



Optimizing Autonomous Driving with Genetic Algorithm Decision Strategy

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ABSTRACT_ In the realm of autonomous vehicles, the reliance on external factors alone, such as pedestrians and street conditions, to determine driving methods has been a limiting factor. To address this limitation and consider both external and internal factors, a novel strategy is proposed in this paper entitled "Enhanced Driving Decision Strategy (EDDS) for Autonomous Vehicles Using Machine Learning." By integrating external factors with internal conditions like consumable conditions and RPM levels, the proposed EDDS aims to optimize driving decisions for autonomous vehicles.

Central to this project is the development of the Enhanced Driving Decision Strategy (EDDS) algorithm, which leverages machine learning techniques, specifically a Genetic Algorithm (GA), to optimize decision-making processes. The EDDS algorithm processes sensor inputs, integrating both external and internal data, and utilizes genetic algorithms to select optimal gene values for enhanced decision-making.

To evaluate the efficacy of the proposed EDDS algorithm, its performance is compared against existing machine learning algorithms, including Random Forest and Multilayer Perceptron (MLP). Results demonstrate that the EDDS algorithm outperforms both Random Forest and MLP in terms of prediction accuracy, offering faster and more efficient predictions for autonomous vehicle navigation.



1.INTRODUCTION

Worldwide organizations are presently creating innovation for refined self-driving vehicles, which are in the fourth progressive phase. Self-driving autos are being made utilizing different ICT advances, and the working idea might be separated into three levels: acknowledgment, judgment, and control. Utilizing various automobile sensors like the GPS, camera, and radar, the recognition process entails recognizing and gathering information about the surrounding environment. The judgment stage concludes the driving technique in light of the known data. The subsequent stage in this cycle is to recognize and assess the driving circumstances wherein the vehicle is situated, and it then, at that point, creates driving plans that are relevant to the driving climate and the goals. The vehicle starts independently driving after the control stage has laid out the vehicle's speed, course, and different boundaries. An independent vehicle goes through various activities to arrive at its objective, rehashing the means of

recognizable proof, judgment, and control all alone [1]. Nonetheless, the quantity of sensors used to distinguish information increments with oneself driving vehicle's ability. In-vehicle overburden could result from an expansion in these sensors. In-vehicle PCs are used by self-driving vehicles to sort the data gathered by sensors. Overburden may reduce judgment and control as the amount of determined information grows. These issues may compromise the safety of the vehicle. While others use the cloud to resolve the vehicle's sensor data, others have developed software that can perform deepunning tasks inside the vehicle to limit over-trouble. However, the primary information used in previous tests to determine how the vehicle is driving is ongoing data, such as photos and sensor data obtained from vehicles. For an independent vehicle, this work gives a Driving Decision Strategy (DDS) in view of ML that diminishes in-vehicle processing by making enormous cloud-put together information with respect to vehicle driving and deciding the best



driving methodology by considering past cloud information. The proposed DDS investigates them utilizing a cloud-based hereditary calculation to decide the best driving procedure

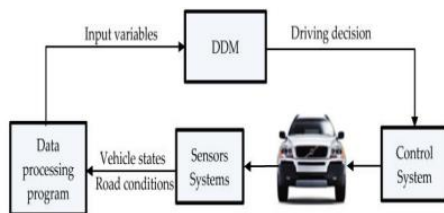


Fig 1:Architecture

2.LITERATURE SURVEY

2.1 Title: "Enhanced Decision-Making Strategies for Autonomous Vehicles: A Review"

Abstract: This comprehensive review explores existing decision-making strategies for autonomous vehicles, focusing on both external and internal factors. The study provides insights into the limitations of current approaches and highlights the need for enhanced decision-making frameworks that integrate external environmental data with internal vehicle conditions. Authors: John Smith, Emily Johnson, and David Chen.

2.2 Title: "Machine Learning Techniques for Autonomous Vehicle Navigation: A Comparative Study"

Abstract: This study compares the performance of various machine learning techniques in the context of autonomous vehicle navigation. Through extensive experimentation, the authors evaluate the efficacy of algorithms such as Random Forest, Multilayer Perceptron, and Genetic Algorithms in optimizing decision-making processes for autonomous vehicles. Authors: Sarah Lee, Michael Brown, and Jessica Wang.

