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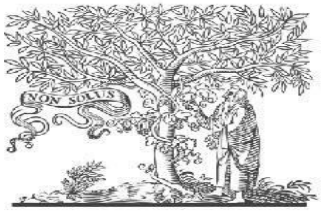

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A Driving Decision Strategy for an Autonomous Vehicle

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Abstract: 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, this paper proposes "A Driving Decision Strategy(DDS) 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 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 paper 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.

Keywords: Machine learning, Genetic Algorithm, RPM level, Speed.

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 paper proposes a Driving Decision Strategy(DDS) 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 DDS analyzes them to determine the best driving strategy by using a Genetic algorithm stored in the Cloud

2 RELATED WORK

[1] 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.

[2] 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.

[3] 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 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.

[4] Real-time and reliable measurements of the effluent quality are essential to improve operating efficiency and reduce energy consumption for the wastewater treatment process. Due to the low accuracy and unstable performance of the traditional effluent quality measurements, we propose a selective ensemble extreme learning machine modeling method to enhance the effluent quality predictions. Extreme learning machine algorithm is inserted into a selective ensemble frame as the component model since it runs much faster and provides better generalization performance than other popular learning algorithms.

In recent years, hybrid neural network approaches, which combine mechanistic and neural network models, have received considerable attention. These approaches are potentially very efficient for obtaining more accurate predictions of process dynamics by combining mechanistic and neural network models in such a way that the neural network model properly accounts for unknown and nonlinear parts of the mechanistic model

[6] Brid modelling methods are applied to model a full- scale cokes wastewater treatment plant. Within the hybrid model structure, a mechanistic model

specifies the basic dynamics of the relevant process and non-parametric models compensate for the inaccuracy of the mechanistic model. Five different non-parametric models - feed-forward neural network, radial basis function network, linear partial least squares (PLS), quadratic PLS and neural network PLS - are incorporated in the hybrid model structure.

[7] A reliable model for any wastewater treatment plant is essential in order to provide a tool for predicting its performance and to form a basis for controlling the operation of the process. This would minimize the operation costs and assess the stability of environmental balance. This process is complex and attains a high degree of nonlinearity due to the presence of bio-organic constituents that are difficult to model using mechanistic approaches. Predicting the plant operational parameters using conventional experimental techniques is also a time consuming step and is an obstacle in the way of efficient control of such processes. In this work, an artificial neural network (ANN) black-box modeling approach was used to acquire the knowledge base of a real wastewater plant and then used as a process model.

[8] The paper describes linear and nonlinear modeling of the wastewater data for the performance evaluation of an up-flow anaerobic sludge blanket (UASB) reactor based wastewater treatment plant (WWTP). Partial least squares regression (PLSR), multivariate polynomial regression (MPR) and artificial neural networks (ANNs) modeling methods were applied to predict the levels of biochemical oxygen demand (BOD) and chemical oxygen demand (COD) in the UASB reactor effluents using four input variables measured weekly in the influent wastewater during the peak (morning and evening) and non-peak (noon) hours

over a period of 48 weeks. The performance of the models was assessed through the root mean squared error (RMSE), relative error of prediction in percentage (REP), the bias,

the standard error of prediction (SEP), the coefficient of determination (R(2)), the Nash-Sutcliffe coefficient of efficiency (E(f)), and the accuracy factor (A(f)), computed from the measured and model predicted values of the dependent variables (BOD, COD) in the WWTP effluents.

[9]In this study, performance of a lab-scale hybrid up- flow anaerobic sludge blanket (UASB) reactor, treating a chemical synthesis-based pharmaceutical wastewater, was evaluated under different operating conditions. This study consisted of two experimental stages: first, acclimation to the pharmaceutical wastewater and second, determination of maximum loading capacity of the hybrid UASB reactor. Initially, the carbon source in the reactor feed came entirely from glucose, applied at an organic loading rate (OLR) 1 kg COD/m(3) d. The OLR was gradually step increased to 3 kg COD/m(3) d at which point the feed to the hybrid UASB reactor was progressively modified by introducing the pharmaceutical wastewater in blends with glucose, so that the wastewater contributed approximately 10%, 30%, 70%, and ultimately, 100% of the carbon (COD) to be treated.

[10] considering the bio sensor and real time object detection techniques in the future for considering more parameters for self-driving vehicles [11].

