A DRIVING DECISION STRATEGY BASED ON AI FOR SELF-GOVERNING VEHICLE

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Abstract: A current independent vehicle decides its driving system by thinking about just outer variables (People on foot, street conditions, and so forth.) without considering the inside state of the vehicle. To take care of the issue, this paper proposes "A Driving Decision Strategy (DDS) Based on AI for a self-governing vehicle" which decides the ideal system of a self-governing vehicle by breaking down not just the outer variables, yet additionally the inside elements of the vehicle (consumable conditions, RPM levels and so on). The DDS learns a hereditary calculation utilizing sensor information from vehicles put away in the cloud and decides the ideal driving procedure of a self-ruling vehicle. This project contrasted the DDS and MLP what's more, RF neural system models to approve the DDS. In the analyse, the DDS had a misfortune rate around 5% lower than existing vehicle entryways and the DDS decided RPM, speed, directing point and path changes 40% quicker than the MLP also, 22% quicker than the RF.

1. INTRODUCTION

Artificial intelligence (AI) uses data, computers and technology to simulate the human mind's problem-solving and decision-making abilities (Anjum, 2021). AI can be defined as "the study of agents that receive precepts from the environment and perform actions" (Harris, 2022). It is essentially the end ever of producing systems with human-like cognitive behavior such as the ability to reason, solve a problem, discover meaning and perceive from past experience and act accordingly. Machine Learning and Deep Learning approaches are combined in AI (Copeland, 2022). Today, AI has numerous uses. AI has increasingly gained importance due to its ability to address various problems in business. AI is making our daily lives more convenient and efficient. One of the growing applications of AI is in the field of automotive industry and self-driving cars are an excellent example of that. (Education, 2022). Self-driving vehicles, also known as autonomous or driverless cars, are cars or trucks which do not require human drivers to take control, for safely operating the vehicles. Such cars are composed of sensors in software to control, navigate and drive the vehicle. Self-driving cars are essentially built using artificial intelligence. In self-driving cars applications of AI can be deployed in conjunction with advanced technological innovations like GPS, radar, camera, cloud services and control signals. AI can further enhance users' experience by adding value features such as blind-spot monitoring, emergency braking and driver-assist steering (Dilmegani, 2022). The problems like poor road safety, lesser independence for the disabled, high costs, less productivity, traffic congestion, high travel time, environmental pollution associated with conventional cars can be prevented with self-driving cars (Benefits of Self-Driving Vehicles, 2018). Today the vehicles are not just machines they are intelligent, highly advanced, technological, and innovative machines. The main motivations behind research on autonomous vehicles (AV) are safe driving, increase in population and vehicles on the road, comfortable and stress free driving and effective use of available resources (Parekh et.al, 2022). According to Bathla et.al (2021) AI powered applications play a major role in designing AVs intelligent system especially in improving the safety standards (2021). The study also emphasized that in order to implement AI in practical complex environments, the autonomous system needs to be integrated with multiple advanced technologies like Internet of Things (IoT), cloud computing and block chain. IoT lets AVs collect relevant data automatically. IoT sensors collect road traffic related data at various traffic signals and AI models use this data to take further decisions. AI powered Natural Language Processing (NLP) and speech recognition applications are used to understand the text and speech instructions in AVs. Safavietial (2021) discuss the functioning of sensors in autonomous vehicles. Advanced neural networks are used to predict the malfunctioning of sensors such as faulty sensor prediction, identification, and isolation.

2. LITERATURE SURVEY

2.1 Ata M. Khan, Ataur Bacchus, Stephen Erwin 2012 [1] were proposed the convergence of information and communication technologies (ICT) with automotive technologies has already resulted in automation features in road vehicles and this trend is expected to continue in the future owing to consumer demand, dropping costs of components, and improved reliability. While the automation features that have taken place so far are mainly in the form of information and driver warning technologies, future developments in the medium term are expected to exhibit connected cognitive vehicle features and encompass increasing degree of automation in the form of advanced driver assistance systems. Although autonomous vehicles have been developed for research purposes and are being tested in controlled driving missions, the autonomous driving case is only a long term scenario. This paper contributes knowledge on technological forecasts regarding automation, policy challenges for each level of technology development and application context, and the essential instrument of cost effectiveness for policy analysis which enables policy decisions on the automation systems to be assessed in a consistent and balanced manner. The cost of a system per vehicle is viewed against its effectiveness in meeting policy objectives of improving safety, efficiency, mobility, convenience and reducing environmental effects.

