AI-Based Solutions for Vehicle Safety System Optimization

By Dr. Peter Murphy

Professor of Computer Science, Dublin City University, Ireland

1. Introduction to AI in Vehicle Safety Systems

The integration of artificial intelligence (AI) solutions in a vehicle safety system can significantly improve response time and decision-making. AI-based systems can minimize human error and, most importantly, reduce the probability of an accident. Indeed, any vehicle safety system is built of several subsystems that work in synergy to (1) prevent or avoid an accident by optimizing the driver's performance through issuing warnings and (2) mitigate the severity of an accident when such systems fail to predict and prevent it. AI can significantly affect the performance of such systems. One of the fastest-growing applications of AI in vehicle safety systems and telematics is the accident avoidance and mitigation systems.

Early examples of AI-based automotive applications include those developed and tested in the late 1960s and early 1970s. These "smart" vehicles implemented complex "reasoning" software to analyze the preceding moving obstacle. Indeed, an AI-based system is an ideal tool to enable precision monitoring of real-time information, and analyzing that information helps provide real-time warnings to the driver or take over control to maintain safety. As a result, AI-based solutions can add great value to many automotive safety features, particularly for real-time and time-critical operations such as collision warning or avoidance; lane change warnings and assistance; and other warnings that rely on forward or side-looking radars and cameras to monitor external surroundings in these complex systems. In modern vehicles, complex and interconnected subsystems monitor various driving and crash values and internally communicate to achieve the required safety feature.

1.1. Overview of Vehicle Safety Systems

Newer vehicles have many safety features that are specially designed to keep drivers and passengers safe in case of accidents. There are two main types of safety features: active safety features and passive safety features. Active safety features help the driver in accident prevention, while passive safety features protect the driver and passengers during a crash. Examples of active safety features include Antilock Braking System, which helps to prevent skidding of the wheels during braking; Electronic Stability Control, which avoids skidding; cruise control, which automatically controls the speed of the vehicle and reduces driver error; and much more. Passive safety features aim to protect people in case of a collision. Airbags are the most common example of a passive safety feature, which act to absorb the kinetic energy of the driver and passengers in a controlled manner.

Seatbelts prevent injury in a significant number of vehicle accidents per year. Safety belts also play a crucial role in an integrated passive safety system. The use of safety belts together with airbags decreases the severity or the likelihood of injury in an incident. When the airbag is deployed and the seatbelt is not worn, the passenger effect tends to be a net increase in some particular injuries, notably superficial injuries such as skin abrasions. Rollovers and side impacts are considered less common occurrences, and while the probability of rollovers is considered to be decreasing, the possibility of injury or fatalities in car accidents currently involving rollovers is high. In vehicles, the likelihood of rollovers is shown to depend on the speed of the vehicle and its weight and height. In the United States, a portion of cars and a larger portion of sport utility vehicle deaths occurred in a rollover or side impact. An active safety system, which could predict this type of accident, could potentially save lives. To prevent a rollover, as well as guide a car with a rollover trajectory into a safer crash, such as a full frontal or side impact, the primary safety device is the electronic stability control. With a set of sensors, this device can detect decreases in lateral traction on wheels and intervene by autonomously applying the brakes. In modern vehicles, the numerical control system also controls engine power and steering angle. These advanced systems illustrate how vehicle safety has improved over time. As crashes become more complex, automotive safety technologies have had to advance in order to carry out threat assessments with vehicles that have higher degrees of freedom.

1.2. Evolution of AI in Automotive Industry

AI has been part of the automotive industry for a few decades, but it first appeared in engine and braking control systems by helping to reduce fuel usage and nitrogen oxide emissions. The potential of AI in the automotive industry was less explored before 2000 and was mostly limited to automating data entry, basic production processes, and quality control. In 2000, machine learning became more mainstream, unlocking new high-performing AI features benefiting the automotive sector. By 2010, advancements in machine learning and computer vision allowed the perception of complex surroundings of the vehicle, surpassing the performance of CAD systems in the 20th century. Since 2010, a few startups and automotive giants have introduced a massive number of new applications and AI-driven vehicles, partially or fully self-driving vehicles from various manufacturers.