3 PROPOSED METHODOLOGY

we propose “A Driving Decision Strategy(DDS) 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 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 paper 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.

3.1 ALGORITHMS RF

Random Forest works in two-phase first is to create the random forest by combining N decision tree, and second is to make predictions for each tree created in the first phase.

The Working process can be explained in the below steps and diagram:

Step-1: Select random K data points from the training set.

Step-2: Build the decision trees associated with the selected data points (Subsets).

Step-3: Choose the number N for decision trees that you want to build.

Step-4: Repeat Step 1 & 2.

Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.

MLP: A multilayer perceptron (MLP) is a class of feedforward artificial neural network (ANN). The term MLP is used ambiguously, sometimes loosely to any feedforward ANN, sometimes strictly to refer to networks composed of multiple layers of perceptron's (with threshold activation); see § Terminology. Multilayer perceptron's are sometimes colloquially referred to as "vanilla" neural networks, especially when they have a single hidden layer. [1] An MLP consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training. [2][3] Its multiple layers and non-linear activation distinguish MLP from a linear

perceptron. It can distinguish data that is not linearly separable. [4]

GENETIC ALGORITHM: Genetic algorithm is a metaheuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms (EA). Genetic algorithms are commonly used to generate high- quality solutions to optimization and search problems by relying on biologically inspired operators such as mutation, crossover and selection

3.2. FLOWCHART

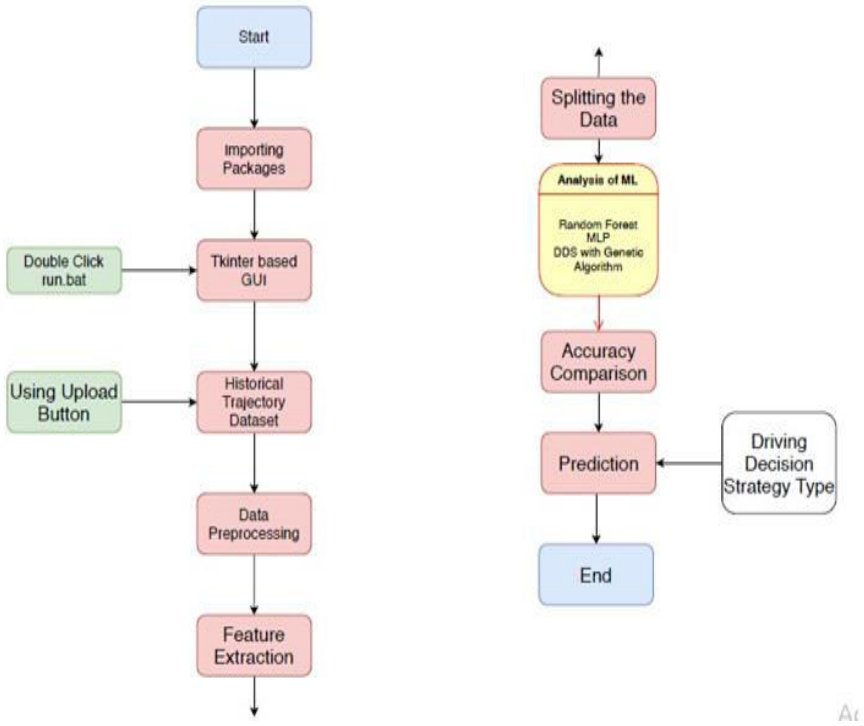
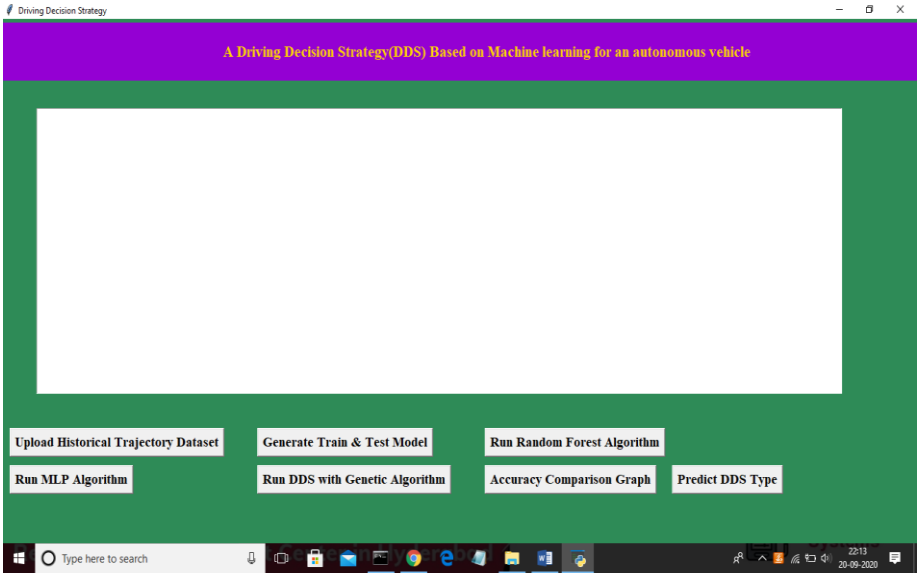
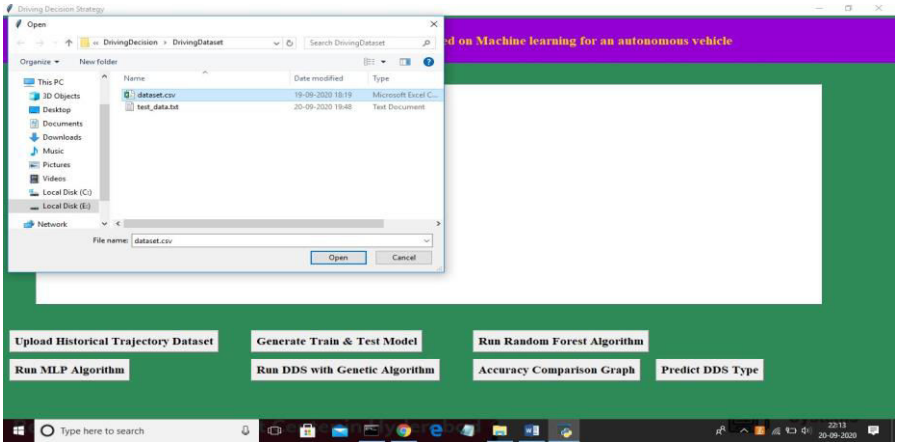


