JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 531-540
https://publishoa.com
ISSN: 1309-3452

Self Driving Surveillance

Mrs. V. SWATHI
Assistant Professor, CSE.
Sreyas Institute of Engineering and Technology, Telangana, India
v.swathi@sreyas.ac.in

S SUBBA SIRISHA
Department of CSE,
Sreyas Institute of Engineering and Technology, Telangana, India
ctamraju@gmail.com

K TEENA REDDY
Department of CSE,
Sreyas Institute of Engineering and Technology, Telangana, India
teenareddy10@gmail.com

C V SUMEDHA
Department of CSE,
Sreyas Institute of Engineering and Technology, Telangana, India
sumedhasri.20
@gmail.com

M NITISH KUMAR
Department of CSE,
Sreyas Institute of Engineering and Technology, Telangana, India
manthrinitishkumar
@gmail.com

Received 2022 April 02**; Revised** 2022 May 20**; Accepted** 2022 June 18**.**

ABSTRACT

Currently, global companies are developing technologies for advanced self-driving cars, which is in the 4th stage. Self-driving cars are being developed based on various ICT technologies, and the principle of operation can be classified into three levels recognition, judgment, and control. The recognition step is to recognize and collect information about surrounding situations by utilizing various sensors in vehicles such as GPS, camera, and radar. The judgment step determines the driving strategy based on the recognized information. Then, this step identifies and analyses the conditions in which the vehicle is placed, and determines the driving plans appropriate to the driving environment and the objectives. The control step determines the speed, direction, etc., of the driving and the vehicle starts driving on its own. An autonomous driving vehicle performs various actions to arrive at its destination, repeating the steps of recognition, judgment, and control on its own. However, as the performance of self-driving cars, an increase in these sensors can cause 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.

Keywords: MLP Algorithm, Random Forest Algorithm, Genetic Algorithm, LiDAR laser.

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 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 a Self-Driving Surveillance (SDS) Based on Machine learning for an autonomous vehicle 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 SDS analyzes them to determine the best driving strategy by using a Genetic algorithm stored in the Cloud.

Currently, global companies are developing technologies for advanced self-driving cars, which is in the 4th stage. Self-driving cars are being developed based on various ICT technologies, and the principle of operation can be classified into three levels of recognition, judgment, and control. The recognition step is to recognize and collect information about surrounding situations by utilizing various sensors in vehicles such as GPS, camera, and radar. The judgment step determines the driving strategy based on the recognized information. Then, this step identifies and analyzes the conditions in which the vehicle is placed, and determines the driving plans appropriate to the driving environment and the objectives. The control step determines the speed, direction, etc. of the driving and the vehicle starts driving on its own. An autonomous driving vehicle performs various actions to arrive at its destination, repeating the steps of recognition, judgment, and control on its own.

Autonomous vehicles are one of the most exciting, up-and-coming applications of deep learning to hit the public. In this guide, you will learn about the theory behind these vehicles and the relevant ML tools leveraged to make them work. We are a long way away from having a true self-driving car. By a true self-driving car. We mean a car that can be essentially driven in any manner as a human driving a car. This is an incredibly hard thing to achieve. Major automobile companies have been trying to achieve true autonomous driving. The main motivations behind the idea are:

- Safer Roads
- Increase in productivity
- More economical
- The movement will be more efficient
- More environment friendly

In autonomous cars, LiDAR is the eye of the car, it is basically a 360-degree rotational camera that can detect any kind of obstacle that comes in its way. The DDS uses a genetic algorithm, using sensor data from vehicles stored in the cloud and determines the optimal driving strategy of an autonomous vehicle, and visualizes the driving and consumable conditions of an autonomous vehicle to provide drivers. Our proposed system will reduce the disadvantages of the existing system and help to reduce the organization’s time to know about the reviews of the customers. Companies won’t have to spend too much time knowing the customer satisfaction with their product. The sentimental analysis will take care of the reviews of the customers.

