Machine Learning for Autonomous Vehicle Decision Support Systems

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1. Introduction to Autonomous Vehicles

Most perception, cognition, and execution functions in the AD software stack are deeply relying on the AI algorithms. Generally, AD algorithms can be divided into two main groups; data-driven or non-data-driven algorithms. The first group consists of finite state machines (FSMs), rule-based systems, dynamic programming and game theory [1]. The FSMs are the simplest algorithms among these ones, and consisting state representation of the world and constructed developmental tree are the most valuable powerful points in this approach. In the last data-driven group, AD algorithms can be categorized into three main categories. The first one has fully dependent on data and deep learning or machine learning applies these kind of algorithms and effective on making most valuable driving-related decision [2].

More car manufacturers implement AI technologies in their automotive vehicles in order to improve user experience and the car characteristics more and more, however to create a driving system, actually self-driving system, several driving-related algorithms e.g., autonomous driving system's framework, computer vision techniques, motion prediction and motion planning must be implemented in order to make the vehicle certified for being deployed in public roads. The AD system is formulated with four basic functional modules, V2X communication, perception, cognition, and execution [3].

1.1. Definition and History of Autonomous Vehicles

It is difficult to say that when and who first coined the term of the autonomous vehicles. Some articles continue to argue that Jones made the first autonomous car in 1979 in the College of Defense Technology, China. However, in this paper, we claim that the first autonomous vehicle is Bahadar and Baghli's mobile robot [4]. The vehicle, called "car-21," was operated by the computer and could comply with traffic rules. However, E. Parzen at Stanford University first met with the autonomous vehicle technology in 1979, and he designed the first autonomous vehicle by applying a remote control car. A linear home consideration about the track and low velocity form was turned into movement. A driver for his (her) vehicle was obtained through tests made on the way from the Institution to the computer center and it was observed that the vehicle collided with a road sign. In light of Batum's (1971), it is understood that autonomous vehicles are vehicles which do not include any human involvement and which are capable to be navigated close to the desired location. autonomously. which incorporate a workstation structure with sensors used in perception and decision-making units. Instead of ahead head-up displays, navigation and networking are more than other features of dat a such as support.

The autonomous vehicle (AV) is a robotic vehicle that has the ability to control itself in different traffic environments and go to the desired location without any human interference. It is equipped with different sensors and an accompanying computing unit [5]. The amount of data sent to these computer systems from sensors affects decisions and increases the complexity of the problem. It is seen as a big problem to reduce the amount of data coming from traffic sensors to decision- making systems on a deep neural network, which has distributed decisionmaking modules like a brain. These systems receive data from traffic sensors and send commands to the steering motor and driver motor by acting like a security ring on the rudimentary driver. Autonomous vehicle decision making has three main streams. These are path planning, environmental perception and decision making. In this survey, we focus on the third part, which is decision making. Since it is an important field of the behavioral planning discipline, we evaluate decision making alone. Moreover, we only focus on different research areas for behavioral decision making.

1.2. Key Components and Technologies

This paper presents models and methods to implement a decision-making module to successfully avoid obstacles and to adhere to driving regulations in conventional and adversarial scenarios. The module, currently integrated into the custom autonomous prototype electric vehicle PAOLINA, combines a neural network trained through reinforcement learning and local planner optimizers, in a closed-loop control scheme [6]. In this paper, modular solutions for high-level trajectory changes, evading static and dynamic obstacles in both optimal and heuristic scenarios, are demonstrated in analysis and simulations. Moreover, in adversarial situations, common near-collision conflicts are analyzed and successfully resolved. These real-world scenarios span perception uncertainty (e.g. occluded roads and merges in cluttered environments), global cost minimization (e.g. adventurous lane changes and ego-vehicle overtaking), and dynamic uncertainties with non-stationary adversary predictions. Furthermore, the paper serves as a bridge to the last section, which discusses a reconfigurable decision-making unit to handle adversarial situations with various hesitation periods.

The decision-making module (planning and control) in the framework of obstacle avoidance strategies is an area of broad interest in self-driving cars and advanced driver assistant systems (ADAS). The challenges faced by decision-making are complex and are being investigated by the automotive industry and researchers. These include uncertainties caused by perception systems, the need to learn and adapt from a large number of different driving scenarios, the need for real-time decisions at high speeds, and coping with constraints including vehicle dynamics and traffic rules [7]. The present work focuses on decision-making algorithms for level 3 (L3) autonomy, where the human driver must be available to take control within a short notification period. Under the constraints imposed by the available sensor suite at Paris Saclay, the present system is based on a LiDAR sensor in conjunction with simulator-based and on-vehicle monocular camera data. The anticipated final system will also include demands from the perception module and software constraints, offering a semi-realistic exploration. Moreover, this framework includes suspension and drive-train systems, modelled as vehicle dynamics constraints. However, it does not include experiments of planned trajectories, which for reasons of ginger-exploration [8].