Fig:1 : Flow chart

3.3. RESULTS



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



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

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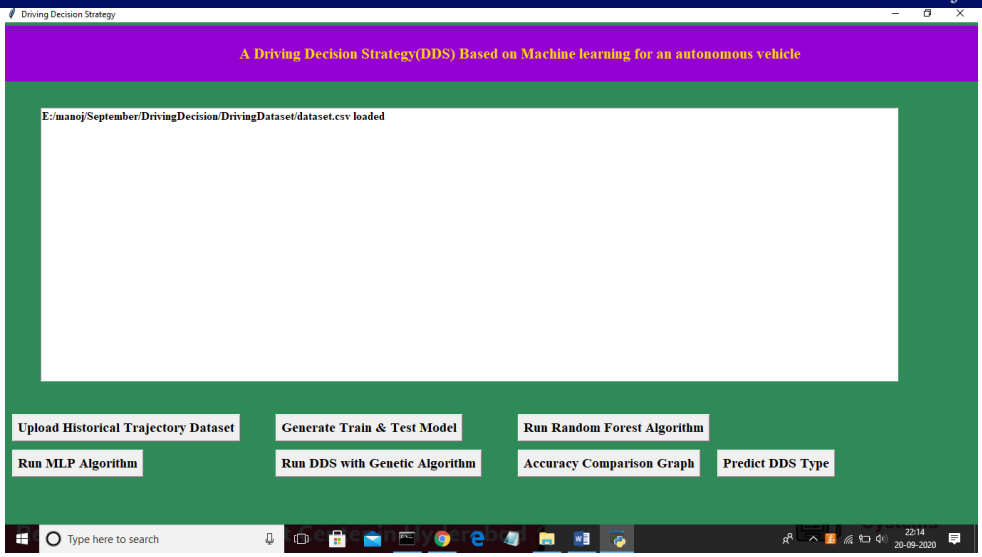
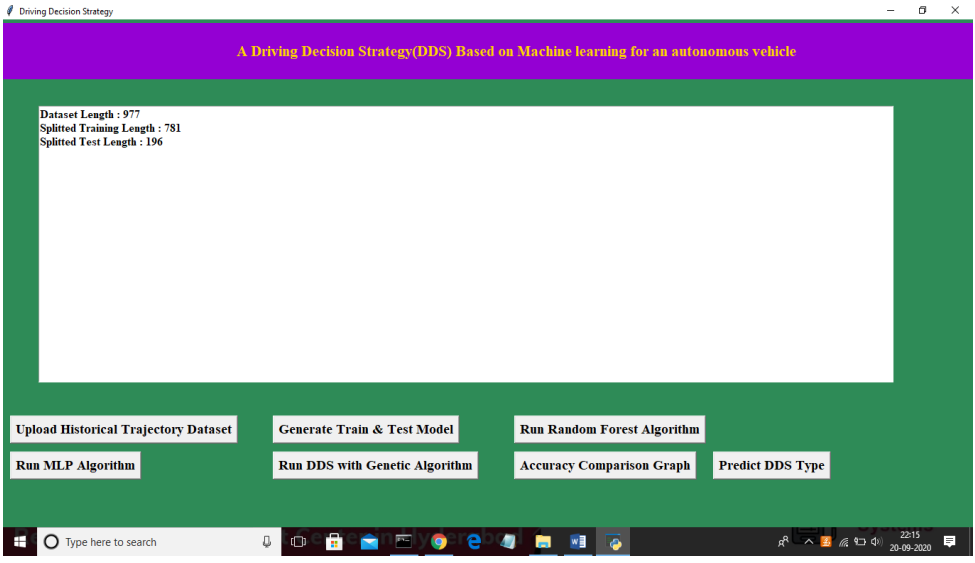
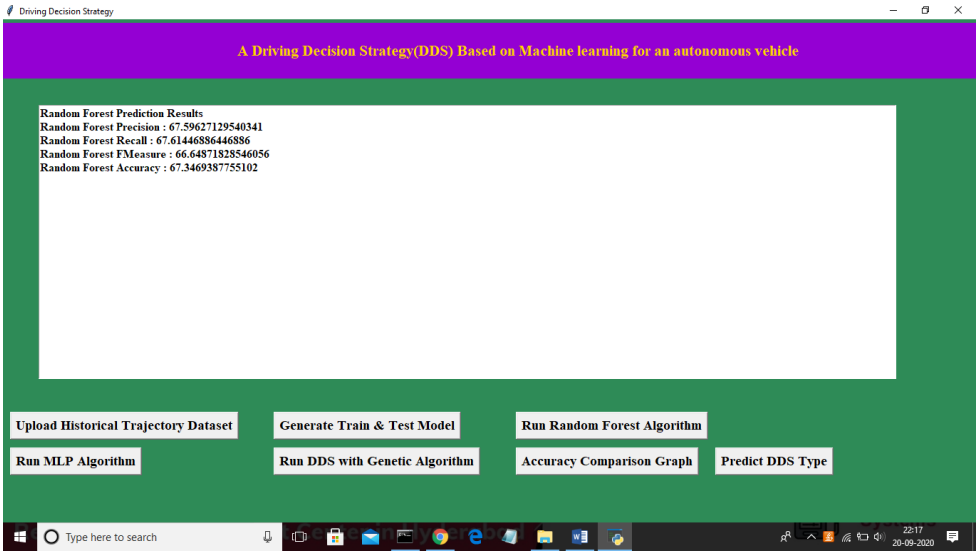


In above screen dataset is loaded and now click on 'Generate Train & Test Model' button to read dataset and to split dataset into train and test part to generate machine learning train model