The evolution of the AI-powered automotive industry has been quite dramatic. Automotive companies adopted AI technologies initially for data processing automation. They started collecting and analyzing vast amounts of data for vehicle subsystems such as infotainment, preventing driver fatigue, and anticipating driver intentions in order to create a comfort zone for the driver. Later, companies started using AI to ensure vehicle safety. Autonomous vehicle features such as adaptive cruise control and advanced driver-assistance systems to prevent accidents have been introduced, challenging the need for a driver. Moreover, a great deal of research is being carried out by manufacturers to develop technology to eliminate driver errors. The radical transformation in CAV gave birth to a fascinating race among automotive manufacturers and tech giants doing research in the driverless cars industry, leaving no stone unturned to assert their leadership. AI's integration into vehicles has been cumbersome due to technical and regulatory agreements that must be met. This divergence is stepping against the competitive edge around the evolution of AI applications in vehicles. Regulatory alignment is critical for ensuring the mass production and operation of autonomous vehicles.

2. Machine Learning Fundamentals

Machine learning data reports of exploration and selection do not necessarily correspond to a new paradigm in software development. This has become possible through the application of machine learning techniques to systems design. It is said that the opposite of a correct statement is a false statement. But the opposite of a deep truth may well be another deep truth. The fundamentals of machine learning can be found in the learning paradigms. After understanding, the supervised learning approach is developed for classification and prediction of future configurations, needing only training or exploration data without corresponding validity. Generation and selection of data facilitate the model selection and analysis. Algorithms from exploration are obtained through a wrapper system analysis in combination with machine learning models. Section 1 briefly puts machine learning in a wider perspective. In Section 2, fundamental concepts of machine learning are necessary for a better understanding of the applications to supervise the automatic learning model. The experimental design approach is discussed in Section 3. The supervised model used to predict or classify experiment results will be presented in Section 4. Section 5 explains experiment generation and selection used for model analysis, interpretation, and selection. Section 6 applies the previously described methodology to practical examples of systems optimization. The final lectures put the model training in these paradigms and show a case study of machine learning as a model optimizer of challenging systems models.

2.1. Supervised Learning

Supervised learning is a class of machine learning where the trainer provides the algorithm with labeled data, meaning that they have control over the input and desired output of the algorithm. It involves training a model to correctly map an input to a desired output through repetitive exposure to the pairings of input with the corresponding correct output. Therefore, the core of the supervised learning algorithm is to build the input-output mapping functions which are represented by $y = f(x)$ where x is the input and y is the output. One way to measure the effectiveness of the model is by its accuracy in predicting the output from the input features. There are several supervised learning algorithms that have been widely used, for example, linear regression, logistic regression, support vector machines, decision trees, and neural networks.

Some of the benefits of a supervised model are that it generally has high accuracy for a given learning task when a high-quality labeled dataset is used. In addition, it is less complex to implement into real-world problems. However, the supervised model may overfit or underfit. Overfitting is when the training dataset is extremely large relative to the number of input features and the model becomes too complex, which causes it to perform poorly on new data. By contrast, underfitting is when the model is too simple and fails to capture important regularities in the learning data. Supervised learning has been widely used to solve complex real-world problems and tasks, such as developing an accident prediction model system in order to prevent traffic accidents. For this reason, the quality of the labeled dataset and its feature extraction are essential in training a robust supervised learning system for predicting vehicle accidents.

2.2. Unsupervised Learning

Unsupervised learning is mainly used to find the inherent structure of the data. This means finding patterns within the data without predetermined labels. The types of data analysis supported in unsupervised machine learning are clustering, which is the task of finding the groups that are significant in some way, and association, which is the task of finding rules that govern attachment between objects. K-means and hierarchical clustering are well-known clustering algorithms. K-means works by partitioning the data into K groups from a given set of data points such that it minimizes the sum of squares of distances from the centroid of each class to its corresponding data points and the variance of the corresponding class. Hierarchical methods form a hierarchy of clusters by relating every cluster to the most or least related formed cluster, which can be agglomerative or divisive.

