Machine Learning for Autonomous Vehicle Road Condition Analysis

By Dr. Manuela Veloso

Professor of Computer Science, Carnegie Mellon University (Branch outside normal colleges)

1. Introduction to Autonomous Vehicles

Autonomous vehicles (AVs) are at the forefront of the automotive industry. This is part of global technological advancements with the ultimate goal of commercialization as modern transportation infrastructures move toward complete automation [1]. Artificial intelligence (AI) platforms include several different functionalities, such as machine learning (ML) or deep learning (DL) algorithms, navigation sensing systems, and others. ML techniques are used to analyze and decide on different situations detected by AVs' onboard sensors. Expert systems with specialized knowledge learned and imparted by diverse ML and DL cybersecurity models monitor the navigation sensory data created by sensors and decide on the real-time conditions of the travel.[2] Autonomous vehicles carry out the driving task (DT) by sensory data resembling human sensory perception. The DT elements of AVs can be categorized into four major components: perception, event prediction, data processing, and route planning. Most ML and DL models for AVs are related to perception systems where changes in real-time driving conditions and the surrounding environment are detected. In order to process all of these functionalities, we need a pertinent processing unit with storage capacities and a high processing rate. New conditions sensed by AVs are categorized as normal or abnormal because AVs analyze these new conditions with the data saved in their storage infrastructures. Turning to normal conditions, AVs themselves take the necessary action. If the detected conditions are abnormal, the specialist system alerts remote AVs' human operators, and the control goes to the AVs' human operators.

1.1. History and Evolution of Autonomous Vehicles

From the early beginnings of the 20th century where Maurice LeBlanc was the first to speak of the high abilities of an airplane and the car and cause among many others also the idea of their autonomous navigation, until the beginning of this century where Google has to retrieve Sparrowhawk, the self-driving cars have passed genes related to the return of the first

Autonomous Car of Lockheed, the Stanford University's vehicles Junior and Stanley, the competition of the DARPA challenges and Google's self-steering car. These vehicles have a range of sensors like lidar, ultrasonic sensors, high definition map for positioning, vision systems for recognition and classification, GPS and odometry [3].

Road vehicles have been evolving together with the computational, electronic, and mechanical development and in recent years engineers from all over the world are trying to solve problems related to autonomous navigation, goods movement and people transportation, reducing street traffic and accidents occurrence, while making transport more effective. These are the reasons why big companies in the automotive sector like the familiar to us the "Alphabet" and "Tesla", startups and university researches are investing a lot of resources to make it possible to have autonomous vehicles driving through streets and cities by themselves [4].

1.2. Current State of Autonomous Vehicle Technology

Autonomous vehicles require four essential components, namely perception, trajectory prediction, sensor fusion, and path planning in order to navigate in their environment. Perception allows an autonomous vehicle to know the current states of the objects surrounding the vehicle using the onboard sensor systems. Trajectory prediction predicts where these objects in the state space in a future time. These trajectories are then fusion of sensor outputs in order to obtain a global belief. Based on this state estimation on fusion, the vehicle generates a path of waypoints to a goal on an on-vehicle route by path planning [5]. SDC-NET is introduced as a real-time multitasking end-to-end self-driving neural network algorithm for camera-based autonomous vehicles by designing multitasking architecture for trajectory prediction and target prediction. Briefly, SDC-NET stands for Self Driving Camera NETwork and is proposed as an end-to-end multi-task self-driving camera cocoon IoT-based system and its main motivation is to overcome the problems caused by multiple sensors to operate in synchrony, obtaining a more focused deep learning model, and establishing more successful communication by shortening the real-time and maintenance costs.

Driving is among the deadliest activities in the world and is a mentally and visually demanding task so that the advent of new automatic technologies with the aim of decreasing the number of traffic accidents also attracts great interest [6]. The current research interest in this field is growing rapidly, with a focus on driver assistance systems that are adept in road and lane keeping. Although it is believed that autonomous vehicle technology has been around for the last decade, initial work using wire-guided vehicles began much earlier in the 1920s. Research works have used an adaptive cruise control system that can follow a vehicle in front without touching any input, being the first attempt with independent control on steering, gas, and brakes, a first attempt. In this era, the capability of obstacle detection has also been implemented. Autopilots, systems and multi-sensor-based controllers were developed and integrated to increase traffic safety through continuous monitoring of drivers and taking necessary precautions before any problems occur. The first visual algorithm on road detection was also created at this time. Furthermore, classical AI methods and conventional road detection techniques were used for two-dimensional road and lane recognition images. In the early 1990s, convolutional neural networks (CNNs) were used for the first time for driving tasks in the field of machine learning [7]. In the current decade, the focus has been shifted from robotics techniques to deep learning, especially CNNs. Many researchers have used CNN architecture to solve other problem sets, such as the driving scene detection task from the year 2011 and the semantic segmentation and instance segmentation task from 2013, that have been attracting attention intensely.