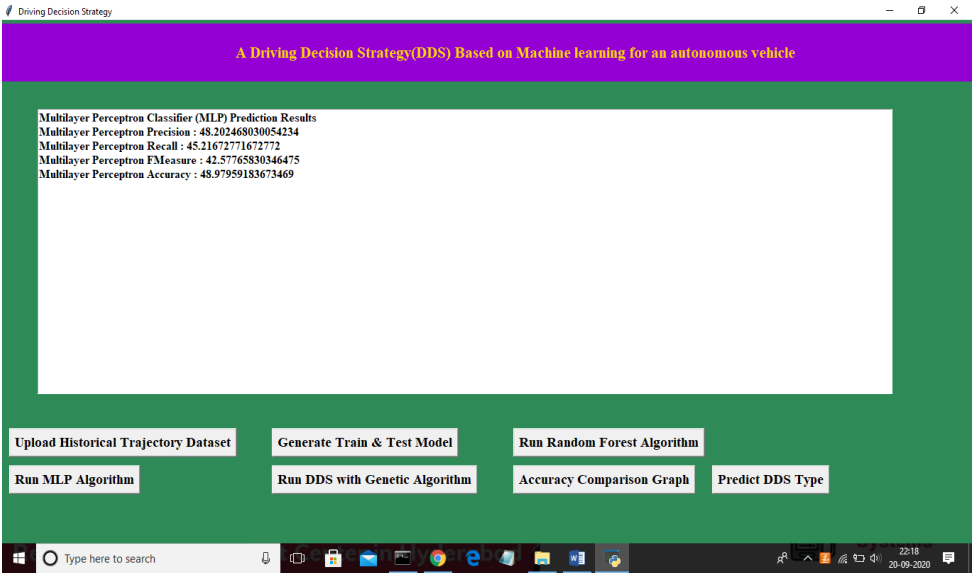


In above screen dataset contains 977 total trajectory records and application using 781 (80% of dataset) records for training and 196 (20%

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



In above screen we calculated random forest accuracy, precision, recall and f measure and random forest got 67% prediction accuracy. Now



click on 'Run MLP Algorithm' button to train MLP model and to calculate its accuracy

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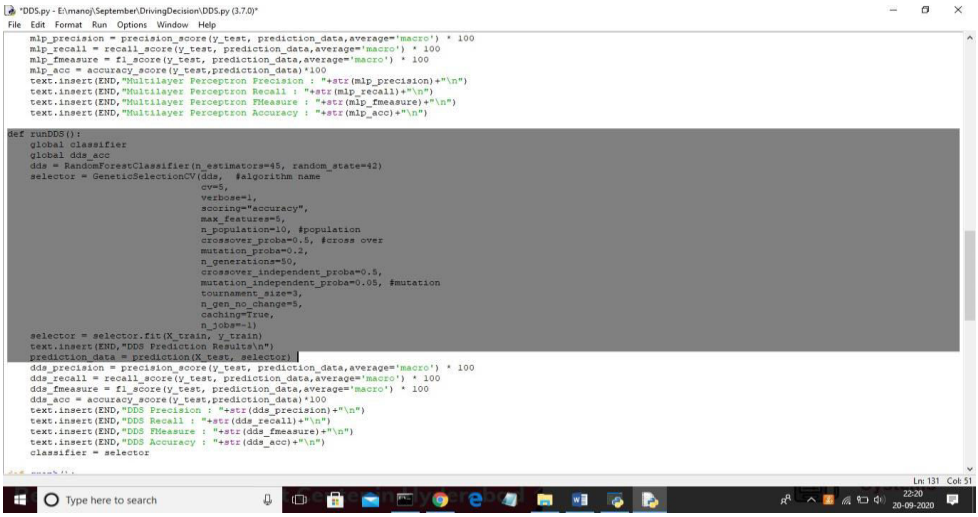
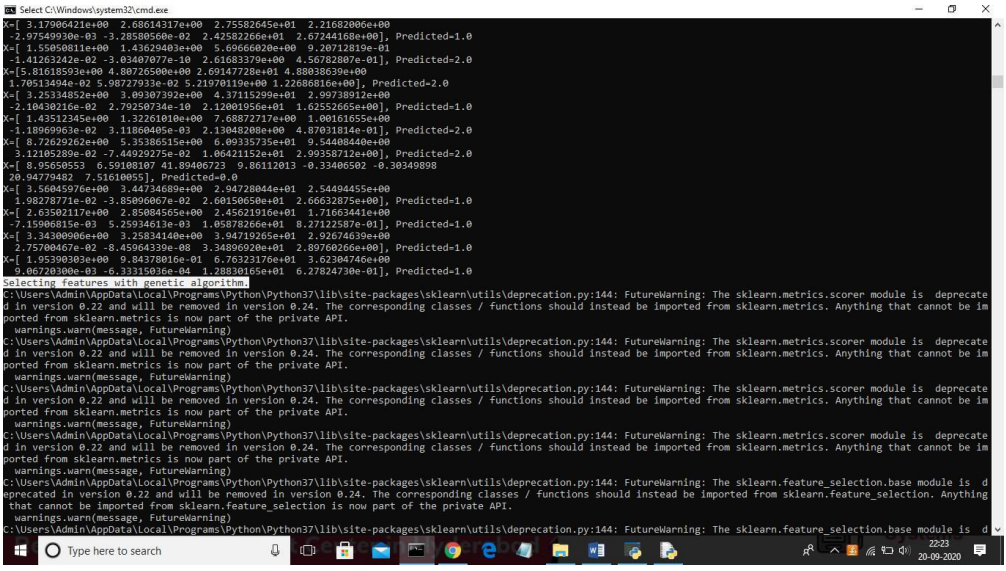
In above screen MLP got 48% prediction accuracy and in below screen we can see genetic algorithm code used for building propose DDS algorithm



