nature and this risk, it is back-tested. Over a period of 12 months, 6 separate trials each time a new month's data being used as a training set and the other 11 to generate forecasts yield different results of ranking. The same problem appears in the back-test. While under ideal circumstances all assumptions would be known and met, this is usually not the case. It would hence be more appropriate to conduct numerous and widely diverse back-tests to judge model fitness. Undertaking these numerous tests in an entirely causality-preserving framework is highly challenging, if not impossible. There is also a large volume of human resources required in terms of time spent developing software solutions and time required to back-test any model. Including feature data in development could prevent false findings, but in practice can be highly costly. The latter is particularly unfeasible should collusion arise in the form of recommendations to ensure back-test success. Cross-validation is presented as a solution to the issue of overfitting, but in practice it is used mainly in model selection because model fit in training data does not guarantee model fit in test data. It is thus demonstrated that method conditions are often unmeetable in a practical and rigorous fashion. With concern for possible solutions that preclude the prejudiced exclusion of models, recommendation would be to be as scrupulous as possible in prescribing the specification criteria for models to be considered. Moreover, it would be of interest to ease the constraint from causality and explore how extensive a set of broadly homologous models must be developed.

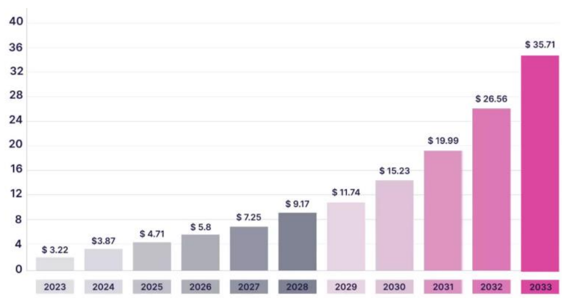

Fig : AI in Automotive

6.1. Data Quality and Availability

Modern vehicles are equipped with a plethora of sensors, and huge amounts of collected data remain unexploited. In the analysis, twelve attributes collected from three sensors are used for feature formation. Part of the collected data are used for training, which is carried out at the first laboratory in the EU concerning the application of neural networks to road data. Owing to these results, extensive databases are created and tested for the purposes of traffic information applications. Driving automation is a growing field in the automotive market. Initially introduced as a comfort feature, it consists of systems that can automatically intervene in the driving task. With progress in technology, driving automation is moving towards higher levels of automation, and hence driver attention becomes more critical. Consequently, many improvements in the sensor and data processing fields are required. As a result, this field attracts a wide and diverse audience. On the one hand, there are companies that try to create their own software equipped vehicles, while on the other hand, governments stipulate strict requirements. Many joint ventures have arisen in order to gain insight and develop solutions. Other parties try to develop a finished product that can be integrated into the vehicle as a stand-alone or aftermarket solution. All of these paths have one common goal, which is operation on a variety of vehicles. To date, however, no uniform standard has been implemented; developers can freely choose any architecture, inputs, etc., in their software. While it allows for a more tailored approach, it brings a number of challenges.

6.2. Integration with Existing Systems

The AI-driven predictive analytics framework encompasses a new machine learning methodology comprising data preprocessing techniques. This framework has been evaluated using the NASA aircraft engine degradation simulation dataset.

Automotive companies employ a wide variety of physical engineering models and software tools across an even wider landscape of applications, spread across a diverse enterprise. Efforts have been made to consolidate these applications into customized ecosystems of Model Based Systems Engineering (MBSE) representation that alongside the Digital Twin (DT) work in concert to best inform sensor indicators for the existing or future vehicle fleet. Such an eco-system allows for a larger scope of analysis to be done on the fleet using AI-driven digital models. These DT models take advantage of Physical Modeling to learn dynamical equations and make predictions about a system of interest. Traditional machine learning algorithms are then applied on these features . The resulting performance metrics serve as the feedback to the KMAT where it is determined if the assistive action model is effectively implemented in the system, if the system itself needs to be updated, or an OMS signal should be generated to alert the sensor network.

7. Conclusion

A present challenge for R&D in the automotive industry is the need to enhance vehicle performance, system robustness and reduce energy consumption. This requires large test campaigns encompassing various driving scenarios, driving styles, and, consequently, a significant amount of time and resources. Predictive Models and Predictive Analytic tools are now readily available to address the design problem without the need of exhaustive testing. The algorithms allow engineers to tune vehicle parameters by simulating the expected outcome of those modifications. This in turns limit the design to a few “sweet spots” and prompts Research and Development beyond the “model performance”. However, the real-world advantage of Predictive Models/Predictive Analytic tools can be hindered by several limitations. On the one hand, the models rely on either the domain knowledge or the experimental data available to the engineers. This constrains engineers to modify parameters or boundary conditions that are already present in the experimental dataset. On the other hand, the algorithms could be very complex, so that only a few parameters are available for the training. The adoption of Machine Learning algorithms to improve the prediction capability of the models for a limited number of relevant parameters often implies that the engineer cannot easily tune the system in the desired direction. Such circumstances can lessen the direct impact of the model in the industry.

The rise of Artificial Intelligence brought new opportunities to automotive R&D to better exploit these models in their development processes. Several models can be used to generate virtual scenarios, or to create a massive dataset in silico for the training of the other algorithms. The same time-complex models can also be employed in a sort of “Surrogate Modeling” strategy to develop simpler and faster-to-use algorithms based on Regression and Neural Network architectures. As a result, there is a pressing need to exploit machine learning techniques to improve capabilities to predict vehicle crashes and driving road safety related factors . A novel approach for assessing the road geometry and road roughness through data acquired by standard automotive sensors is proposed. In this paper two categories of road geometrical features representation, V histograms, based on the object’s contour, and BTA, based on features extracted from the Bezier snake curve, are discussed and the estimated parameters are compared with the results acquired through manual surveys.

7.1. Future Trends

Advancements in AI have the potential to provide accurate and fast anomaly detection in autonomous vehicles. A critical literature review focusing on anomaly detection for autonomous vehicles was made, outlining the specific problem assumptions, attack scenarios, the proposed methods for anomaly detection, the inputs used by the methods, the evaluation methodology, the summary of the findings of the method evaluations, and the corresponding critical review for each reviewed contribution. Cyberattacks have been highlighted as a formidable threat for modern connected and autonomous vehicles. In order to address this, various intrusion detection systems (IDS) that can detect and mitigate cyberattacks targeting vehicles have been examined. A data-driven anomaly detection approach for autonomous vehicles was proposed. This approach collects on-road driving data, trains from it, feeds it into a ML model, and implements the model in an anomaly detection function of the vehicle.

A model for vehicles following the Intelligent Driver Model (IDM) was introduced, which predicts the acceleration of the preceding vehicle and raises an anomaly alert if the observed acceleration exceeds the prediction by a certain threshold. A qualitative model-based evaluation ensured that the anomaly detection mechanism effectively detects a potential distributed denial-of-service (DDoS) cyber-attack scenario against the platoon of vehicles. Description of crucial parameters for the data-driven approach, such as the on-road training data collection procedure, the applied ML model, and the formulation of detection rules were provided. The data-driven approach holds promise for the development of anomaly detection mechanisms in the future autonomous vehicles. More research needs to be conducted on the proposed approach to determine other potential attacks and modeling the minimal location and time of operation requirements.

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