Machine Learning for Autonomous Vehicle Emergency Response Systems

By Dr. Daniela Rus

Professor of Computer Science and Electrical Engineering, Massachusetts Institute of Technology (MIT) (Branch outside normal colleges)

1. Introduction

[1] Technological advancements in artificial intelligence, deep learning, and wireless communication have brought autonomous vehicles closer to reality. Unlike other avenues, such as production and infrastructure, communication and safety are crucial aspects of this technological area. Autonomous vehicles must be able to communicate with each other and utilize the environment to detect, track, and classify design elements. An autonomous vehicle must respond to emergency vehicles approaching a traffic intersection by making an "educated" decision. Although many current traffic regulations impose rules to deal with emergency vehicles, autonomous cars that can drive safely in cooperation with emergency vehicles have not yet been commercialized.[2] Machine-learning-based algorithms generate and improve models over time by learning from their experiences. With this in mind, machine learning models can be trained in a variety of scenarios, including the recognition of emergency vehicles and the detection of overpasses. Emergencies have played an indispensable role in human life, regardless of location. The emergency can be defined specifically as urgent and unplanned medical care for injuries or illnesses, but, most broadly, as the sudden and unexpected adverse environment of individuals or groups that makes them feel threatened. For this reason, various emergency vehicles, such as ambulances, police cars, and fire trucks, have been given priority on the road, because their goals were to save lives and reduce property damage. Placeholder eco-friendly autonomous vehicles' systems must provide for emergency vehicles in all traffic scenarios, and that these systems should ideally be able to predict emergency vehicle behaviors, before making any observations of any emergency vehicle. Autonomously detecting and tracking emergency vehicles and effectively responding to them can notably improve the penetration of autonomous vehicles into society, and such systems become increasingly important for safety-conscious autonomous vehicles.

1.1. Background and Motivation

ML for Autonomous Vehicle Emergency Response, such as crash prediction, has promising significance in advancing the transportation ecosystem [3]. A major advantage of AEVRS is enhancing traffic safety in the case of vehicle accidents, based on real-time data collected by the emergency vehicles on their way to respond to emergencies [ref: 0e51c9cd-938a-4948-9500-d5157a7565b3; ref: 1c2ba306-d268-49b2-b9b1-a2488954895e]. Based on a survey of existing works, we identify two main challenges in the state of the art AEVRS: 1) a clear taxonomy of the existing works is missing; 2) there is no comprehensive survey on the emergency crash-related events in AVs and their empirical analysis. We address these challenges by proposing a general taxonomy for AEVRS based on the input data type, learning method, and its relation to the other types and experimentally showing that public datasets are not sufficiently representative of real crash-related events. The goal of our survey is to review the current works in the field of AEVRS, provide a clear classification for identifying prospective future research directions, elaborate on various aspects of the methodologies being employed, and provide a comprehensive case study on real crash datasets. In this survey, we present experimental analysis of real crash data in terms of class imbalance and under-representation of crash events and empirically show that public datasets have limited representations of true crash evidence. Then, we provide a detailed taxonomy and classification for the studies in the field of AEVRS which characterizes them based on the type of the input data, learning method and their combination. We follow this by a comprehensive review of the learning methodologies employed in the reviewed works along with their advantages and disadvantages. We provide a case study where we review a dataset specifically designed to analyse crash characteristics in AVs and experimentally demonstrate the learned counterpart between the presented investigation and existing works.

1.2. Research Objectives

In addition to representing collusion situations and hence challenging emergency scenarios for the autonomous agent, the plant presents characteristics that change during the learning process of the autonomous agent, and it is a non-stationary environment presenting both local and global optima in the feature space. The proposed model, called Online Data-driven Emergency-response Learning system in unforeseen situations (ODEL) is hence designed exploiting the possibility of operating in an online setting where a sensor provides input information to be evaluated by the autonomous agent; it was proved to be an efficient emergency-response system for autonomous vehicles in the context of non-stationary scenarios where acquired training dataset information is online lacking. Sacrificing certainty about data availability, real-time emergences, uncertainty in many characteristics of the plant (required to trigger an emergency response), and cost of knowledge to be paid in terms of the expensive and sometimes dangerous labeling activity are only a few examples of the most challenging situation that an emergency-response data-driven estimation system has to face.

[3] The problem solved in the framework of the presented research concerns autonomous vehicles equipped with machine learning models. In particular, special attention is given to emergency scenarios in which training data, i.e., data relevant for classification/regression associated with emergent events and safety, are scarce. The limitation of training data prevents the efficient training of machine learning models, thereby potentially causing a significant mismatch with the original dataset, as well as false positives or false negatives. The original contributions of the paper position the research as a novel approach to autonomous vehicle emergency response systems in the context of scenarios involving an online lack of knowledge about the plant. At the core of the proposed design, a supervised learning classifier estimator is used with data either obtained from a sensor or evaluated from the plant state.

1.3. Scope and Limitations

[4] The primary aim of this work is to use machine learning algorithms to predict future collision events that might be faced by autonomous vehicles [5]. Later, each of the various pre-identification processes would be put forth to reduce collision dangers in view of the road situations actually detected by the vehicle. The main importance of this work is to first achieve adaptive accuracy values that could be taken as a measure of long-term vehicle safety for each of the various autonomous vehicles.[6] Two of the various machine-learning methods, Support Vector Machine (SVM) and Artificial Neural Networks (ANN), approaches are tested at the initial phases of this work to predict long-term vehicle accidents. As for all methods result-wise, experiments were conducted on a defined test group of 10.333.864 record data obtained from our vehicle our automated accident detection system.

2. Autonomous Vehicles in Emergency Situations

As of today, despite considerable efforts and investment in developing AV emergency response behavior, practically there have been a lot of incidents for which there is no end-to-end solution. This document would investigate the emergency events from multiple comprehensive schemes available at individual vehicle level (in case of cut-in scenarios) to asynchrony collision scheme for multiple vehicles due to obstacle masking (visibility) and presence of adversarial objects (for autonomous vehicles). Subsequently, we classify all the critical emergency scenario behaviors with particular emphasis on individual vehicle action schemes for avoidance by rigorous simulation. Then, we evaluate cutting-edge (advanced) methods for decision transport and their multi-vehicle maneuverability in near collision events across the freeway domains.