2.2 Rui Zheng, chunming Liu, Qi Guo 2013 [2] were proposed a decision-making method for autonomous vehicles based on simulation and reinforcement learning There are still some problems need to be solved though there are a lot of achievements in the field of automatic driving. One of those problems is the difficulty of designing a decision-making system for complex traffic conditions. In recent years, reinforcement learning (RL) shows the potential in solving sequential decision optimization problems, which can be modeled as Markov decision processes (MDPs). In this paper, we establish a 14-DOF dynamic model of an autonomous vehicle and use RL to build a decision-making system for autonomous driving based on simulation. The decision-making process of the vehicle is modeled as an MDP, and the performance of the MDP is improved using an approximate RL. At last, we show the efficiency of the proposed method by simulation in a highway environment.

2.3 Julius Ziegler, Philipp Bender, Markus Schreiber, Henning Lategahn 2014 [3] 125 years after Bertha Benz completed the first overland journey in automotive history, the Mercedes Benz S Class S 500 INTELLIGENT DRIVE followed the same route from Mannheim to Pforzheim, Germany, in fully autonomous manner. The autonomous vehicle was equipped with close-to production sensor hardware and relied solely on vision and radar sensors in combination with accurate digital maps to obtain a comprehensive understanding of complex traffic situations. The historic Bertha Benz Memorial Route is particularly challenging for autonomous driving. The course taken by the autonomous vehicle had a length of 103 km and covered rural roads, 23 small villages and major cities (e.g. downtown Mannheim and Heidelberg). The route posed a large variety of difficult traffic scenarios including intersections with and without traffic lights, roundabouts, and narrow passages with oncoming traffic. This paper gives an overview of the autonomous vehicle and presents details on vision and radar-based perception, digital road maps and video-based self-localization, as well as motion planning in complex urban scenarios.

2.4 Christos Katrakazas, Mohammed Quddus, Wen-Hua Chen, Lipika Deka 2015 [4] Currently autonomous or self-driving vehicles are at the heart of academia and industry research because of its multi-faceted advantages that includes improved safety, reduced congestion, lower emissions and greater mobility. Software is the key driving factor underpinning autonomy within which planning algorithms that are responsible for mission-critical decision making hold a significant position. While transporting passengers or goods from a given origin to a given destination, motion planning methods incorporate searching for a path to follow, avoiding obstacles and generating the best trajectory that ensures safety, comfort and efficiency. A range of different planning approaches have been proposed in the literature. The purpose of this paper is to review existing approaches and then compare and contrast different methods employed for the motion planning of autonomous on-road driving that consists of (1) finding a path, (2) searching for the safest manoeuvre and (3) determining the most feasible trajectory. Methods developed by researchers in each of these three levels exhibit varying levels of complexity and performance accuracy. This paper presents a critical evaluation of each of these methods, in terms of their advantages/disadvantages, inherent limitations, feasibility, optimality, handling of obstacles and testing operational environments.

2.5 Ning Ye , Yingya Zhang , Ruchuan Wan 2016 [5] were proposed an Intelligent Transportation Systems (ITS), logistics distribution and mobile e-commerce, the real-time, accurate and reliable vehicle trajectory prediction has significant application value. Vehicle trajectory prediction can not only provide accurate location-based services, but also can monitor and predict traffic situation in advance, and then further recommend the optimal route for users. In this paper, firstly, we mine the double layers of hidden states of vehicle historical trajectories, and then determine the parameters of HMM (hidden Markov model) by historical data. Secondly, we adopt Viterbi algorithm to seek the double layers hidden states sequences corresponding to the just driven trajectory. Finally, we propose a new algorithm (DHMTP) for vehicle trajectory prediction based on the hidden Markov model of double layers hidden states, and predict the nearest neighbor unit of location information of the next k stages.