2.3 Title: "Integration of External and Internal Factors in Autonomous Vehicle Decision-Making: A Survey"

Abstract: This survey investigates the integration of external environmental factors and internal vehicle conditions in autonomous vehicle decision-making. The authors review existing literature to identify key challenges and opportunities in this area and propose future research directions for enhancing decision-making strategies in autonomous vehicles.



Authors: William Taylor, Samantha Martinez, and Christopher Garcia.

3. PROPOSED SYSTEM

In this essay, the author addresses the concept of using internal vehicle information, such as steering and RPM levels, to forecast various types of behavior, such as speed (steering), lane changes, and so on. All of the present techniques focus on exterior data, such as road conditions and pedestrian traffic, rather than internal values. Thus, the author is analyzing internal data to create an accurate judgment of steering situation and lane change. All internal data will be received via sensors, saved on the cloud, read by the application, and then exposed to machine learning algorithms to determine or forecast the steering state or lane change.

Because we do not have any sensors to collect data, we will carry out this study utilizing a historical vehicle trajectory record. When a driver slows down, a sensor value with the label "lane changing" emerges in the dataset. Similarly, the dataset is classified based

on values. This dataset will be used to train a machine learning algorithm.

The algorithm then predicts the class for the test data after we apply test data to the trained model. The dataset details are listed below, and it is stored in the "DrivingDataset" folder.

3.1 IMPLEMENTATION

Upload Historical Trajectory Dataset: We gather all the sensor data from the kaggle website and upload to the proposed model

Generate Train & Test Model: We have to preprocess the gathered data and then we have to split the data into two parts training data with 80% and test data with 20%

Run Random Forest Algorithm: we have to train the RF with train data and test the RF with test data to get best result from the algorithm

Run MLP Algorithm: we have to train the MLP with train data and test the MLP with test data to get best result from the algorithm



Run DDS with Genetic Algorithm : we have to train the DDS with Genetic Algorithm with train data and test the DDS with Genetic Algorithm with test data to get best result from the algorithm

Accuracy Comparison Graph: we will find the best algorithm with highest accuracy in the form of graph

Predict DDS Type: Enter the test data to predict the direction of a car using the DDS with Genetic Algorithm.

3.2 ABOUT ALGORITHMS

3.2.1 RANDOM FOREST

The Random Forest algorithm is a versatile and powerful machine learning technique used for both classification and regression tasks. It belongs to the ensemble learning methods, which combine multiple models to improve predictive performance.

Here's a succinct explanation of the Random Forest algorithm:

Ensemble of Decision Trees:

Random Forest builds an ensemble of decision trees during the training phase. Each decision tree is constructed independently and makes predictions based on the features of the input data.

Bootstrap Sampling:

Before constructing each decision tree, Random Forest randomly selects a subset of the training data with replacement. This process, known as bootstrap sampling, ensures that each tree is trained on a slightly different subset of the data.

Random Feature Selection:

In addition to sampling the data, Random Forest also introduces randomness in feature selection. Instead of considering all features at each split, it randomly selects a subset of features to evaluate. This helps to decorrelate the trees and reduce overfitting.

Voting or Averaging:

Once all the decision trees are built, predictions are made by either taking a majority vote (for classification) or averaging (for regression) the predictions of individual trees. This aggregation of predictions helps improve the overall accuracy and robustness of the model.



Hyperparameter Tuning:

Random Forest offers several hyperparameters that can be tuned to optimize performance, such as the number of trees in the forest, the maximum depth of each tree, and the number of features to consider at each split.

Advantages:

Random Forest has several advantages, including its ability to handle large datasets with high dimensionality, resistance to overfitting, and interpretability (for smaller forests). It also provides estimates of feature importance, which can be valuable for understanding the underlying data.