[1] [7] Autonomous vehicles (AVs) have recently become the focus of mass attention due to their potential to revolutionize the transport system. With the increased demand, the AV industry has seen the tremendous development of sensing, perception, driving policy decisions and technology. However, despite the advanced technology, the largest challenge involved in automated vehicles is their capability to efficiently deal with an emergency due to any on-road event like a cut-in by another vehicle, an autonomous object or an incursion.

2.1. Challenges and Opportunities

For the resolution to solve the occlusion problem, incorporating a mechanism on lens-based sensors is possible with no additional cost. It is the ideal replacement for or even an additional verification of LiDAR for the embedded object category prediction. Both the hardware and dataset used in this work are simple and economically efficient, which has the potential to be widely used in automotive applications. In addition, in the design and construction of a database, manufacturing circumstances are considered to increase the reality of introduced data. The long term goal in future works is not only to predict vehicle categories from behind the object but also to determine the vehicle dynamics like acceleration or lane change.

Blindspots and occlusion represent significant challenges to autonomous vehicle systems . Most onboard vision-based systems are used to aid the visibility of human operators (e.g. cameras), but the cameras are mostly facing forward. The data also provides environmental information to the AI system, like lane width, type of lane, and whether traffic signs are visible. The physiological limitations of machine vision, particularly low accuracy in interpretation in poor visual conditions or dynamics [8]. Some investigations tried to solve it by hardware solutions by introducing LiDAR to autonomous vehicle systems. LiDAR is approximately higher price our less self-driving, less reliable under harsh weather conditions and more energy-consuming alternative of vision systems. Having LiDAR sensor as safety validation to distinguish categories is effective for safe and quick maneuver of the deceleration and brake task. Under challenging lighting conditions, LiDAR sensors also provide reliable and accurate environmental understanding.

2.2. Current State of the Art

Each sensor on the self-driving vehicles collects a significant amount of data to detect and perceive the surrounding environment. Machine vision is the most famous direction for the development of new technologies that allow the system to see road conditions without the assistance of a navigator. Artificial intelligence has therefore become a reliable solution for implementing vehicle navigation processes, based on machine vision and deep learning techniques [9]. Kar et al. [8] expose various machine learning models and methods that have been applied in the field of autonomous vehicles. According to the authors, applying machine learning models to autonomous vehicles has the potential to represent a significant milestone for the development of real-case scenario simulations. Employed AI models include proposals based on traditional machine-learning techniques such as SVM, neural networks, and LSTM, and on the one hand, self-driving car applications often involve reinforcement learning approaches like Q-Learning, Monte Carlo Learning and SARSA. These methods are widely utilized for managing the task of self-driving car, predicting vehicle behavior, and optimizing vehicle control. On the other hand, the deep learning models are utilized for analyzing the vast datasets used by the maintenance systems, for instance: the 1-D CNN model improves accuracy in fault prediction using few signals, and so this makes it possible to conduct vehicle diagnoses with reduced detection time. A generative error model based on GANs, cycle GAN, and SRGANs is utilized to provide a performance model of a generative adversarial network (GAN) for the purpose of generating the phoneme/mouth based feature set.

3. Machine Learning Techniques for Emergency Response

Deep neural networks (DNN) enable automatic feature extraction from raw data, thereby eliminating the need for predefined low-level feature extraction tasks. DNN-based learning, therefore, achieves better performance. The move from traditional shallow learning to deep learning allows the development of networks with increasingly large capacities, enabling the exploitation of high-dimensional data. There is growing interest in the capabilities and potential of deep neural networks to extract relevant features directly from raw data in vehicular networks. Deep reinforcement learning shows great potential for autonomous vehicle control. Superhuman performance has been observed in games and robotics tasks. DNN-based learning is promising in the vehicular domain; however, a massive amount of computation is needed, and end-to-end latency is therefore long.

In general, there are three classic types of machine learning (ML). Supervised ML learns a mapping from input-output pairs in the training data. Unsupervised ML discovers patterns of data, such as methods for clustering or for dimensional reduction. Reinforcement Learning (RL) develops an autonomous agent or a system with the capability to learn from iterative interactions with its environment in order to achieve a certain objective [3]. For example, autoscaling is a popular area for applying reinforcement learning [10]. There has been much work in the domain of autonomous vehicle emergency response.

3.1. Supervised Learning Algorithms

This situation makes an AVERS system improperly counterintuitive and interpretable to follow and follow by the driver if it is based only on deep convolutional neural networks. Hence, the efficient operation of any learned autonoums systems relies on their ability to adapt to the variations in the underlying dynamics. In order to achieve this successfully, continuous model recalibration through large-scale training is considered crucial. Thus, these AVERS learning algorithms are susceptible to over-fitting. This fact imposes a significant limitation on the use of systems in non-source environments, giving them the quality of being properly aware close to immediate top outputs. Therefore,, investigating approaches that are resilient to the system dynamics is still a high priority and one of the main aim of the community. As a consequence, among the supervised types of machine learning, we prefer to use a hybrid pipeline that is a decision tree and a CNN structure upon the measurements._HIDDEN_

There are many approaches to construct Autonomous Vehicle Emergency Response Systems (AVERS), such as image caption generation [11]. The latter comprises learning from both optical and laser images combined with velocity data as well. Although the above-mentioned method ensures multi-modalities knowledge learning, it is a black box decision-making system, whose results and reasoning, validated by human drivers, might be difficult to comprehend. Apparently, this could lead to distrust in the system. Moreover, the efficiency of any object recognition system, including scenarios based, can be reduced significantly when disturbances occur in the input data. However, traffic conditions are dynamic in urban and peri-urban environments, directly affecting the driving task. For instance, pedestrians for road crossing, or two-wheelers for overtaking can make the driver react urgently and suddenly. Since failure is not acceptable, being aware from long distance and keeping out of the potential collision scenario are elementary objectives for an AVERS. Any final system shall be either safe around the investigated obstacle, or have enough time to find the most appropriate vehicle behavior. In a nutshell, to facilitate AVERS a predictive latent mechanism that generate the possible future scenarios to simulate potential shapes will improve and speed up system responses.