2.6 Hongbo Gao, Guotao Xie, Lijun Qian, Bin Huang 2017 [6] were proposed a Vehicle trajectory prediction helps automated vehicles and advanced driver assistant systems have a better understanding of traffic environment and perform tasks such as criticality assessment in advance. In this study, an integrated vehicle trajectory prediction method is proposed by combining physics- and maneuver-based approaches. These two methods were combined for the reason that the physics-based trajectory prediction method could ensure accuracy in the short term with the consideration of vehicle running dynamic parameters, and the maneuver based prediction approach has long- term insight into future trajectories with maneuver estimation. In this study, the interactive multiple model trajectory prediction (IMMTP) method is proposed by combining the two predicting models. The probability of each model in the interactive multiple models could recursively adjust according to the predicting variance of each model. In addition, prediction uncertainty is considered by employing unscented Kalman filters in the physics-based prediction model. To the maneuver-based method, random elements for uncertainty are introduced to the trajectory of each maneuver inferred by using the dynamic Bayesian network. The approach is applied and analyzed in the lane changing scenario by using naturalistic driving data. Comparison results indicate that IMMTP could achieve a more accurate prediction trajectory with a long prediction horizon. The problems raised in this system is effectiveness, and practical applicability "This system does not work efficiently. It needs improvement"

3. EXISTING SYSTEM

k-NN, RF, SVM and Bayes models are existing methods Although studies have been done in the medical field with an advanced data exploration using machine learning algorithms, orthopedic disease prediction is still a relatively new area and must be explored further for the accurate prevention and cure. it mines the double layers of hidden states of vehicle historical trajectories, and then selects the parameters of Hidden Markov Model (HMM) by the historical data. In addition, it uses a Viterbi algorithm to find the double layers hidden states sequences corresponding to the just driven trajectory. Finally, it proposes a new algorithm for vehicle trajectory prediction based on the hidden Markov model of double layers hidden states, and predicts the nearest neighbor unit of location information of the next k stages.

4. PROPOSED SYSTEM

We will propose an feature selection with MLP and RF algorithm to compute the sensor data
to determine the optical driving strategy of an autonomous vehicle.

- Impact on Environment

Impact on environment (not OS or SW used), Examples – Reduction in global warming, reduce pollution, simplicity of usage, time reduction etc.,

- Safety

Impact on various areas mentioned (but not limited to) Security (data, network, information), privacy etc.,

- Ethics

General SW ethics for building an application or solution like (but not limited to) – does not harm any person (physically or virtually), securing privacy information of the resources using application (secure login, not exposing personal details in any form) etc.,

SYSTEM ARCHITECTURE

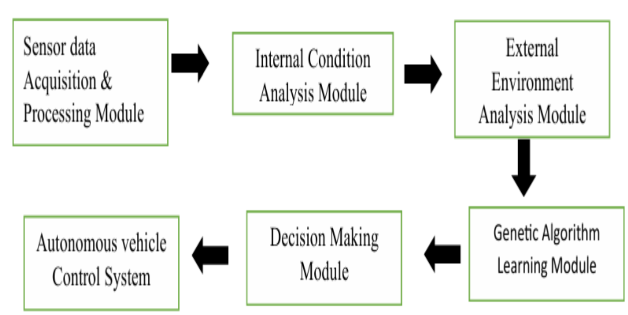

Fig 1: System Architecture

5. UML DIAGRAMS

1. CLASS DIAGRAM

Class diagram is a static diagram. It represents the static view of an application. Class diagram is not only used for visualizing, describing, and documenting different aspects of a system but also for constructing executable code of the software application. Class diagram describes the attributes and operations of a class and also the constraints imposed on the system. The class diagrams are widely used in the modelling of object oriented systems because they are the only UML diagrams, which can be mapped directly with object-oriented languages. It is also known as a structural diagram. Class diagram contains • Classes • Interfaces • Dependency, generalization and association.