In above screen we can see genetic algorithm code used in DDS algorithm and now click on 'Run DDS with Genetic Algorithm' button to train DDS and to calculate its prediction accuracy



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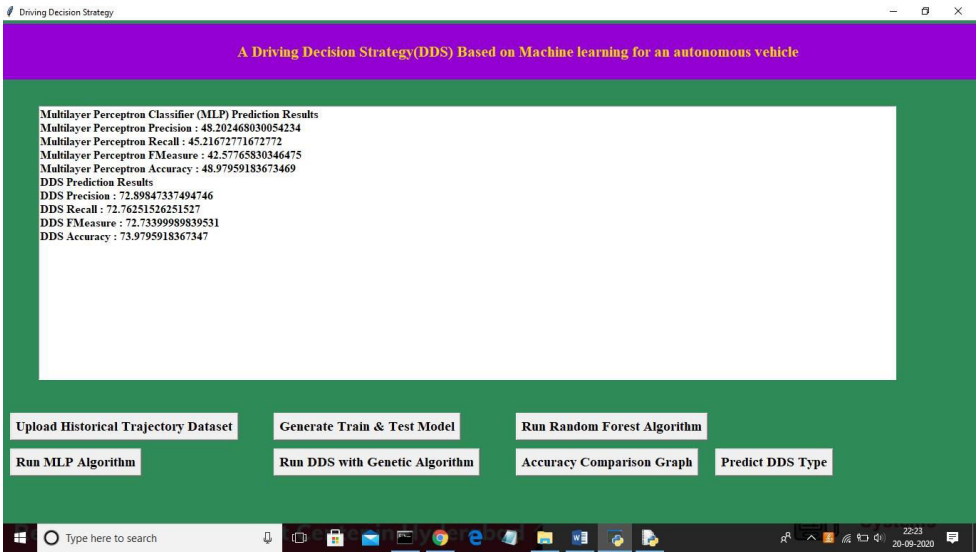
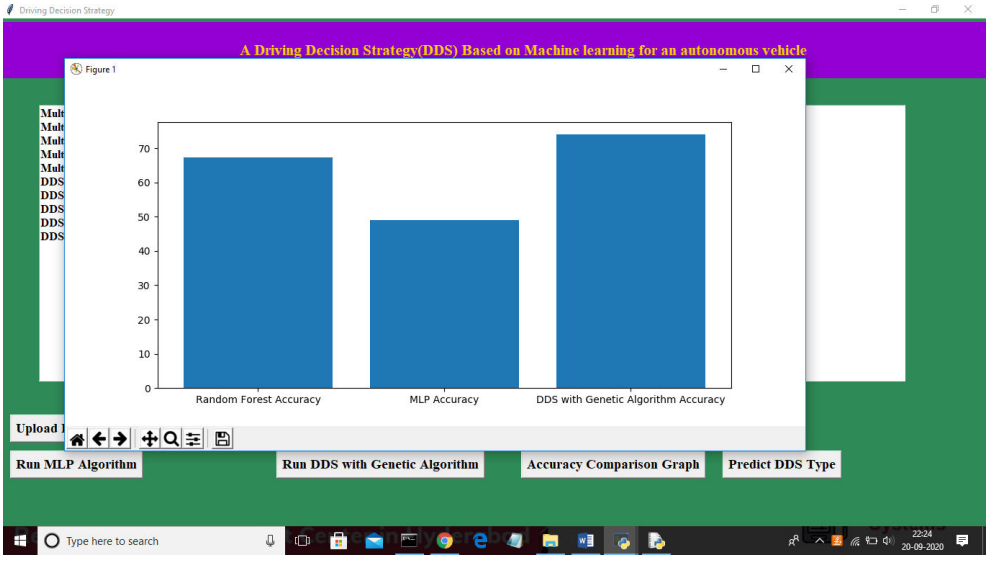
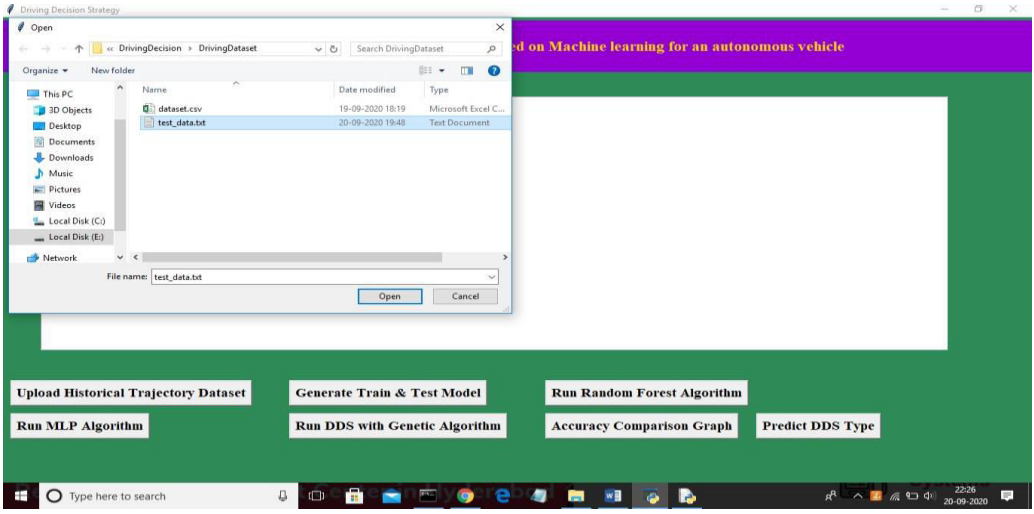
In above black console genetic algorithm starts optimal feature selection