2. Importance of Road Condition Analysis

Descriptions of the technologies involved in different phases, the procedures to test the different layers for the functional use and for the retardation of the thermal energy will be described. The infiltration of the total carbon dioxide in the environments in the two scenarios, to simulated, then the complete scale of the indoors and outdoors, it will be initially analysed. For this purpose it will be also designed and realised two pavements with different integration of stone of Carrara and resin, for the urban area and for the rural area, respectively. At the end we can describe an innovative and self-compacting concrete pavement with sensors that are able to collect data on local humidity, temperature and stress/strains, while taking care to guarantee the best pedestrian comfort and safety for road traffic.

[8] [9] The principal objective of the road condition evaluation is to collect valuable data that allow to understand different road quality profiles. This discussion can be open, in the future, to considering the surface anisotropy, allowing us to characterize in further details the roughness profile. This would provide the possibility to take into consideration also the ISO Standard 11439:2000 - Road vehicles – Test procedure for simulating single, vertical-to-oblique

wheel impacts – Frontal impact into a kerb, published by ISO – International Organization for Standardization (https://www.iso.org), the Technical Specification ISO/TS 11818:2012 - Road vehicles – Test specification for impact testing of pedestrian protection systems – Road-crossing pedestrians, published by ISO – International Organization for Standardization (https://www.iso.org), the International Standard 11320:2011 - Acoustics - Evaluation of human- exposure to vibration in buildings (1 to 80 Hz), published by ISO – International Organization for Standardization (https://www.iso.org) and several other references driver as international standards references albeit dealing with technical issues different from the one considered in the present work. The ROAD-experience Project, funded with the title "Design of new type of road surfaces (in concrete) by the valorization of residues from the stone and marble processing" as part of the Laboratorio Artigian-oriented research: Laboratory for innovative research and production technologies for the implementation of new products or transferable knowledge for various crucial socio-economic fields, Axis 1 - Environment, Tourism and Security, axis of excellence BT7 MAR.LAB, aims at developing a new type of road surfaces in concrete by the enhancement of the residues of the processing of stone and marble, with particular attention to technological, mechanical, functional and, respectively, environmental and sustainable characteristics. The project aims at designing new production processes of the material through refining and functionalization treatments in order to make it particularly suitable in the realization of two new concrete pavements [4 – 6]. The first one is meant to be employed in urban areas and the second one in extra urban contexts.[10] A project is innovative not just in the scope of realization of new innovative materials from a completely innovative chain of production but also for the introduction of a road construction process for both the first and the second pavement made using precast panels upon which a heating system for the scaling and ice removal will be positioned (detailed design and technology of realization). In the particular case we want also to exploit the sunlight energy improving the use of eco-friendly energy and developing a dynamic pavement to use in conditions of adverse weather such as ice, snow and black ice. The final design products will be different kinds of custom-made concretes with the addition of high amounts of stone and marble sludge obtained by cutting of these materials for the production of polished surfaces and low amounts of micro and nanoadditives that will allow to reach high performances in terms of water absorption, resistance to wear, tear and abrasion.

2.1. Impact on Safety and Performance

The impact of non-optimal infrastructure conditions leads to inefficient and costly driving experiences, logistical planning, and vehicle maintenance. To extend the useful life of roads, construction and transportation engineers are employing innovative technological strategies to better monitor and preserve road conditions. The demand for new techniques to visually detect poor road conditions becomes apparent as traditional strategies are slow, costly, and involve an insufficient area coverage. Several studies have recently addressed the road assessment issue and introduced various systems that sense road conditions automatically while driving. For example, literature conducted to detect crack types and classifications has recently gained public attention. For example, Jalal et al. developed a generalized state-ofthe-art review on road distress detection methods, such as roadsurface crack detection and pavement defect recognition and measurement. Justesen et al. proposed a method to detect road surface defects and to grade the road surface quality. Ta et al. presented a vision-based operating system that detects and assesses potholes in road conditions by using gyroscope and accelerometer sensors. Sobotkiewicz et al. proposed a novel edgelet orientations-based image features for pothole idealization and segmentation, In the recent years, image processing-based solutions have gained attention due to the rapid improvements in machine learning and computer vision techniques.