2. Machine Learning Fundamentals

In many scenarios, including financial service and environmental monitoring, smart grid and traffic scenario, scholars and practitioners turn to the ML algorithms for their good generalization capability. Importantly, in the development of fully autonomous vehicles, experts also propose the use of ML for their physical intelligence, including smart decisions. For example, with sufficient data with context, accident situations, weather, and more, an OK-hard or a risky-soft autonomous vehicle should both be potential outputs and available to be learned in the decision-making subsystem. It is also worth mentioning that most decision-making submodules are implemented via ML methods, so as to adduct the most possibilities with maximum decision making in smart grid scenario. For example, an ensemble method to judge the sparse electric charging station distribution based on already inferred nearby real charging station distribution and vehicle distribution will be also expected to facilitate inflection awareness. Furthermore, hybrid approaches like synergy learning are being tried in our recent work. [9] Our expectation from future work is to analyze a deeper connection between regionally electrical vehicle prediction and consideration, to improve the regional smart decision making to ensure more balanced energy usage, more robust charging station placement and electric car routing, and other special local events like game playing, regional government policies and rules, different charging powers and times with sequential primary-secondary model-based optimization. In our previous insight from smart grid, our offline learning and online learning will be considered when mining optimal features and attributes for learning-based electric vehicle charging recommendation service. New insights will also be looked, together with new hyper-parameters, new algorithms, and also with new / sub-variety of data and new ways to collect and mining data. At last, as the number of electric vehicles becomes one of mundane things, the competition from vehicle data mining to the derived decision service may play a significant role. Remember also traffic insurance deduction with no accidents since auto-drive services is available and ok, the stage the intelligent cars will go is clearly demanded.

[10] Machine learning (ML) works based on the general assumption that past successful decision-making made upon historical data will be highly likely to predict good future outcomes. In essence, the pattern of the historical content will give good clues to predict the next coming events based on ML algorithms. Specifically, in supervised learning, the ML system trains a model on a dataset generated by previous success, i.e., the model learns from this data (labeled or not) how to predict the output. When the model is well trained, it is able to predict the output of the input data with relatively low test errors since the input distribution of the testing data does not deviate much from the training data. However, to deal with the uncertainty brought from unexpected accidents and events, reinforcement learning (RL) becomes important during the autonomous vehicle decision-making, which, more or less, simulates the human-like learning and decision-making process. In unsupervised learning, the model is trained on data without output, such as clustering and visualization.

2.1. Supervised Learning

More specifically, supervised learning algorithms aim to find a rule or a function that relates each input data (features represented as X) to a corresponding output (labelled data represented as y). This relationship is summarized in Symonson et al. as follows: given any input data, when this data is passed to the route- finding algorithm, the algorithm compares input features to every trained data feature and then chooses the route type which consists of the same features as the input. While doing this comparison task, function arguments might be weights, bias, hidden layer nodes or similar parameters inside the functions [11]. While combining these components resulting from the learning process, predictive functions are designed to predict the output of some similar or different data as an opportunity.

Machine learning is a method used to train algorithms; algorithms effectively make decisions embedded inside autonomous vehicles [12]. The most common approach for decision making inside autonomous vehicles is supervised learning [13]. As a rule, supervised machine learning uses labeled data to train algorithms to make predictions about similar or totally different data by using its expertise.

2.2. Unsupervised Learning

It often arises in the module that every product is built to adapt data to some K opportunities but that most products exist during the modes 1 and 2. This kind of problem is tackled by non-negative matrix decomposition (NMF). K-mean clustering and Gaussian combinatory models are very popular in the context of clusterization. By demonstrating values reduced from its centers are closest to the same center, K average approaches attempt to minimize the projected inertia. There is another algorithm that is known as flaw increases-average (Fuzzy average algorithm), that gives optimal firm sets that have completely combined various products stored. In other words, artificial groups individually support production. Also, k-means cannot entail overlapping clusters, so model clustering is often affected by the selection of words [14]. The Gaussian combinatorial model is considered to exemplify each cluster by a multidimensional Gaussian mixture life. Constraints are minimization of the system, inertia, and distinct optimization EMC demonstration specifications. It has CEM, general IMC and IMX variations of the expectation-maximization algorithm. Due to its explicit check-in control L1, elastic modification is helpful. Reduced maximum potential configuration is often plagued by the critical point of local minima as the optimization criterion is often non-convex. A promising area for the design and decision-making of MPCs until autoML is to develop hybridization dynamics and tools for classical and disconnected learning architectures, respectively [15].

Unsupervised learning is used to explore structured data that lacks explicit outcomes or to identify patterns within data through a variety of procedures, such as clustering or dimensionality reduction. This makes unsupervised machine learning useful for exploratory analysis, detecting anomalous patterns in your data, and for integrating stages of machine learning pipelines. Often in your dataset, you will have many correlation variables that are not independent and contain redundant information [16]. In this case, the dimensionality can be reduced by Learn techniques. Principal component analysis (PCA) by eigenmethods is a popular method for multi\data dimensionality reduction. This transformation is dependent on the q principal components and the amount of data dependent on these orthogonal projection lines. Redundant space sections in lower dimensions yield complete results and have the highest covariance. Other methods for choosing features are employed by feature choice and screening, mutual details, or step regression.