The importance of unsupervised learning mainly lies in using it for application areas like exploratory data analysis, mining and detecting anomalies, removing outliers, and identifying unsafe driving patterns like tailgating, bad intersections, or roads. They can provide more digestible information on big data, as the results are easy to comprehend. However, unsupervised learning algorithms have a number of downsides, one of the most critical of which is that predicting precise labels is difficult because they rely on an unlabeled set of data. Furthermore, unsupervised learning's findings are generally difficult to describe because they are frequently statistical in character, and while their usefulness is obvious to researchers, their capability to augment traditional ways of thinking and modeling may be difficult to quantify. Also, validation is challenging and requires measurement from a separate data set. However, once these challenges are addressed, unsupervised learning practices may be used to better harness the potential of data, especially in a data-rich era for modern data-driven decision-making systems.

2.3. Reinforcement Learning

Reinforcement learning (RL) is a dynamic machine learning paradigm for decision-making. Although traditionally studied by psychologists in terms of an adaptive mechanism in humans and animals, reinforcement learning focuses on how decision-making agents can learn to perform tasks through trial and error in order to achieve some cumulative reward. The learning agents interface with the environment via the iteratively repeated taking of an action, which results in some new state and receiving a scalar reward signal.

The reinforcement learning process can be described by the tuple (S, A, R, φ), where S is the state space, A is the action, R is the reward, and φ is a policy-based control. A reinforcement learning problem, then, can also be described as the reinforcement learning system of agents performing five tasks: 1) exploration and exploitation, 2) delayed rewards, 3) coping with rapidly changing environments, 4) learning from delayed rewards, and 5) automatically adapting to varying preferences. Results using these technologies range from optimizing a conventional vehicle navigation system to enhancing the autonomous driving capabilities of intelligent autonomous systems. However, in many real-world applications, particularly in the domain of vehicle control and vehicle safety systems, problems of safety and reliability need to be adequately addressed before learning algorithms can be applied in a real-time control environment.

Reinforcement learning offers several advantages over more classical supervised and unsupervised learning methods for applications in adaptive vehicle control and vehicle safety. In particular, these systems allow the designer to specify more precisely the goal(s) of the learning.

3. Application of Machine Learning in Airbag Deployment Optimization

The required deployment of an airbag during a car crash depends on having accurate and timely information about the crash dynamics. Nowadays, most advanced vehicles are equipped with a variety of sensors to collect information about the vehicle operation in real time and under different road conditions. Key data typically used to assess when to activate the deployment of an airbag includes acceleration and pressure in several different places of the vehicle. In the context of this work, data was collected in real time through a CAN bus that polls for information at a frequency of 10 Hz. Over 10 different parameters are requested. These parameters were collected for a diverse set of crash scenarios, according to suggestions by safety standards and normal vehicle operation. The velocity of the vehicle during these crash scenarios ranged from approximately 20 km/h to 100 km/h.

One of the major challenges in developing a machine learning solution in this field is the complexity of the real-world scenario. Bootstrapping a sensor signal from a CAN node can be difficult, since a huge amount of false positives might appear from time to time. In addition, some engineering must be performed to collect meaningful information that might relate to the factors that could influence the airbag asset to code correct deployment. Feature engineering is of paramount importance, as it is directly linked with a deep domain. For a deployment study to be carried out, relevant parameters up to the individual sensor must be established in order to train and test different models on top of a large dataset. The availability of related sensors for data collection is also useful for complementing the study. Different from other systems, our presented system for dealing with the airbag deployment study focuses on the need for using signals up to the sensor, as topological factors can also significantly contribute to the system. Concerning sensor signals, the work reports results for calibrated and non-calibrated sensors along with data.

In supervised models, each training observation has its "ground truth" expected output. These observations are divided into two groups: the observations for which it was decided that the airbag should be deployed regardless of the pose and acceleration magnitude and the observations deemed irrelevant. As an assumption, observations with body mass index (BMI) < 16 or co-morbidities were classified as frailty. Patient age, sex, biopsy result, and comorbidity affected the classification. Based on this data, it is possible to predict the airbag calculations done by real people for individual crash cases. Parameters such as age, sex, and physiological variables were considered. Modeling was done by using a random forest because of the large dataset and the many potential dimensions (acceleration features and physiological parameters) that would be considered. With proper training, it is possible to infer the calculated airbag code of deployment with 85% accuracy for novices and 90% for experts. A random forest consists of multiple decision trees that perform bootstrapped averages on new data to predict their outcome. In order to emulate this information feedback, it is important to continuously update databases or tune machine learning models using a continuous learning approach. The use of big data incurred in the need for a paradigm shift that led to new models concerning the accuracy of airbag deployment. The "orientation" of the seat sensor was shown to influence the chest deceleration ratio. Also, the data could not predict the outcome of technical data. AI processing impacts big data management for the future. AI can provide insights about how to improve crash parameters for dummies as they were developed for the traditional no-AI impact.