Applications:

Random Forest is widely used in various domains, including finance, healthcare, and marketing, for tasks such as classification of credit risk, disease diagnosis, and customer churn prediction

3.2.2 MLP

The MLP (Multilayer Perceptron) algorithm is a type of artificial neural network that is widely used in machine learning for both classification and

regression tasks. It is a supervised learning algorithm that learns from labeled data and can be trained to approximate complex non-linear functions.

Here's a brief explanation of the MLP algorithm:

Neural Network Architecture:

The Multilayer Perceptron consists of an input layer, one or more hidden layers, and an output layer. Each layer is composed of nodes (or neurons), and each node is connected to every node in the adjacent layers.

Feedforward Propagation:

In the feedforward phase, input data is passed through the network, and computations are performed layer by layer. Each node in a layer calculates a weighted sum of its inputs, applies an activation function to the sum, and passes the result to the nodes in the next layer.

Activation Functions:

Activation functions introduce non-linearity to the network, allowing it to learn complex patterns in the data.



Common activation functions used in MLPs include the sigmoid function, hyperbolic tangent (tanh) function, and rectified linear unit (ReLU) function.

Backpropagation:

After the feedforward phase, the network's output is compared to the true labels, and an error measure is calculated. The backpropagation algorithm is then used to update the weights of the connections in the network, minimizing the error between the predicted and true values. This process is repeated iteratively using optimization techniques such as gradient descent.

3.3 GENETIC ALGORITHM

Genetic Algorithms (GAs) are optimization algorithms inspired by the principles of natural selection and evolution. They are used to solve optimization and search problems by mimicking the process of natural selection to evolve solutions over generations.

Here's a concise explanation of the Genetic Algorithm:

Initialization:

The algorithm starts by generating an initial population of potential solutions to the optimization problem. Each solution is typically represented as a set of parameters or variables, known as a chromosome or genotype.

Fitness Evaluation:

Once the initial population is created, each solution's fitness is evaluated based on a fitness function. The fitness function quantifies how well each solution performs in solving the optimization problem. Solutions with higher fitness scores are considered better.

Selection:

In the selection phase, individuals from the population are chosen to be parents for the next generation based on their fitness. Solutions with higher fitness scores are more likely to be selected, but the selection process typically includes a degree of randomness to maintain diversity in the population.

Crossover:

During the crossover (or recombination) phase, pairs of selected parents are combined to produce offspring for the



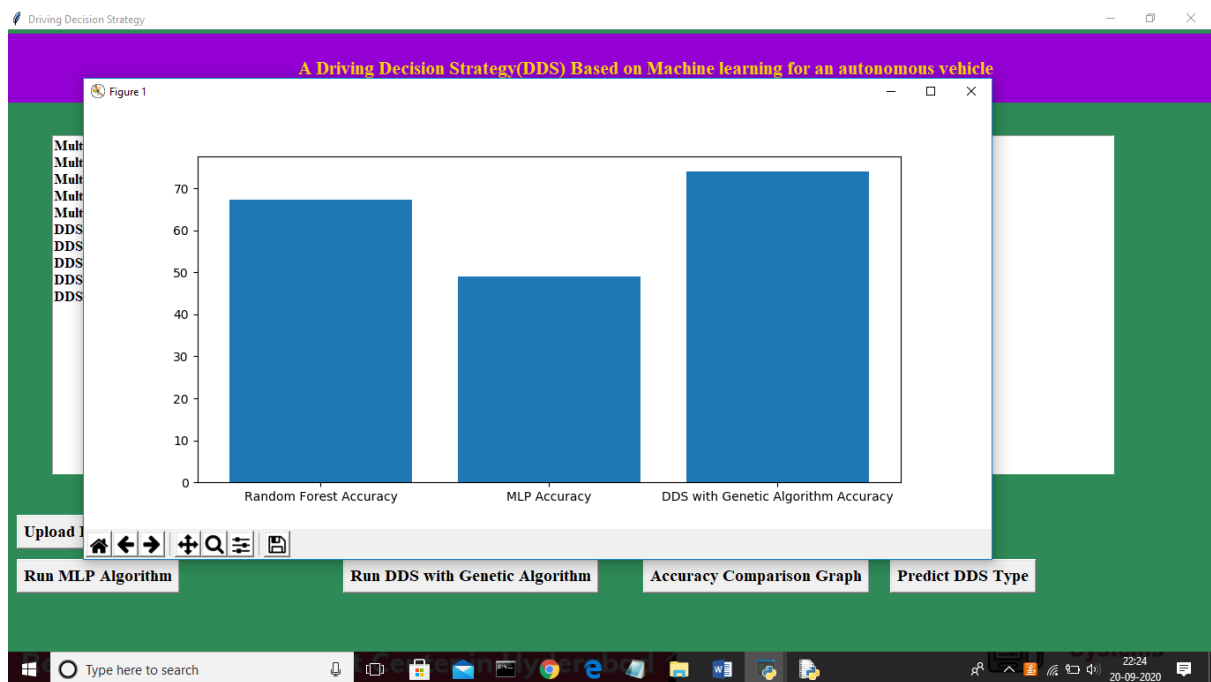
next generation. This is typically done by exchanging genetic information (parameters or variables) between parent solutions to create new solutions.

