As per UGC guidelines an electronic bar code is provided to seure your paper

International Journal for Modern Trends in Science and Technology, 9(04): 88-92, 2023

ISSN: 2455-3778 online
DOI: https://doi.org/10.46501/IJMTST0904014
Available online at: http://www.ijmtst.com/vol9issue04.html

A Driving Decision Strategy (DDS) Based on Machine Learning for an Autonomous Vehicle

Nagalakshmi A, ,Nakka Sridevi, Alluri Lalitha Sri Madhuri, Kurukuri Bulli Raju, Matha Aparna and Pola Charan Adabala

Department of Computer Science and Engineering, Pragati Engineering College (A), Surampalem (East Godavari) A.P,India.

To Cite this Article
Nagalakshmi A, ,Nakka Sridevi, Alluri Lalitha Sri Madhuri, Kurukuri Bulli Raju, Matha Aparna and Pola Charan Adabala. A Driving Decision Strategy (DDS) Based on Machine Learning for an Autonomous Vehicle. International Journal for Modern Trends in Science and Technology 2023, 9(04), pp. 88-92. https://doi.org/10.46501/IJMTST0903014

Article Info
Received: 02 March 2023; Accepted: 25 March 2023; Published: 31 March 2023.

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 project proposes "An Efficient Autonomous Vehicle Driving Decision Making Based on Genetic Algorithm" 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 an self-ruling vehicle. This project contrasted the DDS and MLP what's more, RF neural system models to approve the DDS. In the analyze, 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

However, as the performance of self-driving cars improves, the number of sensors to recognize data is increasing. An increase in these sensors can cause the in-vehicle overload. Self-driving cars use in-vehicle computers to compute data collected by sensors. As the amount of the computed data increases, it can affect the speed of judgment and control because of overload. These problems can threaten the stability of the vehicle. To prevent the overload, some studies have developed hardware that can perform deep- running operations inside the vehicle, while others use the cloud to compute the vehicle's sensor data. On the other hand, collected from vehicles to determine how the vehicle is driving. This project proposes An Efficient Autonomous Vehicle Driving Decision Making Based on Genetic Algorithm which reduces the in-vehicle computation by generating big data on vehicle driving within the cloud and determines an optimal driving strategy by taking into account the historical data in the cloud. The proposed DDS analyses them to determine the best driving strategy by using a Genetic algorithm stored in the Cloud.

Objective

The DDS learns a genetic algorithm using sensor data from vehicles stored in the cloud and determines the optimal driving strategy of an autonomous vehicle. This project compared the DDS with MLP and RF neural network models to validate the DDS. In the experiment, the DDS had a loss rate approximately 5% lower than existing vehicle gateways and the DDS determined RPM, speed,steering angle and lane changes 40% faster than the MLP and 22% faster than the RF.

2.LITERATURE SURVEY

Y.N. Jeong, S.R.Son, E.H. Jeong and B.K. Lee, "An Integrated Self- Diagnosis System for an Autonomous Vehicle Based on an IoT Gateway and Deep Learning, " Applied Sciences, vol. 8, no. 7, july 2018