Many people around the world lose their lives or properties by unintentional incidents such as traffic accidents and road crashes. These accidents are a critical public health issue that requires immediate intervention [11]. It is estimated that the annual economic loss due to the accidents in Turkey is 38 billion and therefore is the priority of the transportation system for every country [12]. On- road epithets of interaction between connected and automated vehicles and the non-vehicular traffic components. Besides, with the improve of connected and automated vehicle technology, it is aware that level of safety has been increased to the upper level to reduce human errors for accidents. In this paper, it is focused on three main themes of driving, weather condition and road surface condition [13]. Intelligent detection methods of driving simulation program is also proposed in particularly.

3. Machine Learning in Autonomous Vehicles

LIDAR that calculates obstructions on road and enables road condition analysis was the primary means of choosing an autonomous vehicle till 2015. This system, however, lacks direct prediction of global features of the road itself and its neighboring road, and is not capable enough to perform in dark, foggy, or under stormy conditions. Computer vision-based systems typically require vigorous data set construction but has the advantage of being unaffected by weather shifts. In later, Android smart-phone with three-axis sensors provide with requirement of low data storage space as unique and pragmatic sensors, and it is allowed by researchers to directly explore the detected multi-road anomaly on account of machine learning (ML). Another shape of this system is the collection of both magnetic and gravity field by inertial measures unit as input to calculate an arbitrary system closed form solution with Kalman filter modularity at point position of the detected anomaly. It is also planned as software for offline use without any communication for vehicles and communication cost energy saving.

[14]Machine learning (ML) is a key technology for autonomous driving (AD) as of today (even though exploitation of it has not yet hit the fina stage) [15]. It is being explored in almost every aspect like prediction of highway curve of sight, trail, and driver behavior. The lane change prediction at the macro and micro level, doing away with training of AI steering control with left/right commands, and terrain sensing techniques has already been found to be satisfying [9]. Various ML algorithms like decision trees, BPN, SVM, etc., have been evaluated and it has been observed that for maneuver classification decision trees perform best with a classification accuracy of more than 90%. For sign aversion, bagging ensemble classifier has been found to outperform other tested ML algorithms. Displacements between neighboring frames and optical flow have been extracted as ST analysis features, respectively, as features for SVM classification. DLMs have also been explored in spotting of different maneuvers on hill. Another way to make a vehicle autonomous is through road condition analysis.

3.1. Types of Machine Learning Algorithms

Machine learning systems have three primary types: supervised learning, unsupervised learning, and reinforcement learning. The types are selected according to the nature of the problem. In task IBM, QD and DRV, different types of ML algorithms were deployed. Supervised learning (SL) is a human-in-the loop process in which an "input" image or frame is fed into a CNN for detecting objects in a scene, whereas "ground-truth" data is feedback from detected objects to rectify the CNN weights [6]. Unsupervised learning (UL) provides output images on the "model prediction (MP)" criterion, which are obtained by pixel-wisely enhancing the model-generated measurement. Reinforcement learning (RL) is similar to UL but also employs image-level reward information and interacts with the environment with policy and value optimization objectives through a terrain following image-formation process. In the task RVR, well-studied SL methods, evolutionary algorithm, extreme learning machine, woke hold fixed weight algorithm, and cooperative group optimization are exploited to adjust depth and semantic labels concurrently.

ML-based techniques, especially neural network (NN) models, have become highly effective solutions in vehicular applications due to the increase in sensor-generated data [16]. Neural network algorithms primarily consist of three main layers—input, hidden, and output. An optimal system can be established by designing a neural network structure according to the particular problem (e.g., number of input and hidden layers, number of neurons in the hidden layer(s), learning rate, and maximum iterations). A hyperparameter optimization phase should be added to achieve a better performance. In autonomous driving, a human-like decision-making method was proposed using Convolutional Neural Networks (CNNs) for tasks such as object detection, tracking, and driving dynamics adjustment. The CNN proposed a method implementing the simultaneous proposals network (SPN) for detecting the target region (Kobashikawa et al. 2018). The proposed learning algorithm showed a steady improvement in detection performance over various proposals on the KITTI dataset.

3.2. Applications in Road Condition Analysis

The other type of task in road condition analysis is pavement crack detection [17]. According to the literature, the study of the pavement condition is known to be important for control tasks, road maintenance, and the safety of drivers. Keeping roads in good condition and ensuring proper management of road repairs provides a substantial benefit. Therefore, frequent road surveys should be made, and the road condition of each travel lane should be reported. In this line of work, detailed surveys are made infrequently. Automatic systems should be considered to complement manual work, especially when public resources are limited. Detecting and reporting the number and positions of pavement cracks would be beneficial for automatic pavement condition surveys. Considering the high quality of the achieved results in classifying pavement cracks and noncrack regions, this method can be practically used as a reliable source of knowledge to feed a road condition assessment system. All approaches have focused on a static solution to find pavement cracks in images, where the vehicles are either stationary or driving slowly. The application of a dynamic solution to perceive road anomalies while speeding up on the road is missing in this domain. So one of the current tasks recently became road condition monitoring systems for the autonomous vehicle.