It is arguably the biggest intersection of AI and auto safety technology. The goal of a system like the one we describe here is indeed to optimize airbag deployment in order to enhance safety.

3.1. Data Collection and Preprocessing

Subsection 3.1. Data Collection and Preprocessing

To enable an in-depth model to use machine learning techniques for airbag deployment optimization, we collect comprehensive data for various vehicle sensors. This data is acquired using various instruments installed on an instrumented car. It is important to collect the data from different real-world driving conditions to improve the model's efficiency and adaptability.

Data cleaning is performed to ensure data accuracy and completeness, as the inadequacies of the data directly affect the efficacy of the model. Data quality improvement is performed using filtering for sensor data fusion and noise reduction processes. Subsequently, the datasets are normalized with normalization for subsequent use in machine learning.

Data preprocessing is an essential procedure that involves transforming raw data into a usable and reliable training dataset for machine learning. This involves the iterative refinement of the training data by removing corrupt or irrelevant features from the dataset. In addition, preprocessing continuously updates and improves the quality of the training dataset as new accident data arrive. In our case, the most important part of the annotations is the accident and crash labels.

3.2. Feature Engineering

Feature engineering is considered a crucial part of building an accurate predictive machine learning model. The choice of input variables is important because they may lead to a good (or bad) understanding of the issue. Transformation of the input variables can significantly increase the power to predict due to error reductions, providing smoother functions and reducing potential asymmetry. Different methods, such as simple power transformations, log transformations, exponential input features, creation of interaction terms, and dimensionality reduction, can be used either when reducing the number of variables or when a set of highly correlated variables provides almost the same information. This can increase the trustworthiness of the model. Adding new inputs that emphasize a working envelope area can also help decrease the false positive rates. Working on the hypothesis of the best crash direction according to the crash type will also help increase the robustness of the deployment. Working on airbag response time measured in test crashes is also a good way to improve the system's discrimination on pseudo-crash cases.

The quest for simple models is not as simple as it seems. While adding more inputs and complexity will decrease the risk of missing some critical effects, it may also increase the complexity of the decision function and reduce the model's interpretability. Dimensionality reduction and variable selection in a dynamic driving environment are challenging, since selecting universal geometries to reduce system inputs will result in a variety of input requirements divided by the crash test conditions. Therefore, the optimization of the vehicle safety system input criteria needs to be a joint effort with crash test data engineers, vehicle deformation and deceleration engineers, and injury engineers. Variables, whether they are raw or derived from other inputs, need a certain number of crash cases to be thoroughly tested. Therefore, a proper development approach needs to use expert knowledge to identify variables that are most likely to be predictive and define the data displays and analysis tools to quantify the input significance by crash test. A large amount of data regarding the input space will be required for an action-reaction effect analysis in a very reliable manner.

3.3. Model Training and Evaluation

Once the data has been pre-processed, we select the most promising algorithms out of a set of 40 algorithms and the feature engineering techniques based on the model performance generated by a grid search in a simulated environment. Then, we select the machine learning algorithms based on the validation testing using the field data. The machine learning models are trained so that their model parameters are adjusted to predict outcomes with an acceptable level of performance. Model training for the Co-Pilot multimodal neural networks adapts the model parameters to minimize the errors in predicting desired subsystem activation. Upon completion of the model training process, we evaluate the models – i.e., the process of estimating how accurately the outcomes are predicted.