A current autonomous vehicle determines its driving strategy by considering only external factors (Pedestrians, road conditions, etc.) without considering the interior condition of the vehicle. To solve the problem, “A Self Driving Surveillance (SDS) Based on Machine learning for an autonomous vehicle” determines the optimal strategy of an autonomous vehicle by analyzing not only the external factors but also the internal factors of the vehicle (consumable conditions, RPM levels, etc. The SDS learns a genetic algorithm using sensor data from vehicles stored in the cloud and determines the optimal driving strategy of an autonomous vehicle. This paper compared the SDS with MLP and RF neural network models to validate the SDS. In the experiment, the SDS had a loss rate approximately 5% lower than existing vehicle gateways and the SDS determined RPM, speed, steering angle and lane changes 40% faster than the MLP and 22% faster than the RF.

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 SDS, experiments were conducted on the Desoto to select an optimal driving strategy by analyzing data from an autonomous vehicle. Though the SDS has similar accuracy to the MLP, it determines the optimal driving strategy 40% faster than it. And the SDS has a higher accuracy of 22% than RF and determines the optimal driving strategy 20% faster than it.

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.

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.

This paper presents a method for segmenting a 3D point cloud into planar surfaces using recently obtained discrete-geometry results. In discrete geometry, a discrete plane is defined as a set of grid points lying between two parallel planes with a small distance, called thickness. In contrast to the continuous case, there exist a finite number of local geometric patterns (LGPs) appearing on discrete planes. Moreover, such an LGP does not possess the unique normal vector but a set of normal vectors. By using those LGP properties, we first reject non-linear points from a point cloud and then classify non-rejected points whose LGPs have common normal vectors into a planar-surface-point set. From each segmented point set, we also estimate the values of parameters of a discrete plane by minimizing its thickness.

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.

In 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 situations 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 the Viterbi algorithm to seek the double layers hidden state 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.

The experimental results demonstrate that the prediction accuracy of the proposed algorithm is increased by 18.3% compared with the TPMO algorithm and increased by 23.1% compared with the Naive algorithm in the aspect of predicting the next k phases' trajectories, especially when traffic flow is greater, such as this time from weekday morning to evening. Moreover, the time performance of the DHMTP algorithm is also clearly improved compared with the TPMO algorithm.

PROPOSED SYSTEM CONFIGURATION

- K-NN, RF, SVM, and Bayes models are existing methods although studies have been done in the medical field with advanced data exploration using machine learning algorithms, orthopedic disease prediction is still a relatively new area and must be explored further for accurate prevention and cure.
- It mines the double layers of hidden states of vehicle historical trajectories and then selects the parameters of the Hidden Markov Model (HMM) by the historical data.
- This proposes an 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.

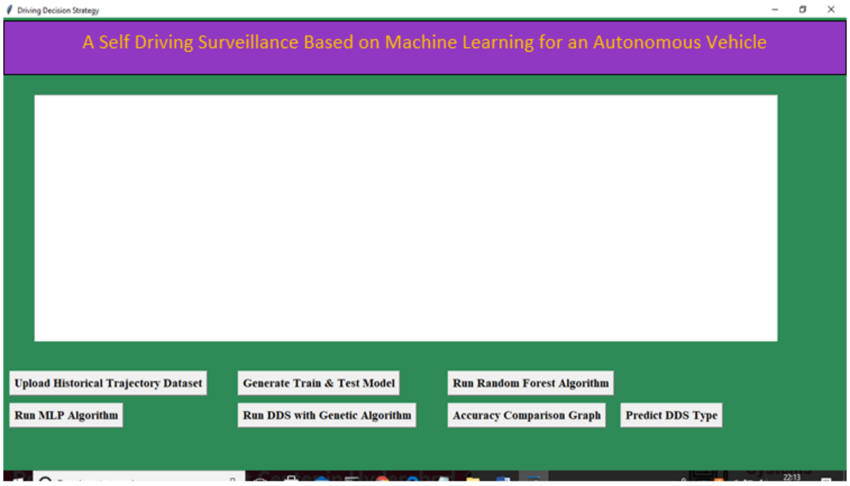
DISADVANTAGES

- Less efficiency and need more data to be explored for prevention.
- Not accurate detection of road.
- Prone to hacking.
- Here we propose "A SELF DRIVING SURVEILLANCE Based on Machine learning for an autonomous vehicle" which determines the optimal strategy of an autonomous vehicle by analyzing not only the external factors but also the internal factors of the vehicle (consumable conditions, RPM levels, etc.).
- The Self Driving Surveillance 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 compares the Decision Strategy with MLP and RF neural network models to validate the Driving Strategy.