This paper proposes "An Integrated Self-diagnosis System (ISS) for an Autonomous Vehicle based on an Internet of Things (IoT) Gateway and Deep Learning" that collects information from the sensors of an autonomous vehicle, diagnoses itself, and the influence between its parts by using Deep Learning and informs the driver of the result. The ISS consists of three modules. The first In-Vehicle Gateway Module (In-VGM) collects the data from the in-vehicle sensors, consisting of media data like a black box, driving radar, and the control messages of the vehicle, and transfers each of the data collected through each Controller Area Network (CAN), FlexRay, and Media Oriented Systems Transport (MOST) protocols to the on-board diagnostics (OBD) or the actuators. The data collected from the in-vehicle sensors is transferred to the CAN or FlexRay protocol and the media data collected while driving is transferred to the MOST protocol. Various types of messages transferred are transformed into a destination protocol message type. The second Optimized Deep Learning Module (ODLM) creates the Training Dataset on the basis of the data collected from the in-vehicle sensors and reasons the risk of the vehicle parts and consumables and the risk of the other parts influenced by a defective part. It diagnoses the vehicle's total condition risk. The third Data Processing Module (DPM) is based on Edge Computing and has an Edge Computing based Self-diagnosis Service (ECSS) to improve the self-diagnosis speed and reduce the system overhead, while a V2X based Accident Notification Service (VANS) informs the adjacent vehicles and infrastructures of the self-diagnosis result analyzed by the OBD. This paper improves upon the simultaneous message transmission efficiency through the In-VGM by 15.25% and diminishes the learning error rate of a Neural Network algorithm through the ODLM by about 5.5%. Therefore, in addition, by transferring the self-diagnosis information and by managing the time to replace the car parts of an autonomous driving vehicle safely, this reduces loss of life and overall cost. This paper proposes "An Integrated Self-diagnosis System (ISS) for an Autonomous Vehicle based on an Internet of Things (IoT) Gateway and Deep Learning" that collects information from the sensors of an autonomous vehicle, diagnoses itself, and the influence between its parts by using Deep Learning and informs the driver of the result. The ISS consists of three modules. The first In-Vehicle Gateway Module (In-VGM) collects the data from the in-vehicle sensors, consisting of media data like a black box, driving radar, and the control messages of the vehicle, and transfers each of the data collected through each Controller Area Network (CAN), FlexRay, and Media Oriented Systems Transport (MOST) protocols to the on-board diagnostics (OBD) or the actuators. The data collected from the in-vehicle sensors is transferred to the CAN or FlexRay protocol and the media data collected while driving is transferred to the MOST protocol. Various types of messages transferred are transformed into a destination protocol message type. The second Optimized Deep Learning Module (ODLM) creates the Training Dataset on the basis of the data collected from the in-vehicle sensors and reasons the risk of the vehicle parts and consumables and the risk of the other parts influenced by a defective part. It diagnoses the vehicle's total condition risk. The third Data Processing Module (DPM) is based on Edge Computing and has an Edge Computing based Self-diagnosis Service (ECSS) to improve the self-diagnosis speed and reduce the system overhead, while a V2X based Accident Notification Service (VANS) informs the adjacent vehicles and infrastructures of the self-diagnosis result analyzed by the OBD. This paper improves upon the simultaneous message transmission efficiency through the In-VGM by 15.25% and diminishes the learning error rate of a Neural Network algorithm through the ODLM by about 5.5%. Therefore, in addition, by transferring the self-diagnosis information and by managing the time to replace the car parts of an autonomous driving vehicle safely, this reduces loss of life and overall cost.

3. EXISTING SYSTEM

Multilayer Perceptron, Random Forest, 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 neighbour unit of location information of the next k stages.The results of above algorithms are not accurate when compared to the proposed algorithm.

3.1. PROPOSED SYSTEM

Our current work uses the Driving Decision Strategy(DDS) algorithm .It mines the double layers of hidden states of vehicle historical trajectories.

Impact on Environment :Reduces global warming, pollution, time etc.

Safety :It provides more security and privacy.

Ethics :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.

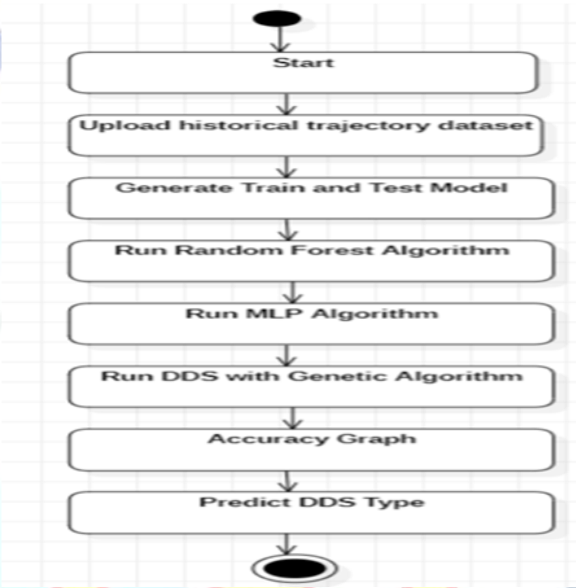
Cost :Cost reduction due to implementation of the project in production.

4. SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture of an efficient autonomous vehicle driving decision making based on genetic algorithm.

ActivityDiagram

Activity diagrams represent workflows in a graphical way. They can be used to describe the business workflow or the operational workflow of any component in a system. Sometimes activity diagrams are used as an alternative to State machine diagrams..



5.SYSTEM IMPLEMENTATION

Module 1: Upload Historical Trajectory Dataset.

Module 2: Generate Train and Test Model.

Module 3: Run Random Forest Algorithm.

Module 4: Run Multilayer Perceptron Algorithm.

Module 5: Run DDS with Genetic Algorithm.

Module 6: Accuracy Comparison Graph.

Module 7: Predict DDS Type.

Module 1: Upload Historical Trajectory Dataset

Upload the historical trajectory dataset which can be collected from the Kaggle thatcontains the features like trajectory id, revolution per minute levels and speed levels. The dataset contains 977 values.

Module 2: Generate Train and Test Model.

In this module generate the train and test dataset from the total dataset. That means split the historical trajectory dataset into training data and testing data. We split the dataset that contains the length 977 into training data of length 781 and testing data of length 196. Training dataset contains labeled data and testing dataset does not contains labeled data.

Module 3: Run Random Forest Algorithm.

