



DRIVING DECISION STRATEGY BASED ON MACHINE LEARNING FOR AN AUTONOMOUS VEHICLE

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Abstract :

Regarding the drive-control plan for self-driving automobiles, the present approach relies on exterior elements like the pedestrian walk indicators and the surfaces of the roads that obscure the internal status significantly. This study with the title 'A Driving Decision Strategy (DDS) based on Machine Learning for an Autonomous Vehicle' goes further by providing a complex model, which takes into consideration the generic external environment and the decision process to identify the most suitable course of the action plans for the self-driving automobiles. In deciding which driving amongst the other result in the best result, this proposed DDS include the genetic system with the cloud-based sensor data acquisition system. In regard to this paper, the applicability of DDS was evaluated in terms of performance difference against conventional models including RF and MLP. Consequently, the study indicates that using DDS provides better accuracy and therefore communicates data at a significantly higher rate than those stated models above. It also proved that DDS is for a 5% normal system error better than other current autonomous systems existent; Besides, revolutionary per mins (RPMs), individual speed, halting distance, steering angle, and lane alteration; It also performs much faster than multi-line perceptron (MLP) by 40% and multifariousness faster than random forest (RF) by 22%. Here, the DDS encodes the sensor data using a genetic algorithm to attain the best parameters that would translate into exploitable positions that the driver can easily make a decision on. Similar changes if done, advocate for future enhancements.

Keywords: DDS, Genetic Algorithm, Random Forest(RF), Multi-Layer Perceptron(MLP), Autonomous Vehicle.

1.INTRODUCTION:

Progresses in self-driving car technology lie in the efficacy of the technology but using more sensors is still an issue since it is a factor that might overload the systems. Besides, as these sensors get information sequentially computers in the car will have to process all of it and this is likely to act as a double-edged sword to possibly slow up the decision-making process and less stabilization. To address this, people came up with such ideas like the utilization of some sorts of ASIC chips, of cloud computations for analysis of the data outside of the automobile, all in an effort to lessen the load on the internal computing components of the car. Bases on Machine Learning there are some of them as follows; the Machine Learning-based Driving Decision Strategy (DDS) that is a self-driving car. It is armored that the data crunching is in-car computing with large portions of data transmitted to the cloud while utilization of data in the past time is used to enhance driving plans. Self-driving cars among them have GPS, cameras, and radar through which they get to size what is out there so that they get proper choices. Such tasks are to be done by the car by the help of DDS setup, identify objects and take decisions, move itself to the desired location which involves no human being. There is need to endeavor to make such steps even better, thus the DDS seeks to enhance safety and efficiency of the self-driving cars, so as to do well on all behaviors.

2. PROBLEM ANALYSIS

The strategy of planning driving behavior of on-road cars in use today is far from perfect since it depends more on the external environment state such as traffic light for the pedestrian and the road condition; yet, internal state of the car in question is usually neglected. It has been the genesis of many an inefficiency and, worse still, poor decision-making, whose consequences are felt at the

business level. Other classical paradigms which include RF, and MLP among others are slower to handle the different sensor data; moreover, more time is consumed in data processing and there are many system errors compared to AI.

Furthermore, there are many data such as RPM, speed, steering angle, etc. and current system is not efficient enough in processing it. Due to the mentioned problems, the study presents the Driving Decision Strategy based on the genetic algorithm that helps increase the speed and effectiveness of the result. The DDS decreases the system error by about 5 percent and the data rate is 40 percent higher than MLP and 22 percent higher than RF; thus, enabling the evaluation of the external and internal stimuli, as well as improving predictive capability and decision-making.

3. SYSTEM REQUIREMENTS:

3.1 Hardware Requirements:

System	:	intel i5
Hard Disk	:	256 GB.
Monitor	:	15" LED
Input Devices	:	Keyboard, Mouse
RAM	:	4 GB

3.2 Software Requirements:

Operating system	:	Windows 10.
Coding Language	:	Python 3.7.0(Anacond3.7, Jupiter)

4. METHODOLOGY:

The Technique focuses on enhancing the decision-making process of autonomous vehicles by integrating both external environmental data and internal vehicle dynamics. Unlike current methods that overly depend on external factors like traffic signals and road surfaces, the DDS combines these with internal metrics to achieve optimal driving strategies. It utilizes cloud-based systems to handle vast amounts of sensor data efficiently, reducing the computational load on the vehicle's onboard systems. Sensors such as RPM, speedometers, steering angle detectors, and lane-change monitors collect critical data that is transmitted to the cloud for real-time analysis.