ADVANTAGES

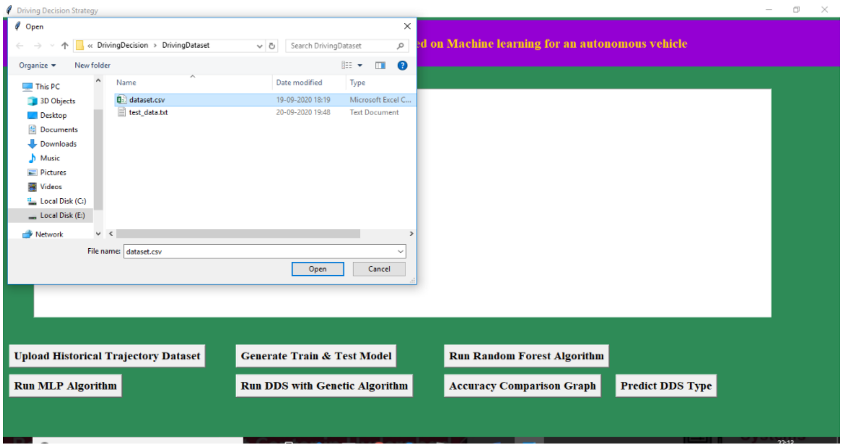
- The SDS will have a loss rate approximately 5% lower than existing vehicle gateways and the SDS determined RPM, speed, steering angle, and lane changes 40% faster than the MLP and 22% faster than the RF.
- These improvement systems control the vehicle based on sensor data.
- Traffic efficiency and Prevention of car crashes.
- Cost savings.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 531-540
https://publishoa.com
ISSN: 1309-3452



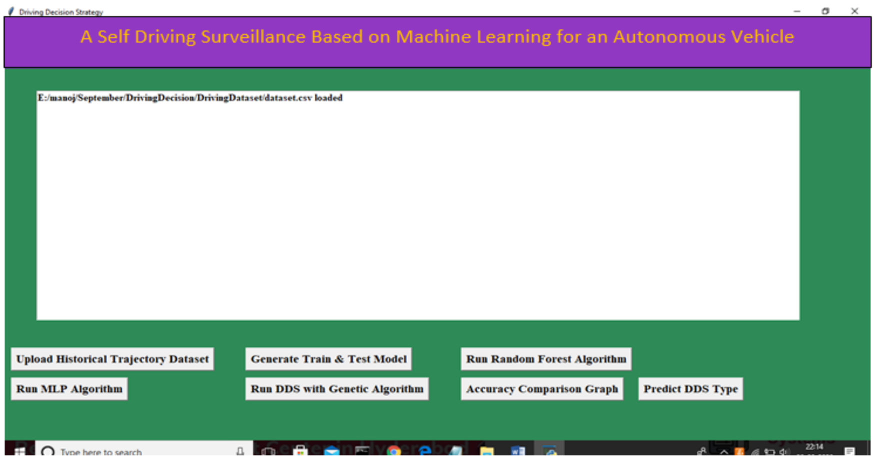
Screenshot 1. Upload historical trajectory Dataset

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



Screenshot 2. Select dataset.csv and click open

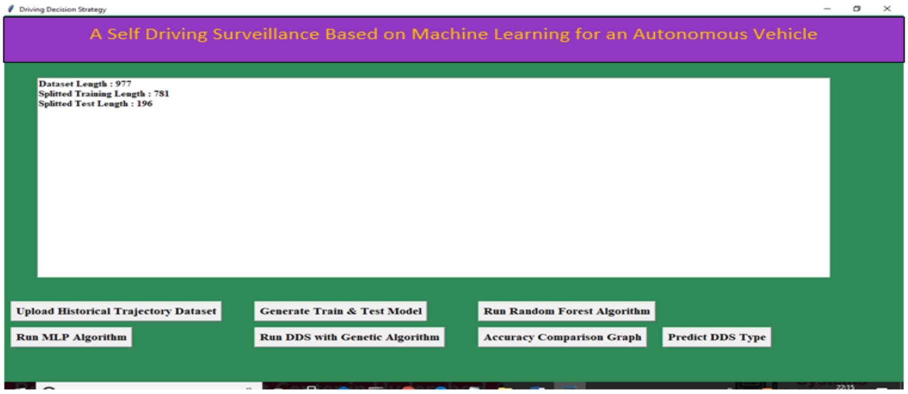
Now select the 'dataset.csv' file and click on the 'Open' button to load the dataset