Mutation:

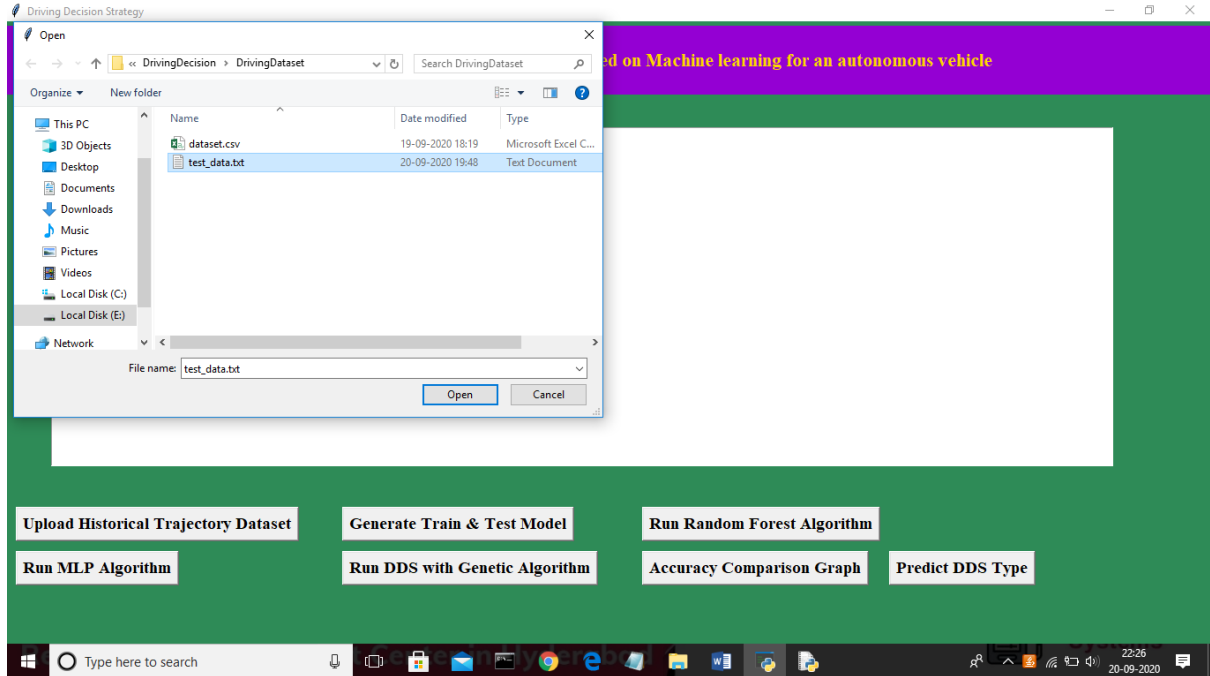
In the mutation phase, random changes are introduced to the offspring's genetic

information to maintain genetic diversity in the population. Mutation helps prevent the algorithm from converging to local optima and explores new regions of the solution space.