The core of the DDS is a genetic algorithm that evaluates multiple driving strategies, optimizing parameters to enhance speed, trajectory, and lane changes. This algorithm refines driving plans by considering both historical and real-time data, allowing the vehicle to adapt dynamically to changing conditions. The DDS was tested against conventional machine learning models like Random Forest (RF) and Multilayer Perceptron (MLP).

It showed superior performance, achieving a 5% reduction in system error and processing data 40% faster than MLP and 22% faster than RF. The system ensures more accurate decision-making by continually learning from real-world feedback, refining strategies over time. This methodology marks a significant advancement in autonomous vehicle technology by offering a comprehensive framework that improves accuracy, efficiency, and safety. The DDS sets a foundation for future innovations, highlighting its potential for ongoing development and enhancement in self-driving systems.

5. SYSTEM ARCHITECTURE:

The Driving Decision Strategy (DDS) model that is aimed to be implemented uses genetic algorithms to collect data from the vehicle's sensors and upload it to the cloud. This data is information of the engine, and any other information pertaining to the car and also the conditions outside like the roads and traffic.

The feature engineering component reads the data and after that pre-process the data and generate a list of features that will be used for machine learning models. The element of the model which involves training and testing of the model employs the genetic algorithm both for the training and testing processes. Closely tied to the prediction model of the DDS is what consists of classical machine learning models like the random forest and the MLP model together with a boosting routine.

Through the use of pattern recognition, it is trained through supervised learning from a labelled set of data and is often tested through the use of test metrics such as accuracy, precision, recall and etcetera After that, the model is incorporated in the decision-making system of the autonomous vehicle where the probabilistic frequencies of all the courses of action are weighed. Hybrid approach for

DDS works by applying boosting techniques that uses one or many models in machine learning that help in enhancing the DDS. It can provide more precise and actual reliable decisions towards self-organizing driving sorts of automobiles.

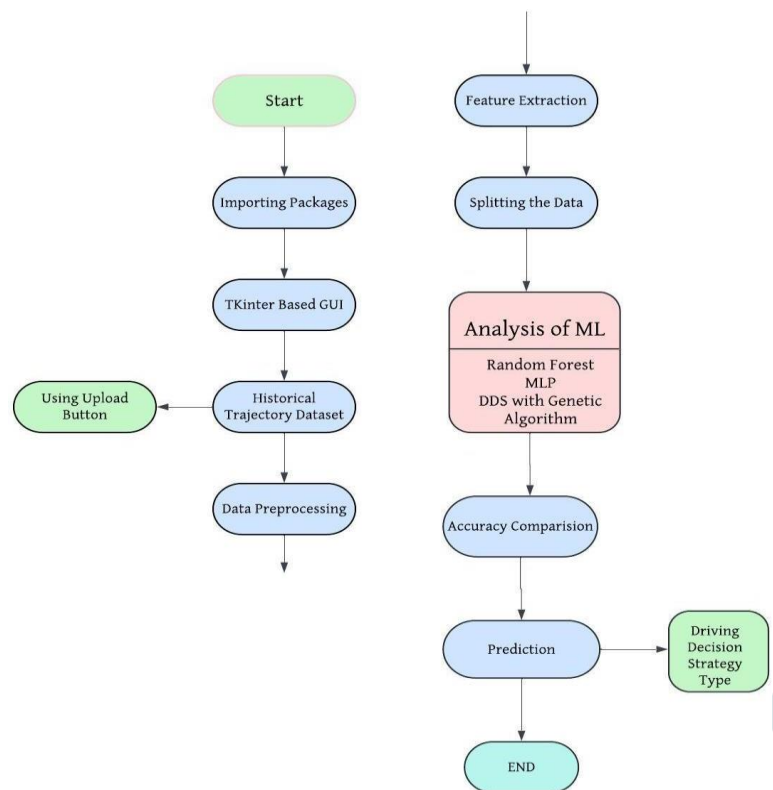


Fig 5 System Architecture

The System Architecture consists the following:

5.1 Historical Trajectory Dataset Upload:

Upload a dataset of the history of the self-driving cars; this dataset should hold all kinds of driving situations, including but not limited to external factors such as pedestrian crossing and road surface and internal factors like revolutions per minute, speed, steering angle, and lane change. The dataset shall form a base for training and testing different driving decision models.