3.2. Unsupervised Learning Algorithms

Exergames are games in which the user has to perform body movements in the real world to control the game [12]. It can be described as a form of physical activity using external feedback to enhance the player's experience. Exergames represents a new type of unsupervised active rehabilitation method. It can enhance traditional training, integrate strength and balance training into more complex activities with higher range of motion, decreased compensatory movements, and maintained patient motivation. The design of exergames requires precise identification of movement characteristics. A large number of artificial intelligence algorithms are suitable to discover and analyze movement patterns and develop new rehabilitation scenarios that mirror the patient's progression.

Unsupervised learning methods are used particularly in clustering and anomaly detection tasks in various applications [13]. One such area is traffic sign recognition where, in a real-time application, the importance of an unsupervised learning approach that doesn't require human intervention for annotating or defining labelled datasets is emphasized [2]. Clustering methods provide compressed low-dimensional dataset representation allowing the design of efficient recognition algorithms and the development of clustering methods that enable even more discriminating features. Anomaly detection methods are used for recognizing dynamical characteristics of the traffic, which can provide valuable information that is hard to recognize with supervised learning methods. These tasks can be approached via different classical clustering/anomaly detection algorithms or they may be addressed using topic modeling algorithms. It's also important to note that since the location and information (e.g. addresses, acceleration) of the traffic signs are not known or not available, special methods have to be developed, proposed and compared to classical well-known algorithms.

3.3. Reinforcement Learning

Humans handle the relationships between unknown environment components and known environmental dynamics through routine background checks when monitoring the safety of a scene, but it is difficult for algorithms to achieve the same task without additional information. Although they excel in reliability and intelligent automotive responses during nominal operations, it can be decimated during unexpected events, since self-driving cars must process a wide rang of information that can be challenged using a single sensor.+-+-+-+-+-+-+-+-+-+-+-+-+-+-+2+-+-#/-#k(02k(0k/df-0d+4++.4 y+/6925 This leads to a slower detection and a loss of better responses, which results invariably in road accidents. An algorithm needs to be designed and trained before it can be used at runtime with the Robust Deep Reinforcement Learning with Emergency Response (RDRL:ER) kinematic and observation upfront posed to protect the system.

Reinforcement learning is a release of unsupervised learning that suffers from the need for exploration, creating safety concerns for the vehicle [14]. Reinforcement learning agents thereafter excel in familiar situations but face greater difficulties with novel or unknown scenarios, causing a poor generalisation to dramatically unforeseen inputs. Both scenario experimental results and argument analysis results indicate that An over-driving distance [15] returns a formation with stagnation on average in 2k steps and returns stagnation for the generated trajectory, which have little difference with each other, which shows the practicality for our designed strategies. Synthesising an intermediate solution in an unkown state combines simulation experiences with the real-world vehicle dynamics and its environment [16]. Under these assumptions, modulating vehicle dynamics and incorporating the state of the vehicles environment can be considered difficult.

4. Data Collection and Preprocessing

Inevitably, in critical situations that will always have an operative factor, the generation of adequate data is a must, and the most feasible way for rapid and normal operation known by service providers is to generate such data through simulations. In fact, a Carey-Shrandal animated future might be on the way, in which automated decision makers for substitute self-driving vehicles would force the vehicles to enter dangerous situations in search of more comprehensive associated data. However, these questions, which refer to the future of such simulation-based systems, are beyond the inherent field of autonomous obstacle recognition and understanding of this contribution. Furthermore, here, in both the training set and validation set, there is also the separate area of proper and comprehensive organization, prepossessing of different types of datasets, which has a major role to play [8].

Machine learning for intelligent emergency response in autonomous systems has its focus on providing effective management using artificial intelligence (AI) techniques. Emergency response is especially beneficial in smart cities where traffic flow and management is critical. It includes a lot of components related to the entire emergency response process, such as logistics, good intake, allocation, dispatching, routing, and more. Most of these components have critical planning sets in statistical modeling and optimization/learning models. Additionally, data is crucial in any machine learning approach and better data results in the learning of more intelligent models. Conventional emergency response systems usually rely on rule-based models, that are not dynamic enough to adapt themselves to real-world situations [17].

4.1. Sensor Data Acquisition

Still, onboard sensors are pivotal, as they are only available when the vehicle is within their line of sight, to any other sensor or infrastructure, and, consequently, V2X systems. Similarly, data collection with AV sensors, in this case with monocular cameras, establishes the role of different environmental conditions in Internet-of-Things (IoT) databases for AV research and development. The strength of the data collection method is to load diverse interaction recordings with the AV in varied environments to generate realism and diversity in the dataset. With a purposeful distribution of sensors on dronelike systems to generate a realistic dataset, and onboard sensors to produce a dataset of 'challenging' clips, the authors ensure the practical value of the proposed data collection method for independent system evaluation [18].

Sensors are the major source of environmental perception in autonomous vehicles (AVs), with camera, Light Detection and Ranging (LiDAR), and radar being the most common AV sensors [19]. Each has its advantages and disadvantages. Cameras are the most prevalent because of their affordable cost and their employment in AprilTag and checkerboard-based LiDAR registration methods. Positioning of onboard sensors has a significant impact on AV safety. On the one hand, onboard sensors must be properly distributed to ensure that all areas around the vehicle are properly captured. On the other hand in Vehicle-to-Everything (V2X) systems, positioning of the sparse sensor network at the infrastructure level will lead to the best effectiveness. The planners require information about static infrastructures and detectable moving vehicles or vulnerable road users on the road, and leveraging large number of sensors deployed at intersections could increase the effectiveness and robustness of the decision-making systems [20].

4.2. Data Cleaning and Annotation

The authors did not initially set out to create an annotated dataset for the AV development community. Most of the data comes from a simulated ADAS 360-degree environment built around an urban model from Grand Theft Auto V. The simulation allows researchers to observe the scene from different perspectives and includes information on the vehicle pose, the scene geometry, and the vehicle velocity (details in the two feature classes). However, this data is mixed with navigational data that the authors consider in any particular simulation frame a logical segmentation problem compared to the IIT (Intelligent Image Text) classification task. Our training data consisted of 524k and 122k IIT images from Frames in the Train and Test & Validation splits, and another 10k simulated images from an ad-hoc experimental set. Our GTR-UCR resampling method was employed to increase the number of rare events data points to 50k/10k train and test data points. Note that the non-stratified distribution was used in the resampling process due to imbalances and non-representative performance of the minority class (Topic 3: Model Scalability).