Screenshot 3. Generate train and test model

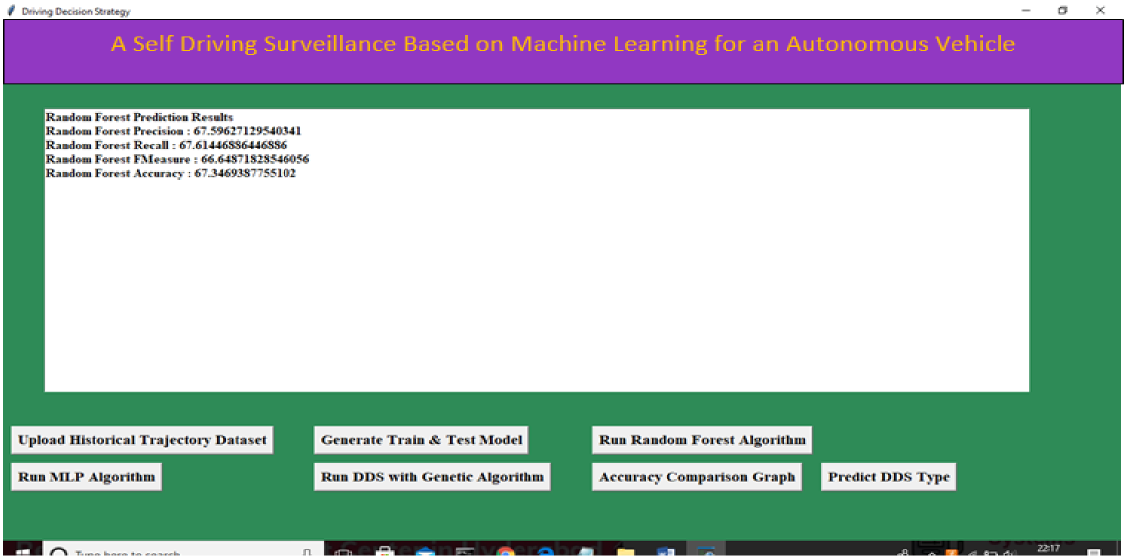
JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 531-540
https://publishoa.com
ISSN: 1309-3452

In the above screen, the dataset is loaded, and now click on the 'Generate Train & Test Model' button to read the dataset and to split the dataset into train and test parts to generate a machine learning train model.



Screenshot 4. Dataset information

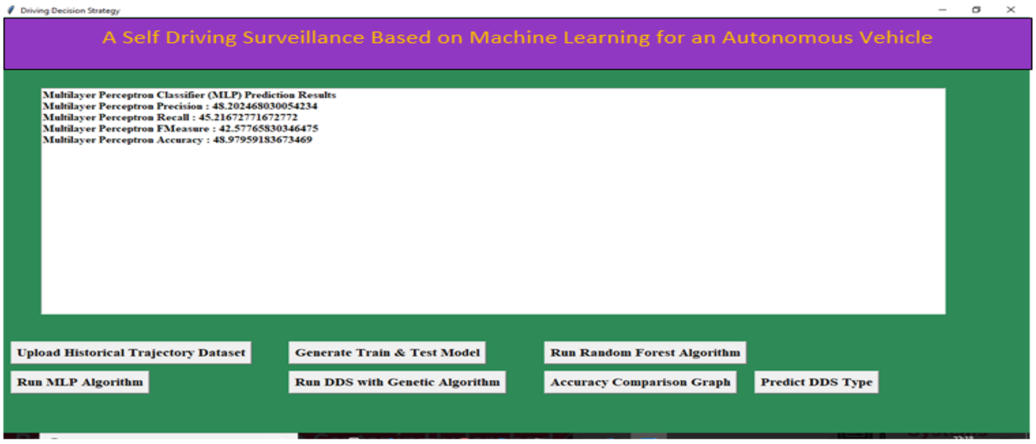
In the above screen, the dataset contains 977 total trajectory records and applications using 781 (80% of the dataset) records for training and 196 (20% of the dataset) for testing. Now both training and testing data is ready and now click on 'Run Random Forest Algorithm button to train the random forest classifier and to calculate its prediction accuracy on 20% test data.