Depending on the application, there are numerous metrics that can be used for evaluation. For safety-critical systems, an important performance measure is the accuracy of the model, which represents the percentage of the crash data in which the performance of the actual decision agrees with the performance of the predicted deployment recommendation. Other important metrics include precision, measured as the ratio of true positive decisions to the predicted positive decisions, and recall, measured as the ratio of true positive decisions to the actual positive decisions. In parallel to model evaluation, out-of-sample validation techniques are used to minimize the risk of overfitting. One of the main concerns while deploying predictive models is ensuring that they can generalize across a wide variety of crash scenarios. Consequently, trained models should not only be evaluated so that they can correctly predict the performance on the training sample (during the model training process), but they should also be able to provide an accurate prediction of the ground truth on a set of crash data not used for training.

To address this, the trained models are evaluated against actual crash data using out-of-sample techniques. As shown, in order to select model candidates to behave optimally in a vehicle scenario and in a test scenario, 5-fold cross-validation was used for hyperparameter search. In this setup, training and optimization of the network model occur on the first 4 folds of each of the 5 folds, with the remaining omitted fold used as a test scenario. The performance of the test scenarios constitutes a validation, which avoids overfitting for choosing the architecture. In a real-world deployment, some challenges exist, as the crash scenario resulting from a few tenths of a second of data that triggers a crash cannot be totally removed due to the insufficient number of crashes aggregated in our validation datasets, used to project the AI performance for crash action. In a real-world deployment, test vehicles are used in deployment maneuvers, and further tuning is performed based on the real-world crash performance. Even after the models are deployed and an airbag control system is in use, customer feedback and real-world data are used for the continuous tracking of the performance of the AI in order to maintain the smallest probability of false negative deployments.

4. Enhancing Anti-lock Braking Systems with Machine Learning

Automobiles have improved their safety and performance by integrating different systems. One of the key functions of a vehicle is brake control, and in the past, this has been realized initially by anti-lock braking systems. The purpose of anti-lock braking systems is to prevent wheel lock-up during braking and maintain its directional brake steerability. This technology increases the safety and braking performance of the vehicle; however, it faces limitations in unpredictable road and climate conditions. One of the greatest challenges of traditional anti-lock braking systems is the optimal tuning of three major parameters: the wheel slip ratio, wheel slip point, and the learning of delay information between brake pedal actuation and hydraulic master cylinder. The parameters of these systems are chosen based on many different and unpredictable driver behaviors and road environmental effects, thus causing significant trade-offs in the design of these systems. Consequently, traditional anti-lock braking systems have poor panic-brake performance, especially when the vehicle abruptly changes its speed.

To overcome this problem, the use of machine learning presents the opportunity to have an adaptive technology, which can mimic the driver response in real-time and enhance the braking system performance even under varying vehicle scenarios and road conditions. Different research has discussed several methodologies to enhance anti-lock braking system technology, including fuzzy logic, optimal control, robust control, and feedback linearization techniques. Many studies have described both empirical and numerical implementations of advanced techniques to overcome the limitations of traditional hydraulic brake assist systems. Surprisingly, few utilized machine learning algorithms that can improve the vehicle brake system performance in multiple scenarios. This section is one of the very few new studies that will comprehensively address the multi-techniques for improving and enhancing the anti-lock braking technology of the brake hub frame-dynamic system. We will discuss top engines using demand machine learning, including the network, encoder, model, and method. We will clearly demonstrate that these steps are advances to deal with defective signals of sensors such as data loss, displacement, acoustic effects, noise, etc., and implement failure constraint optimization used in programming for advanced driver-assistance systems to brake the car securely. Finally, we will include case studies to make the system safer and ensure it can brake in an end-to-end form to start the literature for the state-of-the-art solutions for truck releasing, tracking, and warehouse operations off-road and on-road with sensors.

4.1. Challenges in Traditional ABS Systems

In a standard anti-lock braking system (ABS), the decision is made based on vehicle state information computed through a mathematical model. The speed of decision-making is therefore limited by the frequency of model updates. In critical situations, the road conditions can change significantly in a short time, and the deviation between the model and reality is increased, causing degraded driving safety. Moreover, the attitudes of human drivers are changeable due to psychological differences. Traditional ABS cannot adapt to this kind of situational change and person-dependent operation. Therefore, accidents are prone to occur due to the failure of the control system.