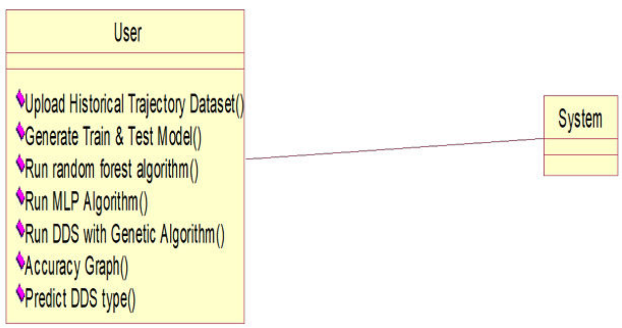

Fig 5.1 shows the class diagram of the project

2. USECASE DIAGRAM:

Use Case Diagrams are used to depict the functionality of a system or a part of a system. They are widely used to illustrate the functional requirements of the system and its interaction with external agents (actors). In brief, the purposes of use case diagrams can be said to be as follows

• Used to gather the requirements of a system.

• Used to get an outside view of a system.

• Identify the external and internal factors influencing the system.

Use case diagrams commonly contains

• Use cases

• Actors

• Dependency, generalization and association relationships.

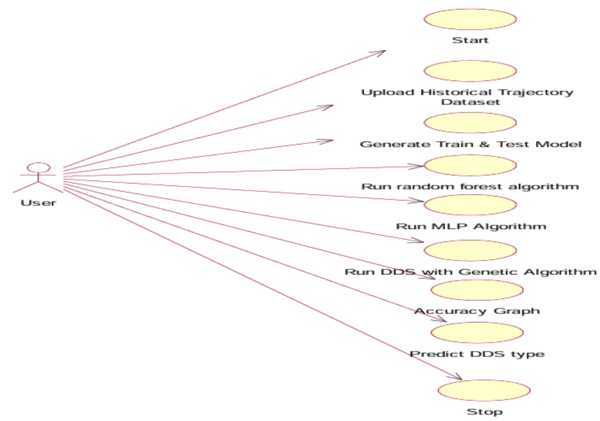

Fig 5.2 Shows the Use case Diagram

3. SEQUENCE DIAGRAM:

A sequence diagram simply depicts interaction between objects in a sequential order i.e. the order in which these interactions take place. We can also use the terms event diagrams or event scenarios to refer to a sequence diagram. Sequence diagrams describe how and in what order the objects in a system function. Sequence diagrams are used to formalize the behaviour of the system and to visualize the communication among objects. These are useful for identifying additional objects that participate in the use cases. These diagrams are widely used by businessmen and software developers to document and understand requirements for new and existing systems.

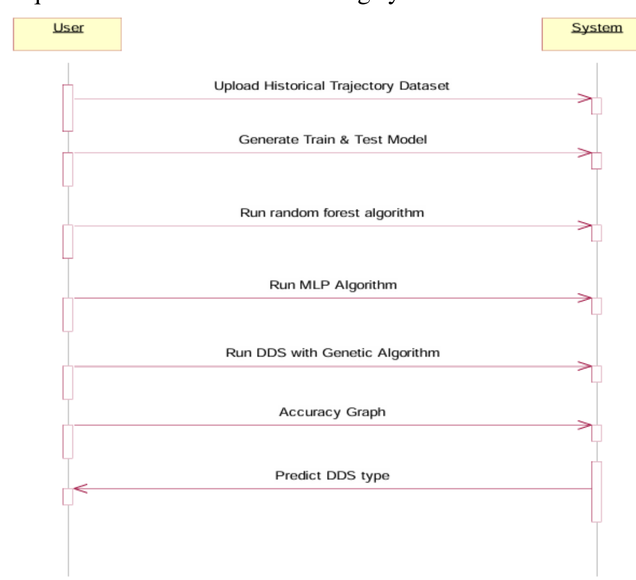

Fig 5.3 Shows the Sequence Diagram

6. RESULTS

6.1 Output Screens

In below screen click on 'Upload Historical Trajectory Dataset' button and upload dataset

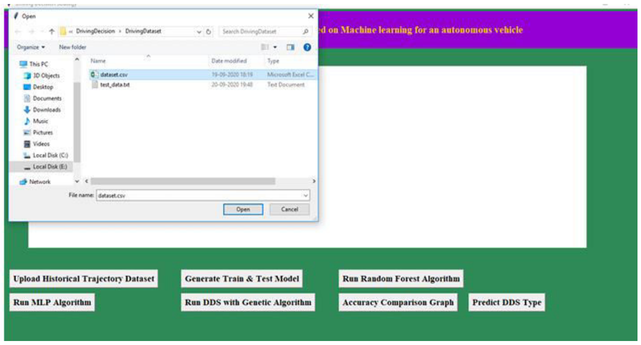

Fig 6.1 Upload the Historical Trajectory Dataset

Now select 'dataset.csv' file and click on 'Open' button to load dataset and to get below screen