The use of visual sensors is a prominent feature of autonomous vehicles. One of the main applications in the field of Computer Vision using visual sensors for an autonomous vehicle is road condition analysis [8]. This is important to make it possible to make the right decision based on the current flow of vehicle traffic on the roadway specified by the traffic rules and guidance. The main tasks for road condition analysis include surface problems such as potholes, gravel, as well as their spatial locations and/or occlusion. To increase the accuracy and reliability of these tasks, it is important to use these sensor approaches with machine learning models. In recent years, a variety of datasets and machine learning models have been introduced. Semantic segmentation is one type of model that is capable of dealing with all of these tasks.

4. Data Collection for Road Condition Analysis

A variety of sensors such as cameras, radars, Light Detection and Ranging (LiDARs), Global Navigation Satellite Systems (GNSSs) are used in autonomous vehicles. All these sensors generate data that can be used for identifying different road conditions and road surface types. During the last decade, many papers have been published on the subject of road condition analysis. However, there is no standard benchmark dataset available, which limits the comparability of the developed road condition analysis solutions. Therefore, collecting a road condition analysis dataset has been set as the first step for developing machine learning-based solutions [8].

The performance of machine learning models heavily depends on the quality and quantity of the training data [ref: 08fee5369e7f390, 459cee8b-7c99-480e-a649-641e67ce8152]. This is particularly true for supervised learning tasks, which are used in many computer vision problems in the automotive industry. Developing machine learning-based road condition analysis tools for autonomous vehicles is not an exception. These tools are designed for conducting road maintenance activities and ensuring road users' comfort and safety.

4.1. Sensors and Data Sources

These technologies paired with existing autonomous veinetwork is able to drive predictively avoiding unreasonable accelerations is an important asset for a semi-autonomous vehicle to urge acceptance within existing traffic. Finally, abundant experimental results have shown that the proposed model is ready to be connected robustly, effectively, and swiftly in various highly asymmetric situations by the ODisict strategy and may drive noticeablv additional stably than the state-of-the-art approaches in comparative studies. This strategy consists of a bidirectional information transfer between a hybrid dynamic model and an action-value network, and it enables real-time functional relevance, multitask learning of multiple sequential tasks.

[18] [19] [20] Autonomous vehicles can perceive their surroundings using different types of sensors and data sources, including cameras, inertial measurement units (IMUs), and global navigation satellite systems (GNSS). Tritrakarn et al. utilize high-speed cameras to allow an autonomous vehicle to observe its surroundings and navigate through a Bengali neighborhood. They propose a graph-based network model that processes multimodal image data and attends to salient regions in each modality before aggregating them into a feature representation. The model demonstrates impressive real-time adaptive behavior and generalizes to unknown neighborhoods. Bull et al. use onboard cameras, LiDARs, GPS and IMU data to enable trucks to exhbt a controlled behavior with respect to the rest of the traffic on highways. Their probabilistic approach reasons over learned behavior models and is backed by an extensive dataset of highway traffic scenarios, recorded with their test vehicle during a pilot experiment.

5. Preprocessing and Feature Extraction

The introduction of the language model-based localization of the environment of interest while introducing a different and complementary discriminating power for the obtained features, we will similarly develop a the training strategy with a mixture of self-supervision and a takemedosthing benchmark similar to. Once we have the final dataset, we will develop a pipeline in three parts. In parallel we perform two self-masked training steps in confidence order makeformed retraining to boost weak ROI at state time all over crossentropy at every ECA of the else network along with the connected stop leak so that we do not backpropagate gradients of out of our background the mask form network into our main network too. This strategy of masking the losses over unsupervised bootstrapping and defusing the Leaks during training schedule is detailed in this section.

[ref: 8271d262-d06a-4953-88b4-262d587ce7f1, d704cce8-fc61-4cee-88ec-8aa54ea26437] The UAV datasets are captured in various environmental conditions and locations. UAV captured images are usually taken at very high resolution for a part of the scene, far exceeding the typical 1920 * 1080 pixel format that neural networks are usually trained on. Hence, prepreprocessing the images is important. Furthermore, false positive detection is possible, in order to reduce the number of false positive detections in the region of interest, one must refer to existing literature to introduce two methods: a detection method based on the use of a Vision-Language Model (CLIP, a Transformer model designed for zero-shot image-text retrieval) to rapidly discard the UAV images that are of no interest, and a full-resolution auxiliary self-supervised tasks aiming to obtain more robust features within which to bootstrap our supervised training can be used. We discuss here the details regarding the employed tools and recent false positives filter strategy from [4,22], including its justification and results.