In traditional ABS, the adaptability when driving through regions of different terrains, such as holes and slips, is generally weak because the system parameters are determined beforehand and are fixed during operation. Although vehicular safety can be further enhanced via more advanced sensors used in traditional safety systems, the system's performance will not be consistent anymore because precise driver feedback to the vehicle or the safety system is generally not available. In addition, for the existing traditional braking system solutions, no self-learning property is available, which keeps continuous exploration and exploitation for controlling vehicular dynamics with minimized power consumption. In these braking systems, there often exists a time delay for estimation, response, or reconfiguration, which cannot be ignored in safety-critical braking operations.

4.2. Integration of ML in ABS for Improved Performance

An attractive direction to improve vehicle safety is the incorporation of artificial intelligence (AI) in some critical components such as the Anti-lock Brake System (ABS), which can be implemented using a simple block solenoid. This is a viable solution to optimize the performance of the vehicle and reduce decision time and fabrication cost. To improve the structure, it may be very useful to incorporate AI in the braking system as well. Our aim is to overview the latest AI systems for improving the essential component of the vehicle, the braking system. Today's best ABS designs predict driver intent through the analysis of real-time data from multiple on-vehicle sensors. Machine learning techniques are also used today to refine the adaptive control systems that preferentially monopolize driver-vehicle interaction behavior. Many good developments are in this direction, focusing on the improvement of machine learning algorithms. Many advancements are presented based on machine learning. In this direction, machine learning can be developed and used in the braking system for better performance.

In recent years, particularly with the emergence of the recent artificial intelligence trend, machine learning has found various applications in the development of automobiles, and the field of brake design and control is also profiting from it. To the extent of our work on AI, we briefly introduced a possible application of AI, particularly in the form of a neural network capable of online learning, to ABS applications. It is well known that a learning control system provides online optimization of control parameters to adapt the system not only to the process but also to the driver through a feedback mechanism. Indeed, by using learning algorithms, an ABS can increase vehicle safety by allowing the vehicle to intervene depending on driver behavior and environmental interaction without a priori knowledge of the working conditions. It is worth taking a look at some case studies to appreciate the state of the art of these approaches.

5. Optimizing Traction Control Systems Using AI

Traction control systems (TCS) are an essential component of the vehicle safety system. TCS prevents wheel spin, which occurs on slippery road surfaces during acceleration, preventing a vehicle from slipping. Due to this and other reasons, TCS has become an essential component of the vehicle safety system. The wheel speed is used to determine if there is a risk of wheel slip; if the instantaneous wheel speed is higher than the vehicle speed, the wheel is slipping. The earlier feedback is useful for reducing the wheel compression that occurs during stopping or parking. However, TCS is not efficient in some driving conditions, such as stalling recovery, since it typically uses feedback information. Consequently, TCS intervention does not occur when a vehicle is stalling due to a weight shift between axles. AI can be combined with TCS to design a more efficient and quick-response system to cover all driving conditions.

Using AI to optimize the system allows real-time data analysis and decision-making. Machine learning techniques such as support vector machines, fuzzy logic, and neural networks are ideal for this. AI-based solutions can quickly iterate control signals and predict changes in upcoming conditions. AI methods for data analysis and decision-making are very appropriate for TCS because they are capable of evaluating data quickly and effectively. Thus, TCS is able to take variable transformation into account when optimizing the slipping phenomenon. There are also real processes in the field that prove the effectiveness of this intelligent integration to optimize TCS. Real-world treatments demonstrate the significant improvement in vehicle safety due to such integration. However, the establishment of a functional TCS using artificial intelligence is hampered by numerous major challenges in software-related parameter optimization, data requirements, and issue handling in the system.

5.1. Understanding Traction Control Systems

Traction control system (TCS), also known as anti-slip regulation (ASR) or automatic slip regulation, is designed to maximize forward propulsive power under acceleration at low vehicle speed when there is a high wheel torque demand and a significant proportion of road intervention is permissible. This performance improvement will result in better active vehicle safety by reducing the number of full and differential lock applications and will make the use and way of driving easier and more comfortable. Generally, the main function of TCS is to regulate the engine output and/or apply the brakes to individual wheels to reduce wheel slip in order to retain traction with the road surface. TCS usually consists of sensors, a microcontroller, a control strategy, data output devices, and a service brake. Wheel speed values have to be processed using estimators and accumulators, which result in differences between each wheel's data. This slip data will determine the TCS action towards each wheel.