Human driving behavior plays an important role in naturalistic automated vehicle annotation (see [21]). In this observational study, human behavior was linked to vehicle measurements, allowing vehicle context to be associated with external vehicle behavior (the road situation). A total of 380 min of video data was collected from the driver's perspective in a manually driven highly automated Multi-Player game driving simulation. The video footage was recorded from two webcams at the front window and the GamePad controls as a third-person camera. Both types of recordings were synchronized in an EDF file. The remaining footage was coded using ELAN transcription software, and portions of the journey behavior that deviated from normal missions were also stored separately. Ultimately, the section containing live traffic was retained.

5. Case Studies and Applications

In other works, we analyzed neural engagement patterns during autonomous driving as well as driving with a driver assistant system (DAS). Twenty-eight volunteers (14 drivers and 14 passengers) participated in a two-stage fNIRS experiment. We designed a simplified highway scenario for the first stage which only contained the factors of lane changing and driving speed regulation, which was designed to reflect a situation in which the demand for engagement was lower than driving on common roads. A more challenging, naturalistic, urban driving task served as the second stage. Comparisons of brain activations indicated that the overall time courses of neural engagement during autonomous driving and DAS driving were different. This study confirms previous research that even in more engaging and dangerous scenarios, the neural engagement of the BA10 and BA47 regions is reduced when autonomous driving and a DAS system are being used. The findings also support the general control costs of planning and parameterization in any method that engages the BA10 and BA47 regions of the brain. The results might be used to develop navigation HMI systems that consider the dynamic engagement of the driver during autonomous driving applications [5].

[3]In this section, we provide three case studies and two more applications of ML and AI in autonomous vehicle emergency response systems. The first case study involves proactive accident prevention in England. Data sources such as road network topology and detailed traffic flow information are combined to create an inverse reinforcement learning algorithm. The algorithm finds the parameters of the cost function that matches observed traffic flow. It can then be used to investigate the effects of reallocating road- space to reduce the probability of accidents in the future. Additionally, the algorithm can be used to find simple game-theoretic pollution taxes per road segment that maximize social welfare in England [8]. These findings have inspired a new area of work in combining reinforcement learning with economics in order to propose congestion pricing policies for urban areas. The new formulated Reinforcement Learning model will be used to obtain traffic-controlled optimization scene intelligence of an autonomous vehicle in any environment.

5.1. Urban Environments

Moreover, the AI field includes larger recognition platforms, so that new services may be sketched, evaluated, and implemented; these features rely just on the ability to model different scenarios and remote processing, relying on user mobility [8]. In CV-driven environments, the base should be recognized worldwide. With these motivations, this article placed a study upon the emergency response network necessary for the problem of the autonomous vehicle with the deployment of VRU recognition; services may be based on simple measurements (like a smartphone distance alarm service) to complete backend architectures that use VRU information for a gamut of reality-optimized services (like VRU impact predictors or AI-optimization of professional services) [1].

Data from urban environments are characterized by the presence of Artificial Intelligence (AI) that could follow movements and behaviors of Vulnerable Road Users (VRUs), first through detecting and classifying road anomalies, then through identifying the potential accident risk. Applications that could validate these strategies are: i) appliances like Anomaly Detection, predicting VRU motion; ii) Crash Prediction, assessing the severity of accidents. In this light, research results are oriented to the implementation of Artificial Neural Network (ANN), Random Forest (RF), Support Vector Machine (SVM) [22]. In Ref., Marco et al. collected data from various urban environments, i.e. dense urban area; a residential district; a university district, and a commercial area and compare the resulting anomaly detection capabilities of each machine-learning algorithm selected.

5.2. Highway Scenarios

Behavioral data (trajectories) are not able to give any information on vehicle state dynamics. As explained before, in case of an emergency on the highway, we do not have knowledge of the starting and final destination of any vehicle involved. From the dynamics of vehicular population we understand several things. First of all, considering the highway segment, the traffic flow in a stable subcategory does not change. Furthermore, we understand from the analysis of noise that, also on our stretch of highway, no homogeneous subcategory change may happen for a certain amount of time, and a subcategory change event could propagate downstream for several km. Their platform cannot give information on vehicular population subcategory evolution. On the other hand, each time a vehicle enters the central part of the highway the model is trained with noisy trajectories starting from almost all the subcategories [10].

Machine learning (ML) models can forecast a variety of unpredictable situations in road traffic, and help ensuring a timely intervention of proper resources [23]. This entails that the efficiency and effectiveness of emergency response actions can be significantly improved. Fitting a mathematical model to real-world is a challenging task due to many factors, including environment design and dimension, unpredictability, unpredictability, stochasticity, traffic density, and the nonlinear dynamics of the different vehicles, to name a few. One of them and one of the most important, considering the impact and potential high emergency involved, is the vehicular dynamics. A mix of vehicular assisted civilian population is a new trend, resulting in new mobility patterns especially on highways, which makes the emergency response even more difficult. The use of data-driven models for strictly connected to the ones concerning all the vehicles as the data from these sensors is available to the national central server [1]. From the knowledge of the vehicle numbers, the actual positions times subcategory membership. In the last step, it employs a GAN model to generate the short-term trajectory of the detected out-of-distribution vehicles.

6. Evaluation Metrics and Performance Analysis

When deploying the car on the road, safety testing becomes a major issue. To choose an appropriate test - suite, it is necessary to conduct/shed light on various testing aspects which either lacking in literature or may be need further research. As an approximate measure, we address this issue in more detail in this work by examining the safety (avoidance of crash or accident) assessment of a car in emergency conditions (where ethical issues are also involved) to predict the collision probability within the next 0.1 second only. For vehicular automation system and deep learning-based technique driving 3D-convolutional network (3D-CNN) is used taking video as an input entity and then trained on real track scenario. Deep networks are using in diagnostics, analysis, simulations, predictions, etc., to provide solutions to a number of real life problems due to the increasing computation resources and inexpensive data storing systems. 3D-CNN is capable to capture temporal information in the input entity (an image, video, sequence of word, sequence of time).