5.1. Noise Reduction and Data Cleaning

Data preprocessing is done to improve to enhance and extract the characteristic signature of the data. The data preprocessing is done to operate the machine learning algorithms for efficient predictions. The machine learning algorithms require very big size of the data to yield good results. It's very difficult to handle and learn through these data; therefore, the data extraction is done and also the features are extracted to learn through the data. The deep learning algorithm require the big size of the data to make the prediction. Therefore, to require a big size of the sample data, first we extracted the cadence related time domain signal for 7 different locomotion activities from the dataset where they have taken 10 km/h and individual foot step length [21].

The ease of connectivity of modern on-board diagnostic sensors (OBD) in modern vehicles helps to replace human inspection of car parts and car parts reliability with the machines' inspection automatically. The extracted generated data is used for the predictive maintenance. Different machine learning algorithms are used by the researchers to assist the users for fault diagnosis or road conditions assessments for Autonomous Vehicle applications. In one research work, the multi-layered architecture of different machine learning algorithms is implemented for the fault diagnosis of mechanical system for industrial purpose. The main aim of the work was to enhance and extract the characteristic signature of accelerometers and establish a database of the spectral characteristic accelerometers and use the data base for training the Random forest classifier and two other classifiers. The machine learning technique was examined on the data of vehicles and was able to predict the vehicle's axis position based on the Data [22].

6. Model Development and Training

On image classification our data pipeline improvement almost doubles the model performance as measured by F-Score. On the center canal detection tests both on the RNT dataset and the RNT-RDDR combined one and the one on the RNT-USGS combined test data set our model loses in performance compared to the one that we fine-tuned on the RNT date G. Our data augmentation with partially distributed labels improves our detection performances significantly. It is important to note RDDR dataset is labeled with photos from actual cracks, potholes, etc. While both RNT and USGS can classify label cracks and undamaged regions. This gives RDDR dataset an advantage. By augmenting both datasets with each other, the model has to learn to classify while maintaining the capability of detection. Our analysis on the effect of some of the discussed augmentation techniques has demonstrated the competitive performance on the real-life data sets.

Creating an effective machine learning model to be used for road condition analysis requires the utilization of a reliable and informative dataset [23]. In the described model, the data generation pipeline is taking information from the U.S. Geological Survey national map and augmenting it with ground truth data from the Road Damage Detector smartphone application. The proposed approach generates a data augmentation pipeline that combines these sources and can use the most recent USGS and RDDR maps in its lifetime [8]. Subsequently, the information from both sources is used independently to generate accurately labeled images for both the classification and detection tasks that the model in the following uses. For a fixed walk, the ground truth labels do not change but could potentially change over time. This pipeline is used solely for generating the augmented data for the training part of this work. The pipeline generates 1024x1024 images that correspond to both the center canal detection task as well as a binary classification task by taking into account the names of the local maps from which the USGS and RDDR names were extracted. As a real world data assessment, we apply greedy optimization based on a cost function that non-linearly combines spatial error, accuracy, and recall and predict in a classification and detection way.

6.1. Supervised Learning Techniques

Autonomous vehicles are capable of recognizing the road surface and analyzing the road environment in a higher degree as the level of automation continues to improve. Classical pixel comparison methods have low robustness, and relevant features that can describe different road terrains are difficult to extract. DL model—convolutional neural network (CNN) is a machine learning algorithm and has now been widely used in autonomous vehicles to assist in road recognition and road condition analysis. Garcia et al. proposed a Multispectral and Multimodal Dataset aimed towards the study of road surface characterization and classification in the context of autonomous driving. They introduced datasets of images concerning asphalt pavement and urban gardens, and, according to the results, the models trained with dataset A using different classifier algorithms demonstrated that CNN models considerably outperformed other algorithms, including SVM, Decision Trees, Bagging, Random Forest, AdaBoost, and Naive Bayes.

Various machine learning (ML) techniques, including supervised, unsupervised, and reinforcement learning, are used in autonomous vehicles for tasks such as efficiently recognizing road signs and lights and recognizing vehicles. Machine learning models, particularly deep learning (DL) models, are more widely used in autonomous vehicles. For example, some works have proposed object recognition methods that use deep learning as their core algorithm, and, to some extent, these methods can achieve real-time implementation to recognize the vehicle's sequential objects of interest. This information can be inferred from the literature review conducted by Osaka .