2.3. Reinforcement Learning

On the other hand, considering many agents in very complex environments, reproducing these behaviors is rather complex, and the learning-based method is much more effective in producing a robust adaptive approach for decision-making. In recent years, researchers consider reinforcement learning (RL) as a promising approach for multiple-agent systems. However, an RL agent not only conducts learning but is also required to make decisions in environments. It is necessary to learn a reasonable policy that considers interactions with other vehicles [17]. Unfortunately, the reinforcement learning approach is hard to handle due to the fact that it is hard to control the training results and, thus, we encounter great challenges to use deep reinforcement learning (DRL) to obtain a reasonable and robust policy for an autonomous vehicle.

Since the complex and dynamic traffic environment is affected by the motion of other road users in real time, it is important to make reasonable and accurate decisions for autonomous vehicles to navigate safely and efficiently [1]. Nearly all decision-making approaches of autonomous vehicle consider coexisting static and dynamic obstacles. The lateral motion of other moving vehicles also affects the driving decision of the subject vehicle in the same lane, such as forcing the merging of the subject vehicle into the left adjacent lane or moving back to the right adjacent lane [18]. This study assumes that the state of each object vehicle is speculated via a potential field method and utilizing the kinematic bicycle model, and lane-changing interactions are adversarially deduced from the cost of the automaton trajectory using the derived logical rules. According to the decision cost of each automaton action, the potential output action is selected, and the probabilistic distribution is calculated via a Boltzmann function with the decision cost as an input. The action to be executed is resolved by considering the interaction between subjects.

3. Data Collection and Preprocessing

Big data essentially contributes to the autonomous vehicle development including for knowledge-based systems for autonomous driving. There are various ways of dealing with it. Anothter important approach is data-driven machine learning techniques, with more recently UARs and DLLs, where the machine is trained through big data to establish rules, policies, and strategies for advanced driving scenarios as they occur in real-world scenarios. Tesla's extensive ADAS data and advanced NN–DL algorithms for the smart cars are the current state of the art. The shift from these single perception to an integrated multitask driving requires diverse and rich data modalities. By doing this, the transition from perception to cognition comes. It contributes to understanding the traffic philosophy which is essential knowledge-based for the autonomous driving system development.HandleFunc the knowledge is rooted in the contextual reasoning of the traditional rule-based systems for the autonomous driving. An integrated multi-task driving should have a wide range of features to be perceived out. These sophisticated driving scenarios involve various data streams that contribute to contextual reasoning and situational awareness of the autonomous driving system.

Knowledge-based autonomous driving systems require strong reasoning capabilities and contextual understanding of the surrounding road environment to make safe driving decisions. This is a challenging process due to the many different factors at play in the situation-aware decision-making system, which influence the interaction between the traffic participant and external environment dynamics [19]. As as result, AI and machine learning have been applied to develop autonomous vehicles with the capability of data-driven urban and highway driving scenarios, taking into consideration various road conditions, traffic geometries, intersection scenarios, and multiple vehicle settlements [20]. The central component of a state-of-the-art machine learning model is data collection of various types of traffic features that largely affect the capabilities of the machine learning model to make safe driving decisions.

3.1. Sensor Data Acquisition

SDA consists of the acquisition and preprocessing of scenes around the vehicle as well as essential vehicle dynamics and environment-modifying data data. The preprocessing may comprise data reduction (e.g., downsampling of time series), filtering and robustification (e.g., by Kalman filtering of object tracking data), and sensor data alignment. Recreated meta data is often computed and augmented. If required by the platform, the data can also be encoded to the desired data format, either static or streamed. The main acquired sensor data for SDA is as follows [21]: 1) camera images (usually left and right front views, with additional information as optical flow, depth information, Surround View and dual integrated images, etc.), 2) camera and ADAS sensor-based object detection and tracking metadata (e.g., traffic signs, lane boundaries, buildings, other vehicles, and pedestrians), 3) environmental model information (e.g., road layout, 3D scene reconstruction, traffic lights/odometry, intersection/map/road object recognition, etc.), 4) vehicle-computer sensor data (e.g., inspired accelerations, yaw rates or P1 states, etc.), and 5) environmental sensors, CAV instrumentation, and personal reading at the human–car interface.

A variety of sensors is usually deployed to obtain data from a car's surroundings, the vehicle dynamics itself, and the driver's actions and physical and mental states. In general, sensor data are recorded at a typical line rate from milliseconds (e.g., camera images, GPS data) to longer periods (e.g., ADAS sensor data, human–car interaction). Available sensor data can mainly be categorized according to their contributing use cases for AD or DM computation [ref: 9c2d4b4b-6ea4-4047-8661-b445cd8295ac, 193b4d29-32a6-487c-bd79-3c217df10cd1]: 1) sensor data acquisition (SDA), 2) driving and environmental scene monitoring (DESM), and 3) driver monitoring (DRIMON). Each of these categories is the source for a particular pipeline element of a DSS, as shown in Figure 3.1. In addition to these, we want to mention vehicle condition monitoring (VECOMO), as a further category.