Screenshot 5. Random Forest accuracy

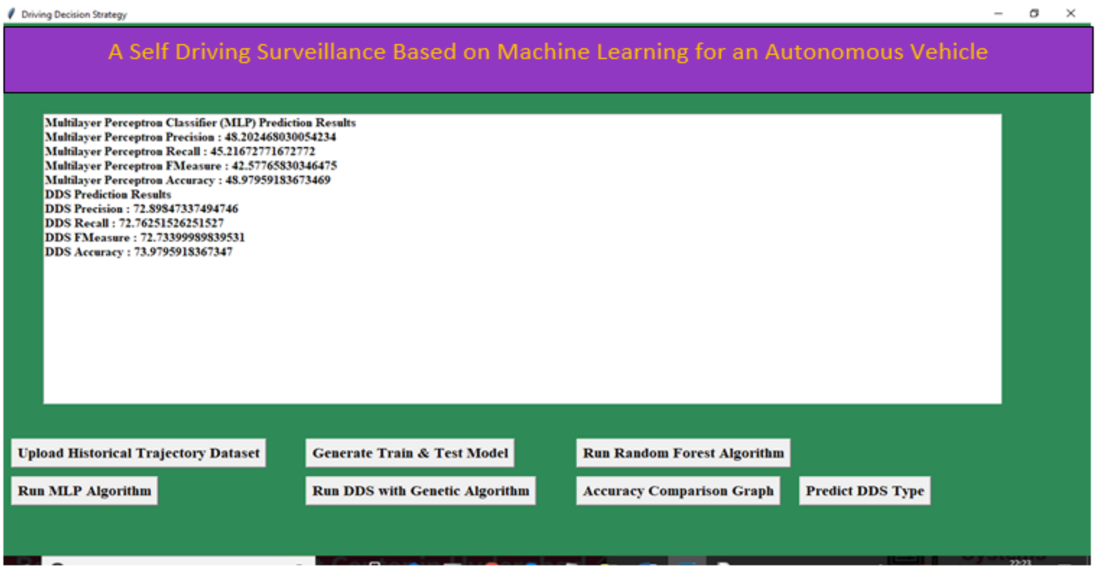
In the above screen, we calculated random forest accuracy, precision, recall, and measure and random forest got 67% prediction accuracy. Now click on the 'Run MLP Algorithm' button to train the MLP model and calculate its accuracy.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 531-540
https://publishoa.com
ISSN: 1309-3452