7. Evaluation Metrics for Road Condition Analysis Models

[9] Performance evaluation metrics play an important role in assessing the effectiveness of a system. In this study, since road condition category classification is a 3-class problem, the notion of accuracy just providing the ratio of the correct cases to the total number of cases was not quite suitable for a multi-class classifier. To account for the class imbalance data distribution by checking incorrect class distribution, precision and recall calculation was necessary to reveal the classification efficiency. The performance of the binary classification

of the majority class (smooth) between rare classes (bumpy or others) is expressed by the specificity level calculated as shown in Equation (9). The opposite case is that the classification efficiency of the majority class (smooth) between the rest of the rare classes includes the measure of sensitivity level (positive predictive value). These rate values can also be presented more clearly from the confusion matrix to be obtained depending on the classification results [24].[25] Algorithm metrics using temporal decision windows illustrate more efficiently the steering behavior prediction performance of the machine learning algorithms used for behind-the-scene modeling of the human drivers. Evaluation experiments performed indicate a significant decline on the steering prediction performance if the decision inputs are obtained from the observed data within the limits of a decision window. The explanation of decision window effect on machine learning algorithm performance in this research should ensure improvement on offline evaluation metrics regarding the autonomous driving systems. If biased development data is preferred to be applied online quality metrics in real autonomous vehicle scenarios, quite possible issues may be presented in front of developers regarding the result system quality. During that performance bias may depend on the simulation model.

7.1. Accuracy and Precision

A proposed prediction model's precision can be restricted to the Populated Area by considering a given Prest for a given area, which may appreciate the fact that a poor model prediction on clear roads can be costlier than on highly-populated areas. The computed precision can be used to establish the behaviors of scores over time. We can also truncate the precision metrics when the True Positives rate is zero in order to avoid issues when the overall score is used for comparing different models. Improved precision also yields improved stability, in terms of an updated algorithm performing better especially on zebra-crossings. The confusion matrices allow better diagnostics especially when dealing with heavily skewed towards one class [26].

The accuracy of the underlying machine learning model for road condition analysis is crucial. We use the term accuracy specifically when a model generates a binary output: road condition as good, where the road and surrounding environment is in good condition. Further discussions are based on the vocabulary used in [17]. Precision measures the fraction of positive (good condition) classifications made by the model that are actually correct and is computed as the ratio of the True Positives to the sum of True Positives and False Positives of the model. In our scenario, precision can be interpreted as the fraction of road attributed as such which are actually in good condition.

8. Challenges and Future Directions

Futuristically, this task should also be clearer for night-time method inventors especially since most dangerous accidents can be linked up to this time interval in several countries. [27] This stage is crucial for performance evaluation, especially for a car following task; therefore, the working conditions for testing the deep learning and conventional edge detector methods fit the reality of both road and traffic condition detection methodologies for some other car-following tasks, such as intent recognition and driver intention estimation. Therefore, the most recent trend in achieving road and traffic condition detection research dependencies upon machine learn- ing techniques like K-Nearest Neighbor (KNN), Principle Components Analysis (PCA), a Support Vector Machine (SVM), and long-short term memory (LSTM) & cetera as the deep learning model.

[8] In addition to recognizing various vehicles and vulnerable road users, an autonomous vehicle can perform edge detection and predict car trajectory by examining the intersection of pedestrian paths. To propose a possible solution, computer vision and machine learning models could be utilized to help cause significantly fewer traffic accidents and fatalities. Detecting roads through computer vision is a perceptually straightforward problem and has been researched for quite some time now. As reviewed in Peters and McMahon, edge detection is the major approach to gather various feature types for signaling. In the context of AS, edge detection would be performed only for road detection and road boundary finding, whereas for LNC, more task-tailored information should be extracted for lane-edge finding while considering shadows, light variations, blockages and other categories of challenging events which would not have a major effect on road surface detection.

8.1. Overcoming Data Limitations

Furthermore, Internet of Vehicles (IoV)-based vehicular ad-hoc networks (VANETs) also offer probabilistic world models and short-term charts for spatial relaxation, which provide the basis for the full road recognition process from the speed bumps to the potential road anomalies. When the experiments are performed under various real-life conditions, responses of the system demonstrate that the proposed approach can be high in response rates, and the results of the classification stage allow machines to reach the attached ground truth by up to 94% in the first 35 test points ([28]). The proposed system has many potential applications, such as its ability to support firefighting (by sensing underground fire line conditions in fog-computing networks), locating water table positions (both inland and submarine), and urban city scanning using autonomous route profiling.