After splitting the dataset now run the random forest algorithm and get the accuracy levels.Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset. This Random Forest algorithm displays 67.34693 accuracy level.

Module 4: Run Multilayer Perceptron Algorithm.

After Random Forest algorithm, this module is used to run Multilayer Perceptron algorithm.Multi Layer Perceptron (MLP) is a type of artificial neural network that is widely used for various machine learning tasks such as classification and regression. It is called a multi-layered perceptron because it has many layers of nodes (known as artificial neurons) that connect to each other. This algorithm displays 48.979 accuracy level.

Module 5: Run DDS with Genetic Algorithm.

In this module, run driving decision strategy with genetic algorithm.A genetic algorithm is an adaptive heuristic search algorithm.It is used to solve optimization problems in machine learning. It is one of the important algorithms as it helps solve complex problems that would take a long time to solve. This algorithm displays 73.989 accuracy level.

Module 6: Accuracy Comparison Graph.

This module contains a graph in which x-axis represents algorithm name and y-axis represents accuracy of those algorithms. Genetic algorithm is 40% faster than Multilayer perceptron algorithm and 22% faster than Random Forest algorithm. From the graph we can conclude that DDS is performing well compare to other two algorithms.

Module 7: Predict DDS Type.

In this module we predict the driving decision type by uploading the test data which contains of length 196.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.

6. SYSTEM TESTING

Unittesting

Unit testing involves the design of test cases that validate that the internal program logic is

functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

6.1.2Integrationtesting

Integration tests are designed to test integrated software components to determine if they

actually, run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfaction, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

6.1.3Functionaltest

Functional tests provide systematic demonstrations that functions tested are available as

specified by the business and technical requirements, system documentation, and user manuals. Functional testing is centred on the following items:

7.RESULTS

Fig7.1 Upload Historical Trajectory Dataset’ button and upload dataset.

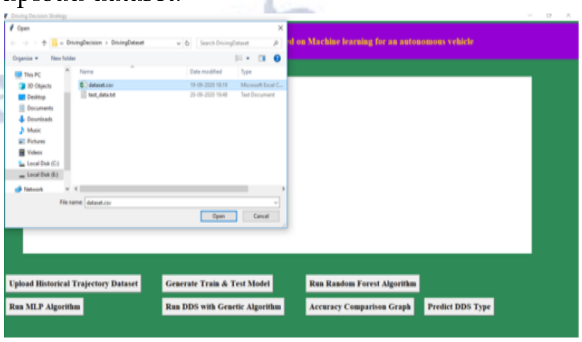


Fig 7.2Open’ button to load dataset and to get below screen.

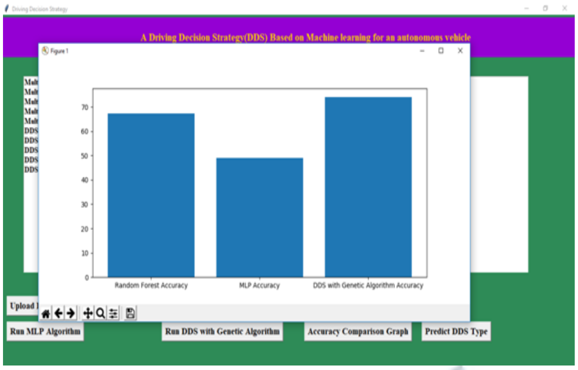


Fig 7.3In above graph x-axis represents algorithm name and y-axis represents accuracy of those algorithms and from above graph we can conclude that DDS is performing well compare to other two algorithms. Now click on 'Predict DDS Type' button to predict test data.

Fig 7.4 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.

8. CONCLUSION & FUTURE WORK

This project 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 analysing 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 studies should test the DDS by applying it to actual vehicles, and enhance the completeness of visualization components through professional designers.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] Y.N. Jeong, S.R.Son, E.H. Jeong and B.K. Lee, "An Integrated Self- Diagnosis System for an Autonomous Vehicle Based on an IoT Gateway and Deep Learning, " Applied Sciences, vol. 8, no. 7, july 2018.

[2] Yukiko Kenmochi, Lilian Buzer, Akihiro Sugimoto, Ikuko Shimizu, "Discrete plane segmentation and estimation from a point cloud using local geometric patterns, " International Journal of Automation and Computing, Vol. 5, No. 3, pp.246-256, 2008.

[3] Ning Ye, Yingya Zhang, Ruchuan Wang, Reza Malekian, "Vehicle trajectory prediction based on Hidden Markov Model, " The KSII Transactions on Internet and Information Systems, Vol. 10, No. 7, 2017.

[4] Li-Jie Zhao, Tian-You Chai, De-Cheng Yuan, "Selective ensemble extreme learning machine modeling of effluent quality in wastewater treatment plants, " International Journal of Automation and Computing, Vol.9, No.6, 2012