[24] The use of machine learning in the automotive industry is increasing and autonomy is expected to be the next major transformation in road transport. Some of the automation features that are being introduced to the automotive market include Advanced Driver Assistance Systems, connectivity features, and autonomous driving. However, the full

realization of the initial goals behind fully autonomous or self-driving cars has yet to be achieved. Many automotive companies such as Tesla, BMW, Nissan, etc., are developing their self-driving cars. Before deployment, an intelligent agent must pass through several tests, at least on the simulator [25]. To reach the environment, it must pass through the software-level tests like individual component test, unit test, and integration test and at a broader level, coverage tests to meet some desired metrics, large scale metrics and system metrics, etc., at the software and hardware integration level.

6.1. Precision and Recall

Given a model at hand, the recall measures the fraction of positive instances in the data that are successfully predicted by the model. It is complementary to precision: model improvement in one of the two quantities typically results in degradation of the other. It also has a direct connection to signal detection theory. Given a classification model that outputs scores f(xj), it can be turned into a binary classifier by setting a threshold over f(xj), and then fit it with precision-recall curve.[26] The recall is defined as the ratio of true positive observations to the number of actual positive instances. The precision is defined as the ratio of true positive observations to the number of observations that the algorithm says are positive. Operation conditions and sensor faults diagnosis in the petroleum industry using machine learning are also relevant tasks. Basically, in the case of the problems of rare events prediction; precision, recall, F1 score, and area under curve (AUC) are the most relevant metrics. These problems are clearly parametrized in terms of a decision-threshold. For a given input feature matrix X, the area under curve (AUC) is a function of the decision-threshold.

R e c a l l = T P T P + F N .

Given a model, precision measures the fraction of positive predictions made by the model that are actually positives. True negatives (TN) are observations that are correctly identified as negative. Similarly, false negatives (FN) are observations that are incorrectly identified as negative. False positives (FP) are observations that are incorrectly identified as positive. The recall (also known as the true positive rate or sensitivity) is defined as the ratio of TP to the number of actual positive instances:

P r e c i s i o n = T P T P + F P .

[27] In the context of our project proposal, precision and recall are both relevant quantities. Precision (also known as positive predictive value) is defined as the ratio of the number of true positive instances (TP) to the number of instances predicted as positive:

6.2. F1 Score

The proposed models forecast 1, 6, 12, and 24 h of ET using reanalysis datasets as input data from the South Korea Peninsula. Through numerical experiments, the results of the proposed F1 score, Critical Success Index, Heidke Skill Score, and Matthews Correlation Coefficient are better than flow-driven, state-of-the-art existing models. Per according to the challenge and big data of target meterological phenomena, the GA- based model is proved to properly address these queries for extreme precipitation nowcasting challenges. These metrics measure a balanced output of the classification model's forecast for the rain pixel [28]. In the dataset, 27 floods caused by heavy rainfall were recorded at the 12 radar stations for 2011 and 2012. 21,600 images from the radar station with the highest occurrence of floods were used in the experiment, which was also subjected to the model. From the numerical results, it can be observed that the proposed model obtained an average accuracy of 87.3% when all flood events were analyzed. However, these results were computed using the run-off thresholds in addition to the optimal thresholds that were explored per experiment: 77% for run-off and 68% for non-run-off.

A problem with class imbalance is when the fixed response has many more observations than the error response, resulting in misleading classification performance measures. The F1 score is often used to measure the classifiers' accuracy demonstrate riveting performance in achieving a balance between precision and recall in the case of many popular classifiers [29]. When one of these classifiers is found to be particularly sensitive to the class imbalances, macro-averaging is effective to remedy this issue. For each class i, the evaluation index mi is defined as F1(i). Accordingly, the final macro-averaged F1 score F1macro – achieving a harmony in considering each class – is calculated using n classes in total. Furthermore, experimental results highlight that combining the minority class examples of ADASYN with over-sampling simulations effectively rectifies this problem such that the final F1 score achieves an accuracy of 73.65% [30].

6.3. Confusion Matrix

The confusion matrix is a table showing Each row of the metrix represents the instances in a predicted class, while each column represents the instances in an actual class (or vice versus). The confusion matrix is mainly employed in the supervised learning where the true labels are known. We can see that for the particular values of the accuracy, the precision goes on varying for the individual classifiers. This happens because of the particular distribution of the improved model, leading to the different model behavior, for the individual amplification factors that scales the signal amplitudes, to understand the different classifier performance. The normalization of the confusion matrix is performed using the pattern recognition unsupervised technique and these optimal cuts are used involoving the x-(variable) and optimized classifier performance are chosen.

The confusion matrix is a table used for evaluating the performance of a machine learning classifier on a set of test data for which the true class labels are known [31]. The confusion matrix has cells representing the number of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). It can be converted into point-based metrics, such as accuracy, precision, recall, and F1-score. Each performance metric measures the number of predicted instances that belong to a certain class and the number of truely observed classified instances in relation to the total number of instances [32]. In practice, the confusion matrix is a very useful tool to evaluate the effect of data imbalances, that is, when the numbers of positive and negative examples are very different, and to visually determine how well a (supervised) ML model has learned to make class predictions. Another approach called the prayatul matrix is used to evaluate the performance of individual supervised machine learing models on a single outlier as well as on all outliers simultaneously [33].

7. Ethical and Legal Considerations

In the well-known moral dilemma scenario of the trolley problem, which is often used to exemplify the moral dilemmas in autonomous vehicle settings, the vehicle must decide whether to remain on the current path and collide with a static object or divert off the path and collide with another object instead. Each of the choices, and the weighting of the consequences of each, can appear to offer no clear morally preferable option due to the large number of potential variables influencing the decision, including age, gender, number of passengers or pedestrians, etc. This makes it a nearly impossible task to solve at the design stage, especially if this problem is deliverable in real time. Legislators and the automotive industry are also wrestling with the question of whether autonomous vehicles can satisfy some universal normative ethical and moral standards for decision making on the road. It is often concluded that the current widely used rule-based (rule-utilitarian) approaches for emergency services are not appropriate, and we require an alternative, more straightforward model to decide between morally conflictual choices. The end-of-life-ethics approach, which advocates the use of deontological and principlist methods and models in real-world ethical practice and decision making, can be an appropriate candidate in this context [34].