In below screen dataset is loaded and now click on 'Generate Train & Test Model' button to read dataset and to split dataset into train and test part to generate machine learning train model

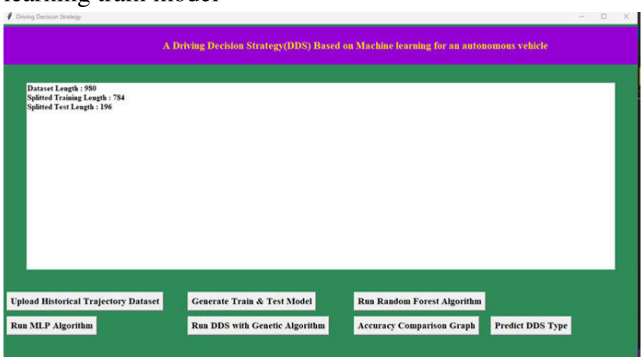

Fig 6.2 Generate Train & Test Model

In above screen dataset contains 980 total trajectory records and application using 784 (80% of dataset) records for training and 196 (20% of dataset) for testing. Now both training and testing data is ready and now click on 'Run Random Forest Algorithm' button to train random forest classifier and to calculate its prediction accuracy on 20% test data.

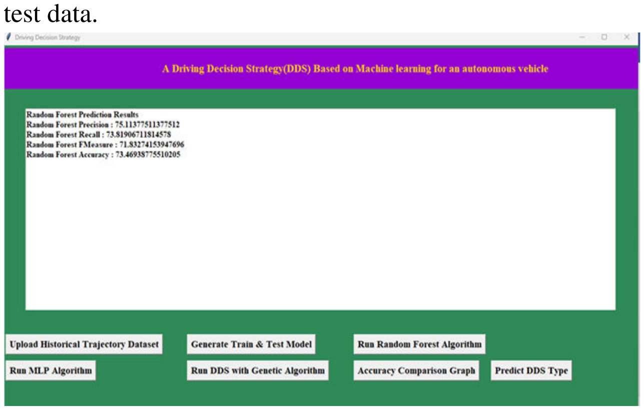

Fig 6.3 Run Random Forest

In above screen we calculated random forest accuracy, precision , recall and f-measure and random forest got 73% prediction accuracy. Now click on 'Run MLP Algorithm' button to train MLP model and to calculate its accuracy.

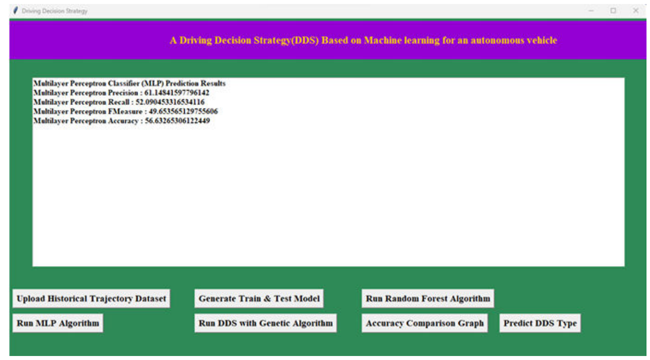

Fig 6.4 Run Multilayer Perception

In above screen MLP got 56% prediction accuracy and in below screen we can see genetic algorithm code used for building propose DS algorithm.