Screenshot 6. MLP accuracy

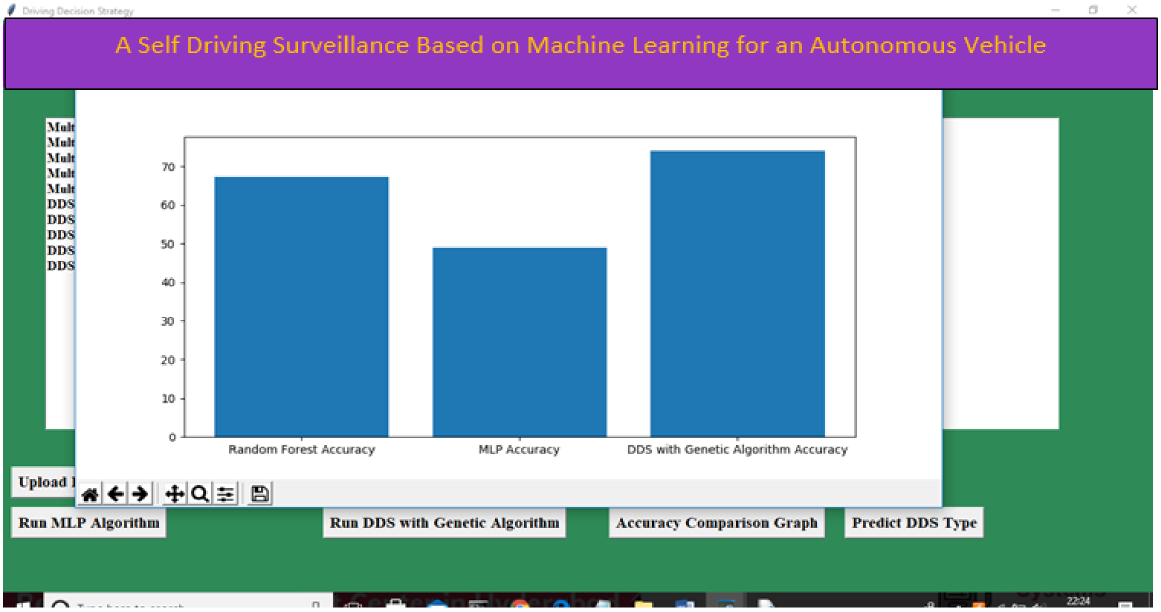
In the above screen, MLP got 48% prediction accuracy and in the below screen we can see the genetic algorithm code used for building propose DDS algorithm.



Screenshot 7. DDs algorithm accuracy

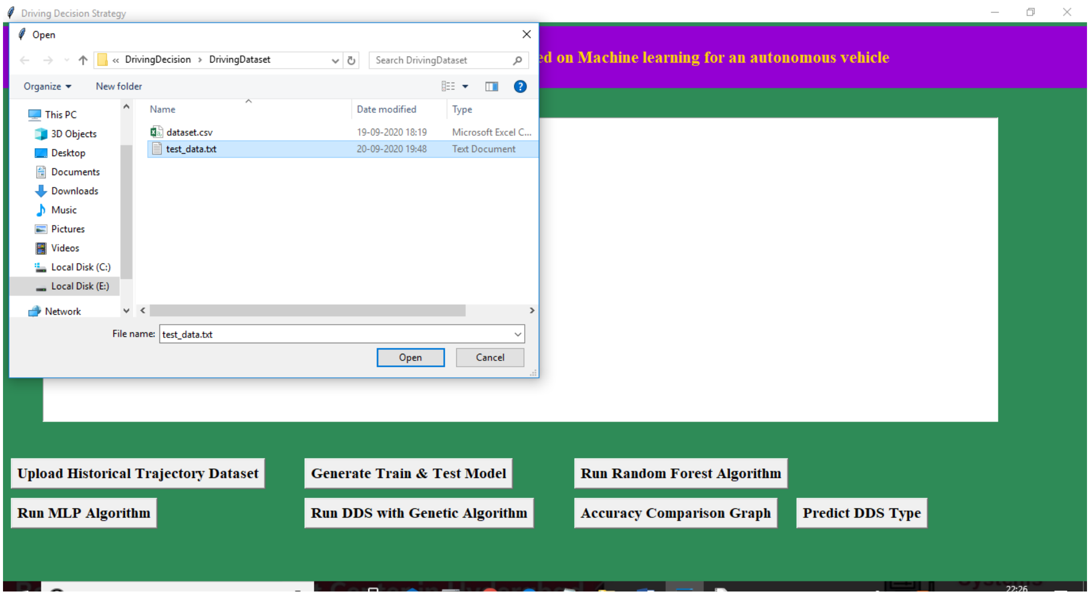
In the above screen propose DDS algorithm got 73% prediction accuracy and now click on the 'Accuracy Comparison Graph' button to the get below the graph.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 531-540
https://publishoa.com
ISSN: 1309-3452