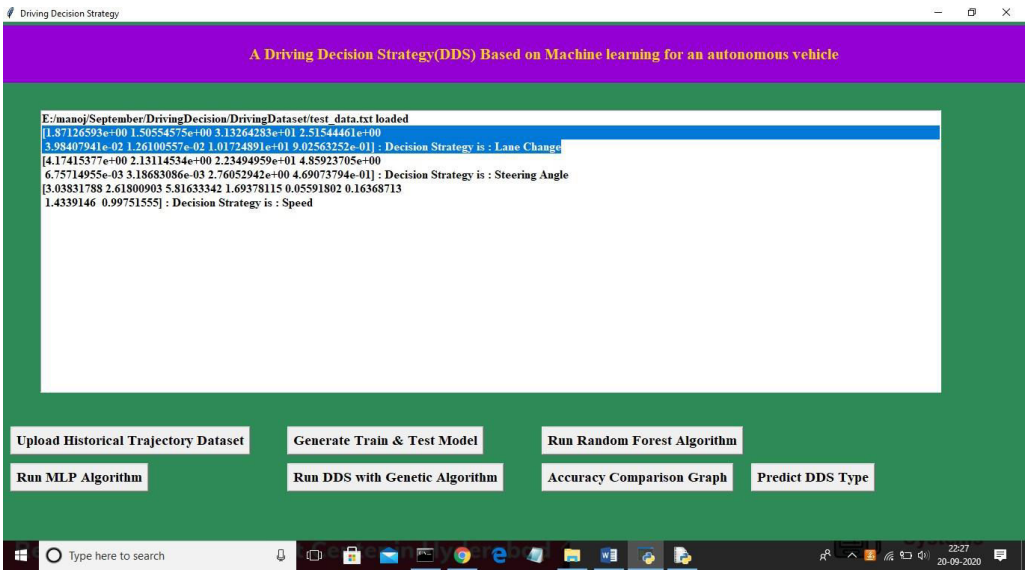
In above screen propose DDS algorithm got 73% prediction accuracy and now click on 'Accuracy Comparison Graph' button to get below graph



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



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

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 analyzes 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.

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