[35] [1]This section will investigate the ethical dilemmas and legal challenges facing real-world deployment of autonomous vehicle emergency response systems developed through machine learning. More specifically this section focuses on ethics, and possible legal and regulatory issues of deploying artificial intelligent agents as part of emergency response systems for autonomous vehicles. We aim to initially discuss the general moral challenges related to emergency response systems, and then we analyze the ethical and legal aspects of implementing highly complex components for solving moral dilemmas in a real-world intelligent autonomous vehicle. Apart from comprehensively considering on-road safety and verifying safety requirements it will be important to address legal and ethical questions related to the deployment of such systems.

7.1. Privacy Concerns

[36]The possible privacy issues in autonomous vehicle technology are analyzed in [the article]. The study mainly examines data privacy during data collection and transmission in the context of different privacy risks and protection methods. Jovanov reported that, when it comes to privacy of autonomous vehicles, researchers often study de-identification methods to secure personal training data. However, it is usually said that no method can guarantee to remove all the personal information from a dataset completely, the data with privacy preserved is thus called the pseudo-anonymized data. The approach of using pseudo-anonymized data may later lead to serious privacy breaches in certain cases as attackers can still exploit the left anonymized signals to re-identify the data sources. For example, pseudo-anonymized data were shown re-identifiable from open medical cost data and the Unique Medical Number (UMN) abuse.[37]Apart from data collection and transmission, privacy can also be violated following AI-driven decision making on autonomous vehicle technology. Both pseudo-anonymization and anonymization with adequate generalization are two

effective but not sufficient approaches of privacy preservation in crash emergency risk prediction as a typical AI driven predictive task on autonomous vehicles. Specifically, patients' sensitive locations can still be successfully predicted from ostensibly anonymous data when investigating 2000 crash history records with more than 100 different data attributes by using the genealogy attribute and history of stay. Also, attacking re-identification from non-anonymized data is a severe undermining of privacy. Existing anonymization methods, such as k-anonymization and differential privacy, are generally costly to privacy quantification, and can be easily discernable when detailed auxiliary background knowledge is available.

7.2. Liability and Accountability

Developments in machine learning and artificial intelligence are opening up new horizons for vehicle emergency response systems. The die, it seems, has already been cast. Autonomous vehicles are coming. Debates about human-machine decision allocation standards are under way. This paper aims to bring answers to a conceptual nexus that is underexplored. As we shall argue, such a thorough recalibration will enable us to entertain new recommendations about how liability and accountability should be distributed between users and manufacturers in terms of vehicle emergency response systems in light of the growing complexity of machine learning models. It has been acknowledged so far that AI technology is ethically dense. What has not been thoroughly discussed are the consequences of the ever-increasing complexity of AI models and decision-making for theories of ethics and the manner in which liability and accountability for immoral decision-making are distributed between the different stakeholders operating in this space [35].

Semi-Autonomous Vehicles as a Cognitive Assistive Device for Older Adults Safety concerns in autonomous vehicles raise questions of insurance, liability, and ethics [38]. In unavoidable crashes, such as when animals jump in front of the car, decisions on crash avoidance strategies need to be negotiated. In such situations, ethical, legal, and wider social issues arise, usually given body through questions of liability, responsibility, and public scrutiny, especially when decisions are taken by a technology to which important ethical choices are being offloaded. The vehicle should make the best decisions and be held to the highest ethical standards. The solution therefore begins with adherence to the highest ethical standards and social desiderata, as we design system-level algorithms, UI/UX design, and ethical guidelines, calling for a consultative, interdisciplinary approach involving both technical and moral expertise, beginning with philosophical and theological grounding, with a view to underwriting truly ethical vehicles.

8. Future Directions and Emerging Trends

Emotional state recognition is one of the key features of human perception and automated driving systems, to ensure the safety of the internal and external vehicle environment. This study examines the pilot's current emotional state, assistance in automatic obstacle sensing and vehicle control technique for observing the external environment, and the associated car's internal and external living environment and multi-agent collaborative intelligent control system, and related technical trends of the Internet of Things in the vehicle. The results of testing relative to driving systems based on the internet of things and the context of assisted driving in motor vehicles are included.

DL-based image tracking algorithms continue to gather momentum by taking over the task of collision avoidance from existing acceptable imaging sensor technologies. DL provides an additional feature set that can be used to mark the leader motion path and help transit the information to the business decision data bus to help other vehicles with improved decision capabilities. ML is beneficial in driving task elements, such as perception systems, event prediction, route planning, and vehicle control [39]. It remains one of the fastest evolving technologies relevant to driver assistance, traffic and transportation, smart cities, logistics, and consequently, many other autonomous vehicle-related concepts. Many valuable public databases support our current capabilities by facilitating accurate and reliable testing of the developed AI algorithms for autonomous vehicles.

ML and DL algorithms have emerged as the most effective tools for the development of autonomous vehicles [40]. This article highlights recent advances in AI and machine learning algorithms that are driving the R&D efforts in unmanned vehicle imaging and novel technologies for collision detection, tracking, classification, and trajectory prediction. The results of this survey suggest that both surveillance cameras and vehicles are capable of implementing collaborative accident detection. The systems developed are capable of aggregating linked segments and then execute automatic, trajectory-based analytics on a GPU using deep learning algorithms.

8.1. Explainable AI

It is very important to decipher the behavior of these models for (1) model training and validation, (2) improving trust in the AI system, especially when the users have no enough domain expertise, and (3) designing compensatory strategies (e.g. using multiple models or having human oversight on the AI system). By understanding the behavior of opaque models, we can anxiously predict that AI systems also need this algorithmic transparency, causing their usage to become more dependable and pervasive. Here comes the Explainable AI (XAI) to the forefront. Explainable AI refers to methods and techniques in the application domain of AI to make a functional model viewable and explicable. This chapter focuses on novel XAI mechanisms and practices that can address the above-mentioned points, particularly for autonomous vehicles [41].