Fig 6.5 Run DDS Algorithm

In above screen propose DDS algorithm got 85% prediction accuracy and now click on 'Accuracy Comparison Graph' button to get below graph

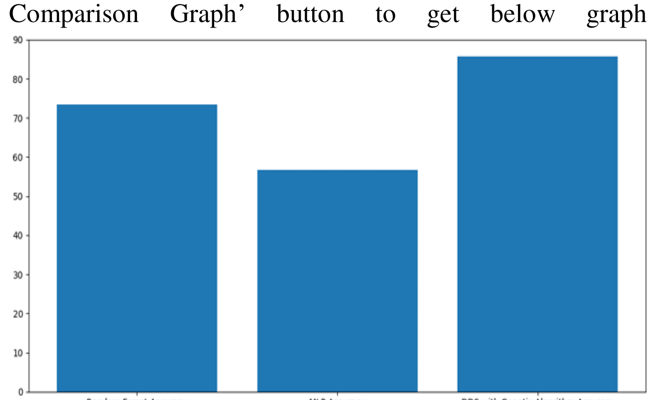

Fig 6.6 Bar Graph

In above graph x-axis represents algorithm name and y-axis represents accuracy of those algorithms and from above graph we can conclude that DDS is performing well compare to other two algorithms. Now click on 'Predict DDS Type button to predict test data.

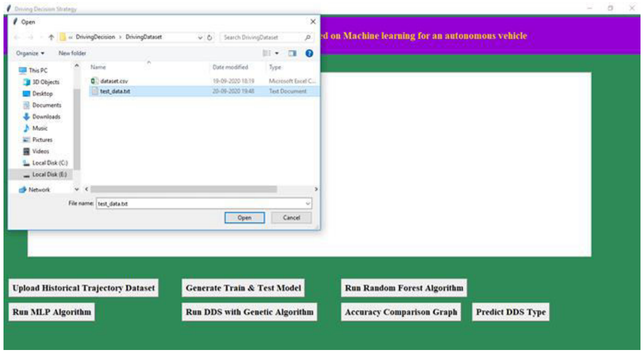

Fig 6.7 Predict DDS Type

In above screen uploading 'test_data.txt' file and click on 'Open' button to predict driving decision

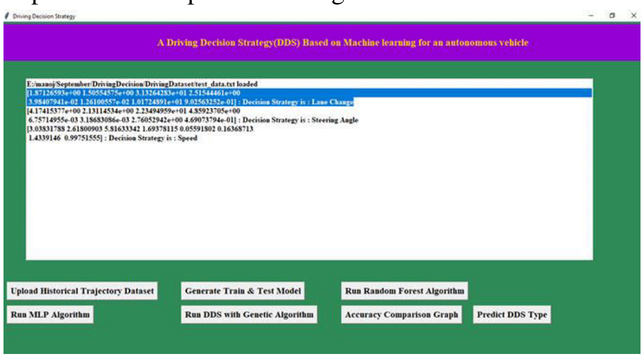

Fig 6.7 Final Output

In above screen in selected first record we can see decision is Lane Change and for second record values we got decision as 'steering angle' and for third test record we got predicted value as vehicle is in speed mode.

7. CONCLUSION

This paper proposed a Driving Decision Strategy. It executes the genetic algorithm based on accumulated data to determine the vehicle's optimal driving strategy according to the slope and curvature of the road in which the vehicle is driving and visualizes the driving and consumables conditions of an autonomous vehicle to provide drivers. To verify the validity of the DDS, experiments were conducted on the DDS to select an optimal driving strategy by analyzing data from an autonomous vehicle. Though the DDS has a similar accuracy to the MLP, it determines the optimal driving strategy 40% faster than it. And the DDS has a higher accuracy of 22% than RF and determines the optimal driving strategy 20% faster than it. Thus, the DDS is best suited for determining the optimal driving strategy that requires accuracy and real-time. Because the DDS sends only the key data needed to determine the vehicle's optimal driving strategy to the cloud and analyses the data through the genetic algorithm, it determines its optimal driving strategy at a faster rate than existing methods. However, the experiments of the DDS were conducted in virtual environments using PCs, and there were not enough resources for visualization.

FUTURE SCOPE

Future studies should test the DDS by applying it to actual vehicles, and enhance the completeness of visualization components through professional designers. Future scopes for the Driving Decision Strategy (DDS) in autonomous vehicles include advanced sensor integration, real-time learning, and human-AI collaboration. Ethical decision-making frameworks, scalability, and robustness against cyber threats are also essential areas for development. Environmental adaptability and collaborative research initiatives with industry partners and regulatory bodies are crucial for validation and refinement. Overall, enhancing decision-making, safety, and adaptability while addressing ethical and security concerns are key focuses for the future of DDS in autonomous vehicle.

8. REFERENCES

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