5.2 Generate Train & Test Model:

Divide the dataset into a training and a testing set. These two will be applied in fine-tuning the predictive models, wherein the training set will be deployed in setting up the predictive model and the subsequent tuning of the model's parameters. Later, it will test on the testing set to see how well they perform. Separation will ensure that the model is actually assessed based on how it generalizes to new and unseen data.

5.3 Run Random Forest Algorithm:

Apply the Random Forest algorithm on the dataset for training. Random Forest is an ensemble learning method where a lot of decision trees are built on top of one another and their predictions are combined to enhance its accuracy and robustness. Now, using the test set, evaluate how well the Random Forest model works in the prediction of driving decisions based on the historical data.

5.4 Run MLP Algorithm:

Apply the MLP algorithm to the training data. Since it is a neural network with multiple layers, it would be able to capture complex patterns in the data. Once the MLP model has been trained, test its performance using the test set to compare how well it predicts driving decisions relative to other models.

5.5 Run DDS with Genetic Algorithm:

Run the genetic algorithm for the Driving Decision Strategy. The strategy will use these cloud-based sensor data to compute the most effective driving strategy. On its part, the genetic algorithm refines this DDS through evolving a set of rules against the sensor data and choosing the fittest values for better predictions. These processes improve the accuracy and efficiency of the driving decisions.

5.6 Accuracy Comparison Graph:

Draw a graph illustrating the accuracy of DDS, Random Forest, and MLP. It can be represented by performance metrics of each model through error rates and processing speed to give one an idea of how effective they could be in predicting driving decisions.

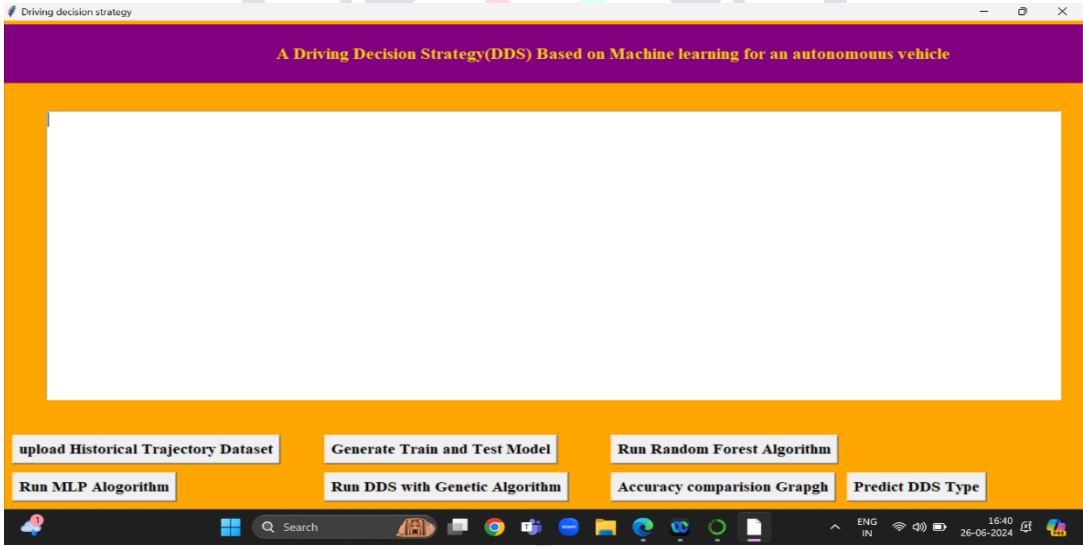
5.7 Predict DDS Type:

Compare the predictions from the DDS with those made by a random forest and an MLP model, and analyze how the former does in comparison to the latter in terms of prediction accuracy, speed, and overall efficiency. The comparison will establish whether the DDS is any good at finding the best possible driving decisions considering the internal and external factors.