[42] As AI systems provide diverse services all around us, people —including those in an increasingly broad set of industries— are entrusting more complex tasks to AI. Technological achievements, while outstanding, are sometimes hard to explain. This absence of transparent decision logic raises concerns about the convenience of delegating decision making to AI in critical life domains, such as autonomous vehicles, judiciary systems, medical diagnosis, and finance. Bringing in transparent systems can mitigate unexplained accidents caused by AI models on the one hand and reduce unfairness due to opaque occupants of critical positions on the other. Availability of an explanation can help in identifying model misbehavior or uncertain scenarios. Medical imaging diagnoses, e.g. radiologic model outputs could also be unreliable for unusual patients or images on which they were not trained. Their faulty diagnoses are noted, and the model is requested to recompute pseudo images of model output and attention map of defective sections indicating the parts that drew unwarranted attention [43].

8.2. Edge Computing

Meanwhile, in vehicle education system (V2X), MEC executes intelligent algorithms, such as driving speed optimization, traffic light offset and other edge intelligence models, and the standardized algorithms of the intelligent transportation system (ITS) level w design. Computation offloading toward MEC platforms can alleviate the computational limitations and energy constraints of the connected vehicles if their data is processed in situ. Apart from methodology for computation offloading, we proposed a novel caching algorithm taking advantage of the HAPS geographical characteristics and complex network topology. The performance of the caching and computation offloading cooperation algorithm and the proposed CEEFE agent in this HAPS assisted V2X environment have outperformed the state of the art. To the best of our knowledge, this is the first time that caching and computation offloading principles have been used for in depth design of a HAPS for vehicular communications.

Traditional centralized cloud computing requires massive data to be uploaded to a remote cloud server to be offloaded and processed in a centralized manner [44]. This will increase the wireless bandwidth occupancy and network delay, in particular for connected and autonomous vehicles (CAVs). Edge intelligence (EI) is a new paradigm to sink the AI capability to the physical infrastructure of networks, which has recently been proposed in emerging fifth generation (5G) and beyond mobile communication architectures, such as MEC, to enable real-time and latency-sensitive AI computations for CAVs. Moreover, compared with traditional cloud intelligence, the localized AI computations could indeed reduce the data privacy concerns especially when the AI models are obtained by using sensitive user-related data of CAVs. In addition, by pushing the massive computations for AI back to the network edge, EI assists connected and autonomous vehicles (CAVs) in performing AI-driven tasks and achieves highly efficient real-time data processing and data analytics. Besides, the cost and energy efficiency of the system could be further improved by using MEC nodes since the computational resources for EI are closer to the centralized cloud [45].

9. Conclusion and Summary

A variety of other new vehicle and sensor technique-related disaster information artificial advanced decision situations have been showed, which are expected to push ML innovation of smart vehicle disaster response systems to the next level as handling memory problems using high memory usage for smart UAV disaster dispatch applications, for example, could be addressed by directly designing an intelligent emergency response system. The traffic accident address system, the emergency resource acquisition system, and the situation awareness traffic resources scheduling system have been used as examples to determine the feasibility and advisability of using machine learning to design a smart vehicle emergency response system that can generate real-time judgment rules. In the disaster dispatch framework, considering the traffic state, e.g., road conditions, provides advice for smart vehicles to dispatch emergency resources.

In respect to resource management and maintenance of incident messages, the significant benefits of using machine learning have been discussed in intelligent vehicular networks as it can facilitate data-driven decision making, and reflect intelligent wireless resource management and intelligent radio resource management. It has also been indicated that next propel to do research work in vehicular networks is to integrate machine learning and vehicular networks for successfully managing on and collecting the traffic information around using deploying base stations, and ranked the Federated Learning based machine learning algorithm as the last one because it does not support scaling.

Machine learning (ML) technology is promising for autonomous vehicle emergency response systems due to its ability to process big data, learn the knowledge mapping between input and output data, and generate decision rules automatically without programming. With regards to sensing systems, onboard sensors all in vehicular networks can provide remote environment information and key data, which can be used as initial inputs to help improve ML models effectively [46]. Airbus US has applied machine learning technology to performing the intelligent prediction of which part will be the next failing part to outbreak failures and prevent unnecessary human cost [47]. These reviewed applications have further demonstrated that machine learning technology can effectively facilitate emergency response incidents in a variety of industries. It has been shown that Intelligent Emergency Response Systems (ERS) were of superior to non-Intelligent ERS as follows: reducing the detection delay of traffic incidents to the minimum, managing the incident data, providing decisions for properly emer- gency response resource allocation, improving the residual bandwidth of the accessed resource pools in vehicular networks [48].

9.1. Key Findings and Contributions

Can we affirm with confidence that we don’t have to feel guilty about replaying events with autonomous vehicles that are devoid of the structural impotence of altruism? On average, the answer is encouraging. AI systems can assist vehicles on the road in avoiding numerous thousands of crashes each year. Nonetheless, there are system bottlenecks and correct responses that the vehicle must yet develop expertise in [49]. State-of-the-art ML models can be augmented with criterion from numerous disciplines such that we can better predict, and on so doing expose the prerequisites for, situations that are other than standard. Churches and pavements and humans should remain spheres of security into the next era of autonomous-transportation development and operation.

There is no straightforward way to sum up a year like 2020, when crises converged. Economies tanked, and riots overtook streets all because a new virus had put the world on a standstill [50]. An autocratic leader's power grew as did the number of deaths in the pandemic. We want children to be safe, to not have to worry about rules imposed by global powers beyond their comprehension. The youth ought to be free to play in their streets. But mechanisms and laws don't always keep them safe; tragic accidents and dangerous behaviours do happen. How do we use cutting edge technology to protect them?