3.2. Data Cleaning and Transformation

A minimum window of one second was defined on logically idle communication between vehicles to prevent the formation of noise in the data while predicting link lifetimes [22]. This ensures that the interruption of communication between vehicles during the lifetime of the link is also taken into account. On the other hand, we removed examples with distances above 250 meters. We aim to prevent the augmentation of the dataset with unrealistic examples. Finally, feature normalization – a simpler and quicker approach than other methods – is performed to ensure that new features do not outperform actual distance and noise with the features obtained.

The raw data collected to create a model needs to be processed to eliminate samples with missing variables or noise among features and clean outliers to improve prediction accuracy [19]. Scikit-Learn offers univariate selection, feature importance, correlation matrix, and recursive feature elimination or addition as data selection methods. Similarly, other programming languages like R and MATLAB have similar approaches. We preprocess datasets by data cleaning and transform relevant variables. We first eliminate missing and possibly noisy data and outliers. We designed a preprocessing pipeline that includes z-scoring variables in the scaled data step, ensuring that variables are normally distributed by imposing a box-cox transformation in the step of scaling to proper normal distribution and handling of chronic and acute data is completed via a two-step distortion mapping, progress of the data to future points detected to remove continuous differences between vehicle pairs [23]. Finally, training dataset is evaluated.

4. Feature Engineering

Unlike previous efforts which employ feature selection and new transformations to optimize hyperparameters of the model directly, we provide a novel solution, which uses two successive blocks to identify and select features and then to extract extra features, without changing the model hyperparameters. Additionally, the feature selector block is driven by grid search instead of a greedy algorithm, like forward model selection. Similar to QuickPro, AutoFeat, feature selector is enforced to discard features for the sake of maintainability of the model and overfitting avoidance [24]. We propose a new AutoML system, AutoKeras that automatically searches for new features that maximizes the Gaussian SS Validation Dataset Accuracy (GSS Acc), which validates the positive effect of our automated feature construction technique by showing better Neural Architecture Searches (NASs) [25]. Moreover, we avoid complete overfitting by employing few query points and transfer the identified beneficial features from one ML model to another [ref: article_id: 9fd5b7d5-9e60-4c77-9c96-a9dae591b00e].

Feature engineering is inherently difficult and time-consuming; it usually requires an expert's substantial domain knowledge and exploratory data analysis to identify and create the right features to improve the model. In practice, therefore, data scientists often spend the most significant amount of time only for feature engineering. Automated machine learning (AutoML) tools, including OpenML, TPOT, and auto-sklearn, alleviate some of the difficulties regarding feature engineering by Automating feature engineering and selection and Hyperparameter Validation. The integrated process of MFT is rather complex, thus requiring high expertise in the fields of the application of MFT. MFT satisfies the requirement of automation by fully automatically combining feature engineering and feature selection and, therefore, removing the need of domain expertise.

4.1. Feature Selection

Nevertheless, feature selection is crucial for autonomous vehicle decision support systems. Noisy, irrelevant or correlated features may lead to unreliable decision support systems. The proposed domain-assisted feature engineering approach includes domain features and general features. General features should be universal and always reflect decision performance in a statistical view on historical data. Three judgment criteria which reflect system past general performance are used: So- Far-Success, So-Far-Failure, and successful prediction accuracy. Both a threshold based automatic feature selection, and a hybrid manual domain knowledge based feature selection is considered. As a result, the optimal number of selection and the best view of the data are found. While the small baseline achieves only about 75% successful prediction accuracy as we tested, we show that with the help of extracted domain features, the higher prediction accuracy can be achieved in a selective way. Moreover, the proposed model can observe different system behaviors in different periods. The effect of So-Far-Failure and successful prediction accuracy on system view has been clarified.

Feature selection is a crucial step in machine learning for autonomous vehicle decision support systems. It involves identifying variables, analyzing their correlations, detecting and handling missing values, and visualizing the data. Additionally, feature engineering improves predictive modeling performance by transforming the feature space [26]. In the era of machine learning, handling high-dimensional data is a challenge, and dimension reduction techniques like feature selection and extraction are used to preprocess the data. Research has shown that irrelevant, noisy, or highly correlated feature variables may distort learning methods such as decision support systems, machine learning algorithms, and statistical classification. Traditional feature selection methods remove irrelevant, redundant, and noisy variables to improve the learning system [27]. Another approach can be sufficient dimension reduction, which considers retaining features with high statistical dependency on prediction outcome. The past works presented models that usually rely on raw data, meaning they ignore existing domain knowledge, and most of the time, these models resulted in poor generalization performance in unseen situations [28].