To address the challenges of big data and limited mobility in fog computing and overcome the data limitations, the proposed road detection system is capable of detecting vertical acceleration anomalies in a time- and cost-efficient manner with high detection accuracy. Specifically, prior to the system being activated horizontally, vertical acceleration data that has previously been obtained from a number of mobile crowd-sourced agents is utilized ([14]). In addition, Google Maps' elevation service is used to extract data on the location of interest. Consequently, upon encountering a target anomaly, the smartphone's sensors send its anomaly-seeking data directly to a fog node along with data on the following working parameters: stable location, the deceleration value in the horizontal direction, the anomaly resistance affecting the system, the comfortable resistance for the suspension, and the steering wheel's turning rate. The anomalous visualizations are generated by the machine learning algorithm in accordance to the implemented genetic algorithm frameworks, where the road is recovered from the visual score of the detected anomalies, providing an easily comprehensible and stable detection mechanism between the detected anomalies ([9]).

9. Conclusion

In this project, we collected road data using a smartphone sensor. The data were used to train three machine learning models and were tested on two different classification datasets. Each classification model detected road conditions. Our machine learning models were trained to classify eight different categories of road conditions in ICDSS-Rone, and five categories on the other which was set in a different paradigm to improve generalization ability. Mean performance of our machine learning models was well in both testing datasets; three models performed similarly on average, . Although we could find some weaknesses, the proposed models showed great promise. Also, the proposed protective models have the potential to reduce traffic accidents as higher detection rates indicated by the regional evaluation results.

Taken together, we introduced a machine learning approach to the analysis of road conditions that used a model of a driver's vehicle. The approach involves a dual scheme of object classification and tracking. Three Bayesian recurrent neural networks (BRNNs) were used to classify the presence or absence of all objects on the road,ic walking robots and smart cars and motorcycles moving on-roadways surround the author, robot tracked object states. When moving, road conditions and the complexity of traffic increase continuously, which makes object detection and tracking difficult. For the moving phase of the BP neural network and Long Short-Term Memory network, the vehicle traffic state in both the vertical and horizontal directions is established by acquisition of data for different off-road traffic conditions. For example, in the detection mode, data collection remains passive and data sources include roads, at roadwayjunctions, and inside tunnels constituting the detection environment of different traffic states; in thetracking mode, data acquisition is active and the tracked objects include on-road walking robots and smart cars and motorcycles moving on-roadways or terrace road surfaces. Humidity will sometimes destroy our previous trajectory but will slowly grow up and the last time point will be larger than the data point.

[14] [8]Concluding, this system was successfully developed to monitor the road condition. The implemented application is integrated with a machine learning model (i.e., NN model) and a GPS sensor to automatically monitor the road. Several machine learning models was implanted into our system and their results for classification of the road condition were compared. It is noteworthy to mention that since our main aim was to propose an easy-to-install application for smartphones, minimizing of the resource of the machine learning models and regulation of the size of the models were of high importance. The proposed predictive models, which are beneficial for decision makers in solving road problems based on the patterns, using the proper classifier model boost traffic flow optimization. We also explored other research work related to road analysis, which have taken a similar classification approach. In initial work, most models used supervised classification for the proposed approach. Kohonen and Multi-Kohonen self-organizing map models were tested for the building of an unsupervised classification model after 2 years of operation of TR). Also, for this analysis, PCA dimension reduction techniques and Decision Stump feature reduction were used. In our future work, the unsupervised models will also be built and the models will be compared. Semi-supervised classification method, autoencoder, VAE, and GAN architectures will also be the models to develop in our future study.

References:

1. [1] S. Kuutti, R. Bowden, Y. Jin, P. Barber et al., "A Survey of Deep Learning Applications to Autonomous Vehicle Control," 2019. [PDF]
2. [2] A. Hossein Barshooi and E. Bagheri, "Nighttime Driver Behavior Prediction Using Taillight Signal Recognition via CNN-SVM Classifier," 2023. [PDF]
3. [3] D. Garikapati and S. Sudhir Shetiya, "Autonomous Vehicles: Evolution of Artificial Intelligence and Learning Algorithms," 2024. [PDF]
4. [4] Łukasz Sobczak, K. Filus, A. Domański, and J. Domańska, "LiDAR Point Cloud Generation for SLAM Algorithm Evaluation," 2021. ncbi.nlm.nih.gov
5. [5] M. Abdou and H. Ahmed Kamal, "SDC-Net: End-to-End Multitask Self-Driving Car Camera Cocoon IoT-Based System," 2022. ncbi.nlm.nih.gov
6. Tatineni, Sumanth. "Cost Optimization Strategies for Navigating the Economics of AWS Cloud Services." *International Journal of Advanced Research in Engineering and Technology (IJARET)* 10.6 (2019): 827-842.
7. Vemori, Vamsi. "Towards Safe and Equitable Autonomous Mobility: A Multi-Layered Framework Integrating Advanced Safety Protocols, Data-Informed Road Infrastructure, and Explainable AI for Transparent Decision-Making in Self-Driving Vehicles." *Human-Computer Interaction Perspectives* 2.2 (2022): 10-41.
8. Mahammad Shaik, et al. "Unveiling the Achilles' Heel of Decentralized Identity: A Comprehensive Exploration of Scalability and Performance Bottlenecks in Blockchain-Based Identity Management Systems". Distributed Learning and Broad Applications in Scientific Research, vol. 5, June 2019, pp. 1-22, https://dlabi.org/index.php/journal/article/view/3.
9. [9] I. Ferjani and S. Ali Alsaif, "How to get best predictions for road monitoring using machine learning techniques," 2022. ncbi.nlm.nih.gov
10. [10] Y. Zhang, A. Carballo, H. Yang, and K. Takeda, "Perception and Sensing for Autonomous Vehicles Under Adverse Weather Conditions: A Survey," 2021. [PDF]
11. [11] R. Trabelsi, R. Khemmar, B. Decoux, J. Y. Ertaud et al., "Recent Advances in Vision-Based On-Road Behaviors Understanding: A Critical Survey," 2022. ncbi.nlm.nih.gov
12. [12] U. Bhatt, S. Mani, E. Xi, and J. Zico Kolter, "Intelligent Pothole Detection and Road Condition Assessment," 2017. [PDF]

13. [13] H. Kim, W. Wan, N. Hovakimyan, L. Sha et al., "Robust Vehicle Lane Keeping Control with Networked Proactive Adaptation," 2020. [PDF]
14. [14] G. Kim and S. Kim, "A Road Defect Detection System Using Smartphones," 2024. ncbi.nlm.nih.gov
15. [15] C. S. Alex Gong, C. H. Simon Su, Y. H. Chen, and D. Y. Guu, "How to Implement Automotive Fault Diagnosis Using Artificial Intelligence Scheme," 2022. ncbi.nlm.nih.gov
16. [16] Y. Yang, T. Dwyer, K. Marriott, B. Jenny et al., "Tilt Map: Interactive Transitions Between Choropleth Map, Prism Map and Bar Chart in Immersive Environments," 2020. [PDF]
17. [17] I. Meftah, J. Hu, M. A. Asham, A. Meftah et al., "Visual Detection of Road Cracks for Autonomous Vehicles Based on Deep Learning," 2024. ncbi.nlm.nih.gov
18. [18] S. Chen, S. Zhang, J. Shang, B. Chen et al., "Brain Inspired Cognitive Model with Attention for Self-Driving Cars," 2017. [PDF]
19. [19] D. Dong and Z. Li, "Smartphone Sensing of Road Surface Condition and Defect Detection," 2021. ncbi.nlm.nih.gov
20. [20] F. Garcea, G. Blanco, A. Croci, F. Lamberti et al., "Self-supervised and semi-supervised learning for road condition estimation from distributed road-side cameras," 2022. ncbi.nlm.nih.gov
21. [21] H. H. Rashidi, S. Albahra, S. Robertson, N. K. Tran et al., "Common statistical concepts in the supervised Machine Learning arena," 2023. ncbi.nlm.nih.gov
22. [22] B. Or, N. Segol, A. Eweida, and M. Freydin, "Learning Position From Vehicle Vibration Using an Inertial Measurement Unit," 2023. [PDF]
23. [23] T. Siriborvornratanakul, "Human behavior in image-based Road Health Inspection Systems despite the emerging AutoML," 2022. ncbi.nlm.nih.gov
24. [24] Y. Qin, J. Wu, W. Xiao, K. Wang et al., "Machine Learning Models for Data-Driven Prediction of Diabetes by Lifestyle Type," 2022. ncbi.nlm.nih.gov
25. [25] F. Codevilla, A. M. López, V. Koltun, and A. Dosovitskiy, "On Offline Evaluation of Vision-based Driving Models," 2018. [PDF]
26. [26] S. Jin, H. Lee, C. Park, H. Chu et al., "A Visual Analytics System for Improving Attention-based Traffic Forecasting Models," 2022. [PDF]
27. [27] L. Mora, X. Wu, and A. Panori, "Mind the gap: Developments in autonomous driving research and the sustainability challenge," 2020. ncbi.nlm.nih.gov

28. [28] H. Fahmy and S. Mahrajan, "Vehicular Safety Applications and Approaches: A Technical Survey," 2022. [PDF]