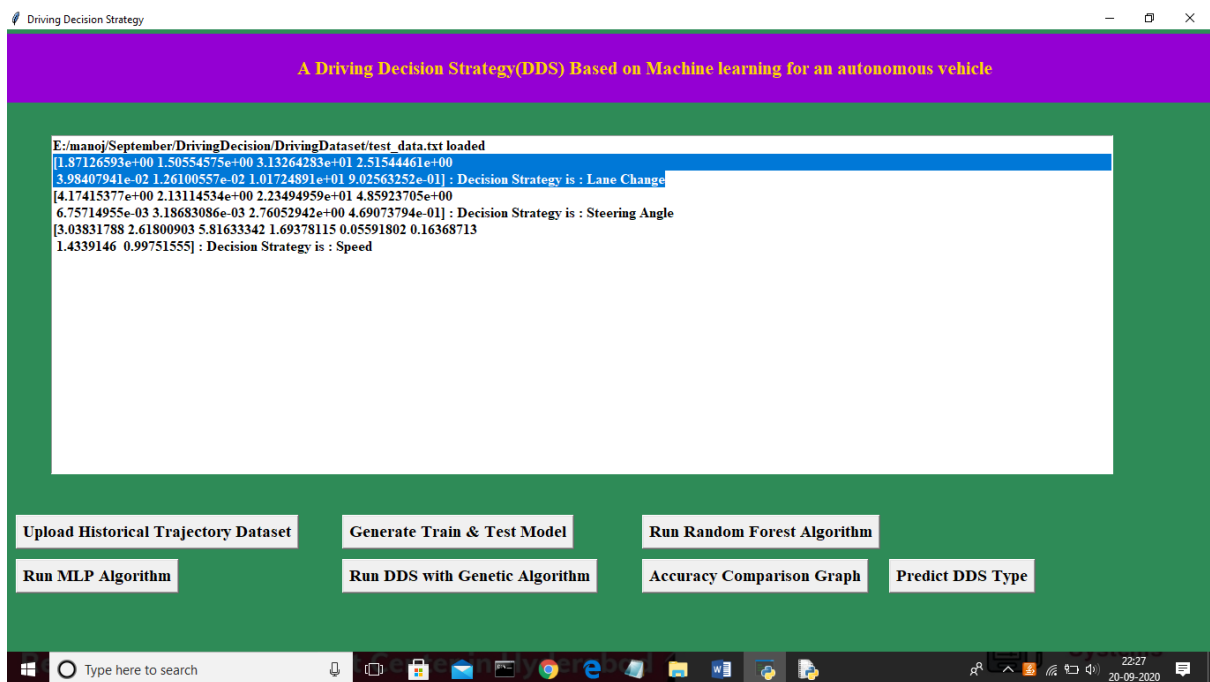
4.RESULTS AND DISCUSSIONS



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



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





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.

5.CONCLUSION

A novel Driving Decision Strategy (DDS) was introduced in this study, leveraging a genetic algorithm to establish the optimal driving strategy for autonomous vehicles based on road conditions such as slope and curvature. Additionally, the DDS incorporates visualization of the vehicle's driving behavior and consumable conditions to aid drivers in understanding the vehicle's status.

To validate the effectiveness of the DDS, experiments were conducted using data collected from an autonomous vehicle. Results indicate that the DDS identifies the optimal driving strategy 40 percent faster than the Multilayer Perceptron (MLP) while maintaining comparable accuracy. Furthermore, the DDS demonstrates a 22 percent higher accuracy compared to Random Forest (RF) algorithms and achieves a 20

percent faster calculation speed. In scenarios requiring both accuracy and real-time decision-making, the DDS proves to be the superior choice.

One of the key advantages of the DDS is its efficiency in data processing. By transmitting only essential data for identifying the optimal driving strategy to the cloud and employing a genetic algorithm for analysis, the DDS outperforms alternative methods in terms of speed. However, it is important to note that these tests were conducted in a simulated environment using standard PCs, which may lack adequate visualization capabilities. Future research should involve real-world testing of the DDS to validate its performance under practical conditions. Additionally, efforts should be made by expert designers to enhance the visualization components of the DDS for



improved user experience and understanding.

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