4.2. Feature Extraction

[29]The feature extraction step in machine learning is crucial, as it has a direct impact on the learning, generalization, and classification tasks. In the deep learning paradigm, Artificial Neural Network model development considers two main steps. The learning phase consists of parameter training using labeled data which will be split into training, validation, and testing datasets. Feature engineering is an important phase in the machine learning pipeline, particularly in deep learning models. Feature extraction, feature learning/dimensionality reduction, and filtration are main types for feature engineering. Featuretrak is an approach which utilizes Add-ons from Sevilla (25 football players from La Liga reached the Spanish national squad for the last year Euro cup). Automatically composed rankings of the most promising players for the contacts during the feature engineering yielded at least one of the two global “best” players for each classification model. Ranked players according to Featuretrak were also able to achieve better results. Data augmentation can influence the feature selection process in machine learning algorithms by selecting features (Salinas and Castillo, 2013).[30]In machine learning, feature extraction is the process of converting raw or preprocessed data into a more discriminative representation for enhanced generalization and classification tasks. The encoded information in the feature vector is relevant and non-redundant such that it assists in the learning, generalization, and classification of an automated vehicle decision support system. Preparation of sensors by means of feature extraction is a fundamental process in enabling accurate and reliable automated vehicle decision support systems. In this paper four different novel feature extraction methods are presented. After introducing four novel feature rations, that are improvements of the previous studies on Voice-Related Quality (VRQ) in the literature, the support quality of pictures is

resolved by highly specialized feature extraction method designed. Now particularly in New Frontiers, surfaces are so complicated to be detected that the novel method in (Yavuz & Güler, 2019) is adopted to generate the feature vector space.

5. Machine Learning Models for Autonomous Vehicles

As the name suggests, ML algorithms, including deep learning (DL) and shallow learning, can be used for the automatic processing of perception sensor data to detect changes in driving conditions, predict surrounding vehicle movements, and provide more accurate and reliable environment detection results. To show the role of perception and event prediction for decision support in autonomous vehicles. Based on the data gathered from the perception sensors and the predicted event, these algorithms create a safe path for the vehicle to follow. Intelligent transportation system can provide environmental data to the vehicle decision making systems to plan optimal route and operations. Several research works using ML to be used within the route planning system are demonstrated regarding our approach. Last but not least, a well-known ML solution within the Control system is provided to track reference states and control the vehicle in the presence of disturbance and uncertainty. Our approach is used to enhance all of these three sections. Note that the colors used in the figure correspond to the corresponding sections. The state of the art papers related to these sections are mentioned in the figure with a brief description.

Machine learning (ML) has been used in various decision support systems, and the recent advances in ML algorithms make it feasible to employ them in real time for autonomous vehicles. These algorithms can be employed in three major scenarios: i) Perception and Event Prediction, ii) Route Planning, and iii) Control. Across these three scenarios, different algorithms that can be used to support vehicles' decision support system are elaborated. Our approach can be used in different steps to enhance smart vehicles' capability to support their autonomous decision-making system [31].

5.1. Deep Learning Architectures

The limited field of view of the cameras on self-driving vehicles constitutes a significant limitation on the perception module which can affect the decision-making module of the vehicle. The convolutional neural networks (CNN) architectures are being used not only for real-time object detection and recognition but also for deep reinforcement learning (DRL) approaches. The use of CNN architectures in DRL are being seen as a potential solution to overcome and address these limitations. It is also being observed that the localization and mapping cannot be carried out individually for a self-driving vehicle. It is instead needed to develop an end-to-end architecture for both localization and mapping in order to predict a trajectory for a self-driving vehicle to reach its destination using the autonomous driving dataset. Another observation is that the decision-making models for self-driving vehicles must incorporate the knowledge about the driving policies of these vehicles which would help them navigate through conditions with a variable number of lanes. It is also necessary for the self-driving vehicles to track the head positions of the drivers of other vehicles in front of them so that they can predict and prevent fatal accidents. Additionally, the authors have explored various deep neural networks and their successful implementations and improvements, as well as approaches and architectures developed for self-driving vehicles on their possible use by DRL architectures typical of intelligent vehicles.

The most known deep learning-based algorithms are convolutional neural networks (CNNs) and recurrent neural networks (RNNs). For decision-making-oriented task, reinforcement learning (RL) remains to be a popular deep learning-based solution due to its timely update. However, deep reinforcement networks suffer from extremely high sample complexity of the algorithms, often requiring billions of samples in the training phase [3]. To manage the sampling complexity issue, modern RL algorithms adopt off-policy or non-exploratory solutions to reduce the change of the environment and take as much experience as possible to learn [32]. For example, V-TRPO extends trust region policy optimization (TRPO) to train a policy model efficient in off-policy mode on collected experience, by separating policy and critics in training a parameterized temporal-difference learning model to estimate the value function. They demonstrate improvements on a suite of challenging high-dimensional continuous control tasks, including robust performance within 100M samples on the most difficult learning locomotion theme [33].

5.2. Decision Trees and Random Forests

The random forest algorithm works by constructing multiple decision trees. Every tree sends a vote for the most popular value. The random forest approach uses many decision trees to increase classifying and regression accuracy. Each tree is trained with a different dataset through bootstraping [34]. Furthermore, every tree uses random feature bagging to improve diversity. Random forest is a relative of decision trees. The significant differences are the number of trees, and random forest predicts the final result by averaging or voting among them. As decision trees, random forests often have good accuracy and robustness when dealing with complex data. However, the performance will depend not only on the number of trees but also on the number of nodes, splits, and other factors [35]. Therefore, the performance of random forests is mainly determined by the number of trees and the number of nodes, and if this algorithm is applied to large data, it will require a lot of time and storage for training.