6.RESULT:

Machine learning Models	Precision	Recall	Fmeasure	Accuracy
Random Forest	48.2024680	45.21672	42.5776	48.97959
MLP	67.59627	67.61776	66.64871	67.34683
DDS	76.284909	76.73382	76.4574	77.04081

Error rate evaluation table



Home Page



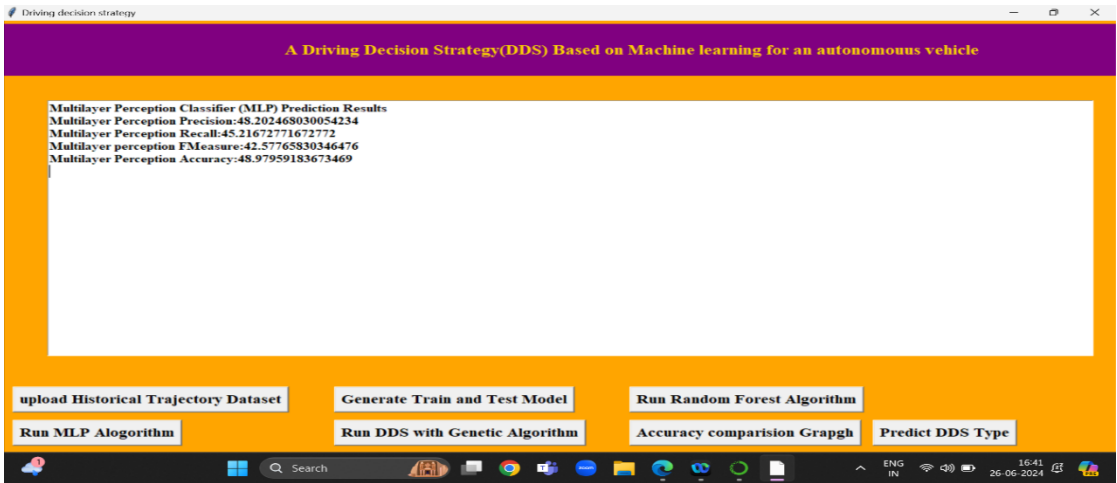
Dataset Uploaded



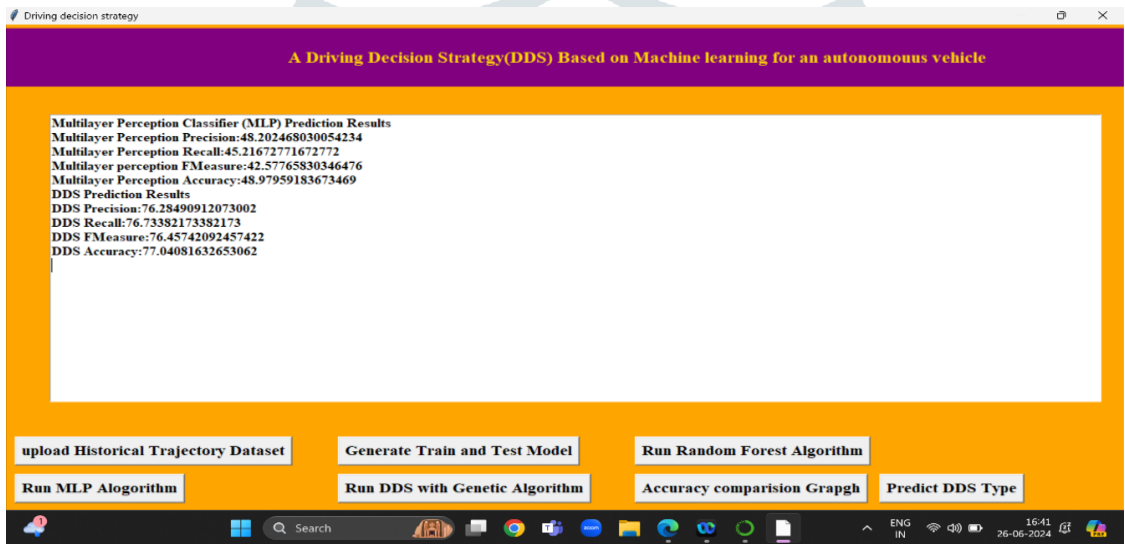
Data Trained and Tested



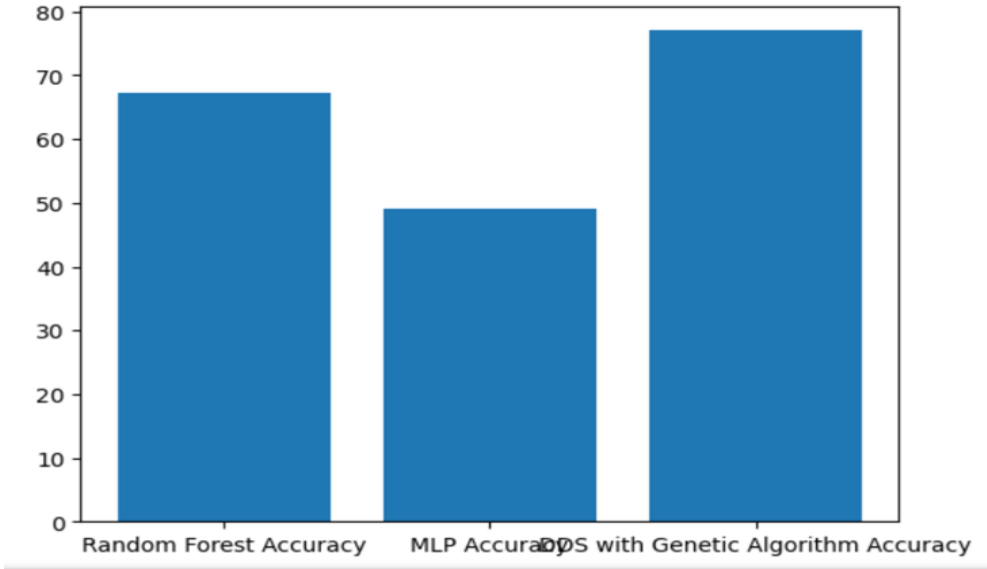
Run Random Forest



Run MLP Algorithm



Run DDS



Comparison Graph

7. CONCLUSION:

So, the study proves that the developed Driving Decision Strategy (DDS) enhances the decision-making of autonomous vehicle by incorporating both the external and the internal data and serves to remove the void created by the existing approaches. The DDS's genetic algorithm and cloud-sensed data acquisition provide notably better results and quicker processing than Random Forest and Multilayer Perceptron models. Parameters are adjusted for more correct predictions and accurate driving decisions due to the faster data processing with the reduced level of the system error, which is 5%. Algorithms of this approach improve not only present-day self-driving methods but also present a basis for future development.