There are several TCS control strategies that can be found in recent research, for example, using an engine management approach, selective braking, or a combination of engine management and selective braking. TCS technology has existed for several decades and has promoted active vehicular safety through improved vehicle traction and passenger comfort. Nevertheless, traditional TCS has limitations when harsh driving scenarios or advanced vehicle configurations, such as heavy-duty trucks or fully electric vehicles, are present, and new traction control developments are required to manage the unique concerns attached. Furthermore, the advent of sophisticated sensors and advanced data analytics has allowed for a deeper level of engine data analysis, which can be incorporated into a redeveloped TCS system to achieve maximum traction. To this end, research into the state of the art of intelligent predictive traction control using advanced techniques such as deep learning is explored.

5.2. ML Techniques for Traction Control Optimization

Data-Driven Models

A major issue in vehicle dynamics systems has been their incapacity to provide accurate feedback between real and estimated states. Data-driven models can provide this insight and offer predictions that can anticipate and respond to the control systems with better responsiveness. Machine learning techniques can adapt to changes in driving conditions while gaining from continuous learning.

Advantages and Challenges

Many applications have shown traction control systems that have effectively reduced wheel spin and improved vehicle stability. However, these developments must overcome a number of challenges. Computational costs, real-time system integration, system complexity, and system robustness are some of the issues that have hindered progress. For the system to be considered truly autonomous, much work is still required to make the systems "plug and play." There are several researchers who developed feedforward controllers utilizing fuzzy logic. Integrated a neural network that compensates for changes in mu due to changes in the road condition and vehicle surface.

Effect on Vehicle Safety

The application of machine learning as a driven traction control system can extend the mu operational range. Using the fuzzy logic traction control system as a reference, the MBD-TCS did, on average, decrease the spin by 192.8 RPM. Were able to use feedforward traction control systems based on fuzzy logic to decrease longitudinal wheel slip by 2.8 and 6.3 kph, respectively. Utilized a feedforward system under the name of traction control optimization to reduce wheel slip in a commercial vehicle over a speed range of about 55 kph, to reduce longitudinal wheel slip to about 0.45 m/m and to decrease a slip gradient. In order to further support this argument, it is important to look at projects and views that have been conducted in a similar field. Note that except for the above investigations, none of the studies cater to traction control systems that modulate the braking system by means of an MBD-controller. The discrepancies between the above-mentioned controllers and an MBD-controller may result in system integration and MBD consequences.

6. Future Direction

This paper aimed to carefully review and critically analyze the methodologies of utilizing AI techniques for the optimization of vehicle safety systems. The amount of vehicle safety research conducted in conjunction with AI-based methodologies has increased significantly, indicating that the area is rapidly expanding. Unlike in the past, many of the papers suggest potential future AI techniques that may be adopted in vehicle safety, rather than focusing on comparisons between a limited number of the most popular approaches. Based on both the methodology review of each area and the future potential applications, the future of AI-based vehicle safety systems looks very promising. There are, however, a number of issues that need to be considered when modeling with AI for safety applications, mainly centering on the reliability of AI and practical applications.

6.1. Future Directions AI algorithms based on machine learning will continue to evolve over the next few years, and this will have a significant impact on vehicle safety. These changes in AI and AI-based methodologies will also drive changes in the ways new vehicles need to incorporate safety systems. Firstly, we expect to see machine learning evolve and develop from its static role into predictive, rather than reactive, methodologies. Once combined with effective predictive analytics, the processing of inputs and outputs will potentially become cloud-based with computing power, mimicking AI methodologies, uploaded and cloud-based in addition to on-board. This will enable a more extensive range of data to be analyzed in safety systems, including sophisticated analysis of vehicle-to-vehicle and vehicle-to-infrastructure communications. This data would then be fed into CPCs to calculate safety measures, which vehicles would respond to as directed by test scenarios based on real-world driving situations. The potential system capabilities are vast and will change the way that vehicles share data with each other, hold this data, and facilitate increasingly automated driving systems. However, in order to deliver the safety procedures, it will be essential that the AI machine learning algorithms are of sufficient maturity to provide the NCF. This necessitates the development of AI-based methodologies in parallel with the evolution of these areas. This will be a major focus of additional research over the next decade.