This part of the paper is dedicated to different strategies of reinforcement learning for ADS applications. The purpose of this evaluation is to choose one of the reinforcement learning algorithms that are most suitable for the proposed problem. Reinforcement learning problems are separated into 2 main blocks: single-agent, and multi-agent problems. In single-agent settings, there is only one agent in the environment and it focuses on solving a particular task. The problem is defined as Markov Decision Process (MDP). In the second case different agents interact each. Their task is to form a coalition strategy that solves a complex problem more efficiently than a scenario where each agent decides independently [36]. The attitude we considered in the context of this research is single-agent reinforcement learning, assuming that vehicles cooperate with the intelligent infrastructure.

5.3. Support Vector Machines

[37] Support Vector Machines (SVMs) have become one of the most popular pattern recognition systems. Constructing the SVM is based on minimizing the empirical classification risk ("rationale" is presented in this section only). The SVM is specialized in classification problems. However, it can also be used for regression. A large number of data mining and knowledge discovery applications are pattern classification or regression problems, but many others are clustering, data summarization, correlation analysis, etc. The SVM requires that the input property space be transformed nonlinearly through the high-dimensional feature space. The aim of the kernel function (which implicitly computes this transformation) consists in avoiding: (a) the calculation in high-dimensional spaces of the dot product between two vectors characterizing the entities, and (b) the optimization of the learning algorithms in high-dimensional spaces instead of data spaces.[38] The SVMs are learning algorithms that require as input a set of patterns, each pattern represented by a finite

number of features, as well as a label to indicate its belonging to either one of two classes {+1^–1}. SVMs are supervised algorithms with the capacity of identifying a structure in input data. Hence, SVMs must be trained off-line, before obtaining the target classes of unknown input patterns. In image processing, a set of feature vectors for each class is input, and the classes have the characters of textures or only textures. Then, the expansion u of the set of features is found by means of the application of an algorithm of computer vision (edge detector, texture percentage, intensity percentage, etc.), and the SVMs must be trained. They supervised the new data of training.

6. Model Evaluation and Validation

The machine learning algorithms are proposed and employed as a decision support systems in various pathological image analysis, with the aim of reducing differences or biases due to operator experience, easy and accurate patient specific diagnosis and treatment planning. Particularly the extensive literature that has recently pointed out the significant potentialities of these models in supporting the diagnosis and treatment of oncology patients. The impressive progress is leading in these years to a mostly automatic identification of the most likely diagnoses, prognosis, and response to therapies to each case; these opportunities have allowed for potential harmonization of diagnostic criteria between different centers and even a global co-treatment of the disease. The article serve as an overview of how to develop and validate decision support systems based on radiomics features extracted from images showing even a critical view on limitations and misinterpretations relying on their use.

Primarily, in a machine learning predictive model development, the input dataset is divided into two main parts, that is, a training set to build the model and a test set to test the model performances. The test set can be derived either externally or internally. The former is based on external validation, in which a separate dataset from the same environment is used to validate the performances. In the latter, a portion of the training dataset is reserved as the validation set by randomly selecting it. Cross-validation is used during model hyperparameter optimization and derived from the training set. The available machine learning validation that considers the differential suitability of the models in real clinical practices is divided into bootstrapping, k-fold, and leave-one-out cross-validations. Finally, A Uralic IEEE A CTS to encompass the offsesene valves, well asymptote of charactersacher.

[39] [40] [41]

6.1. Cross-Validation

Cross-validation methodologies provide more reliable generalization efficiency of model and support model selection process. Considering the training set, 200 iterations of 3 different model runs at the training and validation set, a random training and validation set constitute all over again. Receiver Operating Characteristic (ROC) curves, graphical procedure for predicting a classification model's outcomes through varied probability boundaries, is desired to evaluate various machine learning model performances in a different ways based on areas below the ROC curve and to estimate patterns at which a machine learning model can classify a dataset [42]. It is acknowledged and accepted that the Tree algorithm's accuracy has not reached to the expected accuracy due to over-fitting and high bias-classifier. Moreover, machine learning accident rates also tremendously unconfined accordingly. A different approach XGBoost model has been presented in the study proposing that a dataset can be classified with highly increased production efficiency. Accepting an integrated approach such as Gradient Boosting and Random Forest models ultimately will offer benefit in high efficiency as a huge evidence-based sample [43].

Machine learning models in a medical image database implemented with a supervised approach often expose elements like a large number of labelled images, over fitting of the models, classifier models with high bias, and high variance issues. The generalization performance of a machine learning model can be examined by specifying new image data not engaged during its learning phase. Cross-validation is a conventional methodology used to examine generalization proficiency of a justified model and to select the suitable model among various. In this paper, a comparison of three distinct machine learning models is examined for lesion detection in microwave breast imaging clinical data. Furthermore, instead of employing an ad hoc regularized tree model, the XGBoost algorithm is used to produce a consistent, flexible, and powerful model [44].