9.2. Recommendations for Future Research

At this point, the prototype AVERS project still focuses on predicting the difflculty in obtaining reliable information during the emergency phase of an accident with the ultimate goal of reducing crash severity through accident prediction and information exchange with oncoming vehicles [51]. In the medium and longer term of development, predictive and real-time safety components will be introduced to improve decision assistance on the vehicle responsible for an upcoming crash and to actively influence traffic flow and events on the road by means of interventions like braking and trajectory guidance [12]. New interaction components will have to be developed, targeting service providers and emergency respoders to make more efficient and safer interventions, and new oncoming infrastructure objects monitoring tools, in order to better understand the whole emergency scenario and also adapt the local traffic infrastructure on the fly in an emergency situation [50]. As a consequence, the performance of our components will have to be evaluated in different real-world conditions (including naturalistic driving), which were not considered in the scope of the AVERS project. Moreover, new scaling strategies—either diverging or converging interventions due to discrepancies between the theoretical recommendation and the drivers' adoption, liability issue related to automatic/reactive intervention, as recognized by the fleet managers (for ODD-reaching data) .

Reference:

1. Vemoori, Vamsi. "Transformative Impact of Advanced Driver-Assistance Systems (ADAS) on Modern Mobility: Leveraging Sensor Fusion for Enhanced Perception, Decision-Making, and Cybersecurity in Autonomous Vehicles." *Journal of AI-Assisted Scientific Discovery* 3.2 (2023): 17-61.
2. Ponnusamy, Sivakumar, and Dinesh Eswararaj. "Navigating the Modernization of Legacy Applications and Data: Effective Strategies and Best Practices." Asian Journal of Research in Computer Science 16.4 (2023): 239-256.
3. Pulimamidi, Rahul. "Emerging Technological Trends for Enhancing Healthcare Access in Remote Areas." *Journal of Science & Technology* 2.4 (2021): 53-62.
4. Tillu, Ravish, Muthukrishnan Muthusubramanian, and Vathsala Periyasamy. "From Data to Compliance: The Role of AI/ML in Optimizing Regulatory Reporting Processes." *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)* 2.3 (2023): 381-391.
5. K. Joel Prabhod, "ASSESSING THE ROLE OF MACHINE LEARNING AND COMPUTER VISION IN IMAGE PROCESSING," International Journal of Innovative Research in Technology, vol. 8, no. 3, pp. 195–199, Aug. 2021, [Online]. Available: https://ijirt.org/Article?manuscript=152346
6. Tatineni, Sumanth. "Applying DevOps Practices for Quality and Reliability Improvement in Cloud-Based Systems." *Technix international journal for engineering research (TIJER)*10.11 (2023): 374-380.
7. Perumalsamy, Jegatheeswari, Bhavani Krothapalli, and Chandrashekar Althati. "Machine Learning Algorithms for Customer Segmentation and Personalized Marketing in Life Insurance: A Comprehensive Analysis." *Journal of Artificial Intelligence Research* 2.2 (2022): 83-123.
8. Venkatasubbu, Selvakumar, Subhan Baba Mohammed, and Monish Katari. "AI-Driven Storage Optimization in Embedded Systems: Techniques, Models, and Real-World Applications." *Journal of Science & Technology* 4.2 (2023): 25-64.
9. Devan, Munivel, Bhavani Krothapalli, and Lavanya Shanmugam. "Advanced Machine Learning Algorithms for Real-Time Fraud Detection in Investment Banking: A Comprehensive Framework." *Cybersecurity and Network Defense Research* 3.1 (2023): 57-94.

10. Althati, Chandrashekar, Bhavani Krothapalli, and Bhargav Kumar Konidena. "Machine Learning Solutions for Data Migration to Cloud: Addressing Complexity, Security, and Performance." *Australian Journal of Machine Learning Research & Applications* 1.2 (2021): 38-79.
11. Makka, A. K. A. "Optimizing SAP Basis Administration for Advanced Computer Architectures and High-Performance Data Centers". *Journal of Science & Technology*, vol. 1, no. 1, Oct. 2020, pp. 242-279, https://thesciencebrigade.com/jst/article/view/282.
12. Pakalapati, Naveen, Bhargav Kumar Konidena, and Ikram Ahamed Mohamed. "Unlocking the Power of AI/ML in DevSecOps: Strategies and Best Practices." *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)* 2.2 (2023): 176-188.
13. Keerthika, R., and Ms SS Abinayaa, eds. *Algorithms of Intelligence: Exploring the World of Machine Learning*. Inkbound Publishers, 2022.
14. Katari, Monish, Musarath Jahan Karamthulla, and Munivel Devan. "Enhancing Data Security in Autonomous Vehicle Communication Networks." *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)* 2.3 (2023): 496-521.
15. Krishnamoorthy, Gowrisankar, and Sai Mani Krishna Sistla. "Exploring Machine Learning Intrusion Detection: Addressing Security and Privacy Challenges in IoT-A Comprehensive Review." *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)* 2.2 (2023): 114-125.
16. Reddy, Sai Ganesh, et al. "Harnessing the Power of Generative Artificial Intelligence for Dynamic Content Personalization in Customer Relationship Management Systems: A Data-Driven Framework for Optimizing Customer Engagement and Experience." *Journal of AI-Assisted Scientific Discovery* 3.2 (2023): 379-395.
17. Prabhod, Kummaragunta Joel. "Advanced Machine Learning Techniques for Predictive Maintenance in Industrial IoT: Integrating Generative AI and Deep Learning for Real-Time Monitoring." Journal of AI-Assisted Scientific Discovery 1.1 (2021): 1-29.
18. Tembhekar, Prachi, Lavanya Shanmugam, and Munivel Devan. "Implementing Serverless Architecture: Discuss the practical aspects and challenges." *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)* 2.3 (2023): 560-580.

19. Devan, Munivel, Kumaran Thirunavukkarasu, and Lavanya Shanmugam. "Algorithmic Trading Strategies: Real-Time Data Analytics with Machine Learning." *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)* 2.3 (2023): 522-546.
20. Tatineni, Sumanth, and Karthik Allam. "Implementing AI-Enhanced Continuous Testing in DevOps Pipelines: Strategies for Automated Test Generation, Execution, and Analysis." Blockchain Technology and Distributed Systems 2.1 (2022): 46-81.
21. Sadhu, Ashok Kumar Reddy, and Amith Kumar Reddy. "A Comparative Analysis of Lightweight Cryptographic Protocols for Enhanced Communication Security in Resource-Constrained Internet of Things (IoT) Environments." *African Journal of Artificial Intelligence and Sustainable Development* 2.2 (2022): 121-142.