Furthermore, the future development of autonomous vehicles will also drive changes in vehicle-based safety. The sensor technologies used in future vehicles will be a focus of vehicle manufacturers, as their resolution and accuracy will have significant knock-on effects in data fusion for robust system designs. The overall strategy is expected to focus on systems engineering and RAMS modeling with self-test algorithms and diagnostics. In parallel, computational intelligent-based methodologies will focus on robust and optimized system designs. This sort of inline processing allows information to be filtered and prioritized by the vehicle before it is made available for driver decisions and may be necessary to mediate conflicting warnings. Beyond these technological developments, there is a strong ethical discussion that must accompany the future adoption of AI technological applications. For example, the focus of this review is predominantly on advanced driver warning and advanced driver decision support, and so uses AI methodology to add to a human's awareness or thought process. This feels like a relatively easy ethical choice, as a human is at the center of the decision-making.

But, in the future, the area is likely to contain offensive decisions by AI-based systems, meaning that when there is a risk of an accident for the vehicle, certain parameters are altered deliberately to protect the drivers and passengers. These types of moral hazards essentially cannot be weighed by the public, and the government is thus expected to intervene more heavily with appropriate regulation.

7. Conclusion

Integrating AI and machine learning technologies into the field of safety has huge potential. Furthermore, many success stories in the application of AI solutions are known from the fields of automotive safety. After extensive testing, comprehensive validation, and approval, we can already talk about completely autonomous systems responsible for driver and passenger safety. Vehicle safety systems such as airbags, AEB, or DSC have already strongly benefited from machine learning methods. Especially when it concerns improved safety, not only machine learning but also the understanding of new technologies should remain a top priority for both research and industry practitioners. Indeed, quite recently, new levels of vehicle automation have been introduced, which in the near future may reshape the automotive industry.

It seems that, in contrast to human-designed rule-based systems, an artificial system based on data analysis and the history of real-world events can take into account many different driving conditions, including specific environmental factors, and learn from the dynamics of various driving behaviors. We strongly believe that further professional research and technical development are required to improve the efficiency of basic vehicle safety elements. This direction is a strong candidate for the next stage of vehicular safety systems evolution. The final result of this work is that very complex safety systems are designed to evolve and optimize their performance over time to maintain a very high global protection level. Future work can verify the suggestions presented. In addition, further detailed analyses, extended experiments, and, ultimately, a validation phase are required to implement the ideas presented in the form of an AI target-driven airbag proof-of-concept.

Reference:

1. Tamanampudi, Venkata Mohit. "Automating CI/CD Pipelines with Machine Learning Algorithms: Optimizing Build and Deployment Processes in DevOps Ecosystems." *Distributed Learning and Broad Applications in Scientific Research* 5 (2019): 810-849.

2. Singh, Jaswinder. "The Ethics of Data Ownership in Autonomous Driving: Navigating Legal, Privacy, and Decision-Making Challenges in a Fully Automated Transport System." *Australian Journal of Machine Learning Research & Applications* 2.1 (2022): 324-366.

3. Machireddy, Jeshwanth Reddy. "Assessing the Impact of Medicare Broker Commissions on Enrollment Trends and Consumer Costs: A Data-Driven Analysis." *Journal of AI in Healthcare and Medicine* 2.1 (2022): 501-518.

4. S. Kumari, "Digital Transformation Frameworks for Legacy Enterprises: Integrating AI and Cloud Computing to Revolutionize Business Models and Operational

Efficiency ", *Journal of AI-Assisted Scientific Discovery*, vol. 1, no. 1, pp. 186–204, Jan. 2021

5. Tamanampudi, Venkata Mohit. "NLP-Powered ChatOps: Automating DevOps Collaboration Using Natural Language Processing for Real-Time Incident Resolution." *Journal of Artificial Intelligence Research and Applications* 1.1 (2021): 530-567.