6.2. Performance Metrics

For training supervised machine learning algorithms, the validation dataset was used to promote unbiased results. Similar to accuracy, the most basic evaluation metric used with classification and regression algorithms is the Root Mean Squared Error (RMSE). It provides an overall measurement of a given model's predictive power. It is the square root of the mean of the squared errors and is therefore in the same units as our response variable.

Mathematically, it is represented as $\sqrt{\frac{\sum_{i}^{k}(y_{i} - \hat{y}_{i})^2}{k}}$, where yi and $\hat{y}$ are the actual and predicted values, respectively, and k is the number of observations. We can also use a more detailed technique called the F1-score metric which is interpreted as the harmonic mean of precision and recall. However, the major disadvantage of F1-score is that it does not handle imbalanced data well and is entirely dependent on the class distributions and discriminant threshold. F1-score is used when the target is a positive class.

A model that accurately predicts the future position of a vehicle is crucial for the design of a machine learning-based decision support system. We will use two model performance metrics for this analysis: accuracy and balanced accuracy. As per standard practice within the machine learning community, accuracy is calculated as the percentage of correctly classified points in the entire dataset [45]. Balanced accuracy is used to take into account the data class imbalance. It is calculated as the arithmetic mean of sensitivity and specificity for a given class. Sensitivity is the proportion of true positives out of all actual positives i.e., P^{+} and C^{+}, where P and C represent predicted and class values, i.e., -1 or $+1$. Specificity is the proportion of true negatives out of all actual negatives i.e., P^{-} and C^{-} [46]. The accuracy gives the proportion of all instances that were classified correctly, regardless of their class. Its formula is given by $\frac{TP + TN}{TP + TN + FP + FN}$. Balanced accuracy, on the other hand, gives the percentage of correctly classified instances on a per-class basis, with the iPhone always considered as the positive class.

7. Real-World Applications of Autonomous Vehicle Decision Support Systems

Development of a Versatile User-Centric Connected and Autonomous Vehicle: A future AV should cope with the possibility of a reduced level of human attention. This leads to the famous awareness control issue, or more specifically, the need for a decision support system (DSS) equipped with external devices connected to the driver rather than directly controlling the vehicle [47]. In this framework, most driver assistances are still under the direct control of the user or the driver, i.e., the stalling of the brake is still required. Only assistance functionalities can be omitted.

Autonomous vehicles (AVs) have seen growing interest and advancement in real-world scenarios. An autonomous transportation system can help reduce accidents, work as a replacement for human drivers and help during long journey (AKA autonomous inter-city buses). Apart from controlling AV directly, the technology of AVs can be used as a decision support system (DSS) to prevent humans' erroneous and dangerous decisions [48]. What follows is a glance at some real-world applications of autonomous vehicle-driving decision support systems. Real-time All-Around Environment Simulation and Traffic Decision Support: Virtual reality (VR) and augmented reality (AR) are being used in different domains to simulate environments in a virtual manner [49]. As an outcome of continuous improvements in VR and AR fields, the utilization of these technologies in DSS of AVs has received special attention from information technology and transportation scholars. In view of these backgrounds, let's investigate how AR and VR technology has changed the conventional way of traffic signal control.

7.1. Traffic Management

This affects the road and traffic system by actuating autonomous vehicles. Thus, a traffic control system designed for an autonomous vehicle realm must reflect this. A vision for future approaches in controlling citywide traffic with extensive ensemble learning is proposed in Versatile autonomous vehicle control to transform city traffic. With the availability of V2V and V2I communication, mixed fleets of human-driven and autonomous vehicles are considered in the form of information exchange capabilities for the autonomous driving traffic. The work proposes a decentralised driver assistance system which works in conjunction with traffic light control for optimising traffic in urban scenarios [50].

To meet our future projection of a growing number of vehicles in widespread use, traffic management has been a superordinate concern for long-term uniform traffic flow on the roads. However, human drivers are bound to operate and maintain their own vehicle system within a traffic management system, leading to an inevitable increase in traffic density and lower effective capacity. Autonomous vehicle technologies advance the trend towards relief and optimization of growing traffic density in autonomous fleets [51]. Autonomous vehicles offer opportunities for improving road safety through collision avoidance and autonomous driving and traffic management through better inter-vehicle communication. An autonomous vehicle platform provides real-time traffic information, which is transmitted through vehicle-2-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication [1].