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, "Predicting Vehicle trajectory based on Hidden Markov Model," *The KSII Transactions on Internet and Information Systems*, vol. 10, no. 7, 2017.
- [4] YiNa Jeong, SuRak Son, E. Jeong, B. Lee" An Integrated Self-Diagnosis System for an Autonomous Vehicle Based on an IoT Gateway and Deep Learning. Ning Ye, Yingya Zhang, Ru-chuan Wang, R. Malekian *Computer Science KSII Trans. Internet Inf. Syst.*2016. Vehicle trajectory prediction based on Hidden Markov Model.
- [5] Al-Tahmeesschi, A., Abu-Zaiter, A., & Jaber, F. (2020). A machine learning-based system for autonomous driving: Sensory data integration, dynamic object detection, tracking and prediction. *IEEE Access*, 8, 93595-93606.
- [6] Neufville, R., Abdalla, H., Abbas, A., & Abbas, A. (2022). Potential of Connected Fully Autonomous Vehicles in Reducing Congestion and Associated Carbon Emissions. *Sustainability*, 14(11), 6910.
- [7] time series - Changing the training/test split between epochs in neural net models, when doing hyperparameter optimization - Cross Validated.
- [8] Internet of Things ; Model Moda Layanan Sistem Transportasi Internet of Vehicle | Anwar | *Proceeding Sinaptika*.
- [9] Sivanantham, K., & Praveen, P. (2024). Automotive Vehicle Data Security Service in IoT Using ACO Algorithm.
- [10] Vehicle trajectory prediction based on Hidden Markov Model.