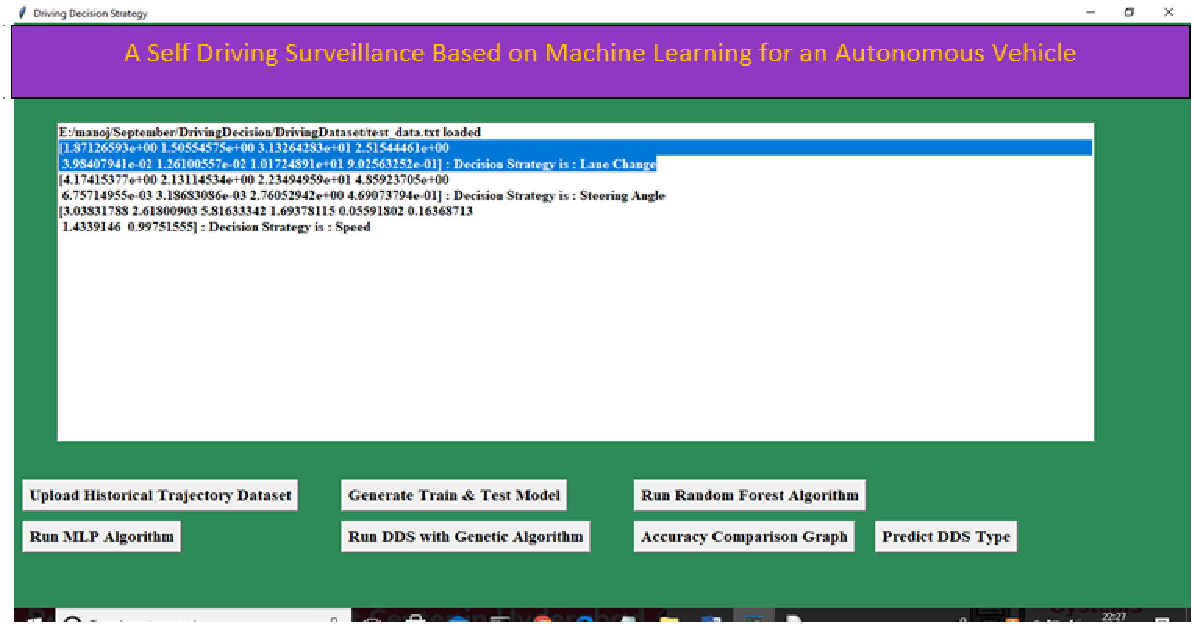
Screenshot 8. Graph representations

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



Screenshot 9. Uploading test_data.txt

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 531-540
https://publishoa.com
ISSN: 1309-3452



Screenshot 10. Decision for lane change

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

CONCLUSION

The project 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 SDS, experiments were conducted on SDS to select an optimal driving strategy by analyzing data from an autonomous vehicle. Though the SDS has similar accuracy to the MLP, it determines the optimal driving strategy 40% faster than it. And the SDS has a higher accuracy of 22% than RF and determines the optimal driving strategy 20% faster than it. Thus, the SDS is best suited for determining the optimal driving strategy that requires accuracy and real-time. Because the SDS sends only the key data needed to determine the vehicle's optimal driving strategy to the cloud and analyzes the data through the genetic algorithm, it determines its optimal driving strategy at a faster rate than existing methods.

FUTURE SCOPE

- Future studies should test the DDS by applying it to actual vehicles, and enhance the completeness of visualization components through professional designers.
- It can be used on hilly roads.
- More complex algorithms can be used so that it can be helpful in drunk and drive situations.
- Installing new night vision sensors so that there will be clear vision during the nighttime.

REFERENCES

1. Thailand Motor Vehicle Registered. CEIC Data Global Database.
2. Linda, S., Can public transport compete with the private car? Iatss Research, 2003. 27(2): p. 27-35.
3. Liu, M. and N. Choosri.. A technical solution to improve the red cab for touring in Chiang Mai: Chinese tourists' perspective. in 2016 Chinese Control and Decision Conference (CCDC). 2016. IEEE

4. Farooq, M.U., A. Shakoor, and A.B. Siddique. GPS-based Public Transport Arrival Time Prediction. in 2017 International Conference on Frontiers of Information Technology (FIT). 2017. IEEE.
5. Bin, Y., Y. Zhongzhen, and Y. Baozhen, Bus arrival time prediction using support vector machines. Journal of Intelligent Transportation Systems, 2006. 10(4): p. 151-158.
6. Maiti, S., et al. Historical data-based real-time prediction of vehicle arrival time. in 17th International IEEE Conference on Intelligent Transportation Systems (ITSC). 2014. IEEE.
7. 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.
8. 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.
9. 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.