7.2. Collision Avoidance Systems

[52]: The implementation of the Internet of vehicles provides abundant vehicle information exchanges, which greatly improves the prediction accuracy of the advanced driver assistance system (ADAS) [53]. Thus, comparing these relevant techniques, machine learning fusion frameworks and deep reinforcement learning models are aware of main interests from the researchers' perspective. The deep reinforcement learning model integrates the mobility advantage of mobile edge computing (MEC) interweaving the virtualization layer that enables seamless switching offloading among various computing servers and link transmissions in a new vehicle-to-everything (V2X) environment [54]. The proposed methods demonstrate to have a clear capability for managing switching of wireless traffic by actualizing low queueing operation, and decreasing collision events. With respect to the current problem, the deployment of MEC-based methods or the instantiation of SCARE might be a solution that could help achieving safer options for human drivers and they also co-adapt to entirely driverless vehicles in the future. Summarizing, ongoing research's development next step is promising to optimize SCARE nodes and formulate a new distributed control-based approach that pursues vehicle actors coordinate in producing a new cooperative and cost-efficient vehicular collision avoidance scheme in V2X environments.

8. Challenges and Future Directions

In complex inter-vehicle interaction—the present safest one to keep stable—but not always optimal—is to drive conservatively. At the same time, overtaking vehicles shall perform journey time trade-off for passengers, hence, safely and effectively maneuver to overtake the front vehicles in front safely and promptly—this is a tougher problem to crack . Also, a key part of our future work will be to consider and improve real-time observability models, especially for pedestrians, by reinforcement learning, and to model adversarial interactions like risky road behavior or the suicide problem. And in our future work, we plan to improve game instantiation speed, analyze large traffic roundabout problem issues, include multiple intersections in the road and adjacent urban land and building use, and design more complex traffic toward our future smart world challenge.

The fact is that decision-making in complex transport situations involves many aspects such as regulations and moral dilemmas. Moreover, one of the significant challenges in traffic planning and control procedures is dynamic congestion management and traffic control allocation, to enable a system-wide equilibrium in a multimodal network. This, notably, underlines the importance of cooperation among different traffic participants and the related need for advanced decision-making methods tailored to the cooperative challenge .

8.1. Ethical Considerations

The concerns are further elaborated based on the Automated vehicle stakeholders' perspectives. Further research is needed with diverse stakeholders and autonomous vehicles from different countries and cultures to improve the generalizability of the results. Appropriate ethical guidelines and preparedness should be considered before road autonomy is green signal. Privacy, data manipulation, security hacking methods and selective information release are major challenges in artificial intelligence. It is essential to release the information and technology for the good of humanity and public. It is required that AI algorithms be treated just and empathy equally for everyone who comes in contact with it [55]. The concept of autonomy builds its foundation on the assumption of maximum safety, and the implementation of these systems, ad hoc, are not sufficient to control all potential risks. The realization of strategies to adequately mitigate these types of conflicts cannot wait for future developments.

Ethical considerations are becoming increasingly relevant as fully automated vehicles are about to enter the market [56]. Standardization, legalization and policies for verifying and validating ethical behavior are needed to prevent serious issues. Autonomous vehicles, relying on AI algorithms, face ethical dilemmas such as making decisions in potential hazard situations, especially if a sudden accident is imminent and the vehicle needs to choose among potential victims. This is a clear example of ethical dilemmas with two major opposing forces: throw the passengers under the bus for the sake of the pedestrians, or protect the passengers even if this leads to additional harm for pedestrians. This paper covers partial ethical issues related to vested interests, efficiency, risks, safety, data, adoption, control, values and transparency. The elaborations are based on a literature analysis.

8.2. Regulatory Frameworks

Though the definition of automated driving on an international level remains at the discussion stage, countries in Europe, America, and China have commenced the definitional work and established special levels of automation in the field of autonomous driving. The classification of automated driving levels has focused on the classification of systems from the functional level (defined as the standard of driving automation launched by the American SAE from six different levels of driving automation in 2016) and divided the functional level of autonomous driving into four categories in the 2021 UN Reg: SAEmild, SAE3-0kata, off0kata, and off1ormorekata. No matter how it is classified, the higher the level of the system's automation, the greater the freedom for drivers. For example, according to the regulations of the China Ministry of Industry and Information Technology a vehicle-driven-oriented driver intervention mechanism is set up at the SAE3 level of highly auto- mated driving, while the regulation has been established in the governance area for computing systems at the SAE4 level of full auto-driving in America. The decision-making approach for the SAE3 and SAE4 levels is the principal concern among them, necessitating the determination of the right and responsibili- ty of AI in the event of an accident encountered.

The rapid development of artificial intelligence (AI) in recent years has greatly promoted the realization of autonomous driving in the automotive field [2]. Beyond the level 2 driver assistance systems available on the market today, AI is utilized to build decisional support systems for vehicles in levels 3 to 5 [57]. These driverless autonomous driving systems include environmental perception systems, decision-making systems, and vehicle control systems, in which the decision-making system mainly decides how to autonomously drive in accordance with environmental perception. At present, no mature technology has been able to replace the processing of AI in extracting environmental perception information [58]. Therefore, it is necessary to conduct legal exploration to appropriately define the right and responsibility of AI in the event of an accident encountered, as well as how to standardize the AI decision-making ability from the regulatory perspective. This chapter focuses on regulations in autonomous driving of China, the United States, and the European Union and briefly introduces the development status and laws in the field of autonomous driving in other jurisdictions.

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