

A NOVEL APPROACH FOR DRIVING DECISION STRATEGY (DDS) USING A STACKING APPROACH FOR AN AUTONOMOUS VEHICLE

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ABSTRACT:

A contemporary autonomous car selects its driving strategy based solely on outside influences (In terms of foot traffic, state of roads, and so on), ignoring internal state of vehicle. This work offers "Driving Decision Strategy with using a stacking approach for an independent vehicle" which decides ideal technique of an independent vehicle by breaking down not only exterior aspects, though additionally internal state of vehicle to solve problem (consumable conditions, RPM levels, etc.). DDS builds an evolutionary algorithm and produces the best driving strategy for an automated car based on data from automotive sensors saved in the cloud. In order to verify DDS, this study compares it to two other neural network models, the multi-layer perceptron (MLP) and the recurrent fuzzy network (RF). When compared to conventional vehicle gates, DDS's loss rate was about 5% lower, and it was 40% quicker at determining RPM, speed, turning angle, and position shifts.

1. INTRODUCTION

However, the number of data-recognition devices is expanding along with the improved performance of autonomous vehicles. Adding more of these instruments to a car can make it difficult to operate. Sensing data is processed by processors located within the vehicle. Overload can delay judgement

and control as the volume of calculated data grows. These issues could compromise vehicle's stability. Some studies have produced hardware capable of doing deep-running processes within car, while others use cloud to handle vehicle's sensor information. Additionally, data is gathered from cars to reveal how people are operating them. In order

to reduce the amount of processing power needed within the vehicle itself, this study suggests a Driving Decision Strategy with using a stacking approach for an independent vehicles. This DDS reduces the amount of data processed locally and instead stores all of the relevant information in the cloud, where it can be analysed and used to create the optimal driving strategy. Using a Cloud-based genetic algorithm, suggested DDS analyses them to find optimal driving approach.

1.1MOTIVATION

Global enterprises are currently in fourth stage of developing technologies for advanced self-driving cars. On basis of various ICT technologies, self-driving automobiles are being created, and operating concept may be categorised into three levels: comprehending, evaluating, and managing. During the identification phase, the car employs its various instruments, such as its cameras, GPS, and radar, to identify and gather data about its immediate surroundings. Once recognisable info is processed, a moving plan can be determined. The process then locates the car, analyses its surroundings, and uses this information to create an optimal driving strategy based on the given circumstances and goals. control stage decides car's speed, direction, etc., and vehicle then begins driving on its own. Repeating phases of identification, judgement, and control, an autonomously

driving vehicle executes a variety of manoeuvres to reach its objective.

1.2 OBJECTIVES

DDS builds an evolutionary algorithm and produces the best driving strategy for an automated car based on data from automotive sensors saved in the cloud. In order to verify DDS, this study compares it to two other neural network models, the multilayer perceptron (MLP) and the recurrent fuzzy network (RF). When compared to conventional vehicle gates, DDS's loss rate was about 5% lower, and it was 40% quicker at determining RPM, speed, turning angle, and position shifts.

1.3 OUTCOMES

It visualises the driving and utilization states of a mechanized vehicle to give users with this information and runs a hereditary calculation in view of gathered information to decide optimum driving strategy for vehicle based on incline and curves of road on which vehicle is travelling. Desoto was used in trials where data from a driverless vehicle was analysed to find the best driving strategy and the viability of DDS. Although DDS and MLP have comparable precision, DDS calculates ideal driving strategy 40% faster. And DDS is 22% more accurate than RF and 20% quicker in determining ideal driving approach.

1.4 APPLICATIONS:

This tactic employed in Automobiles

2. LITERATURE EVALUATION

In recent years, the development of autonomous driving technology has gained significant attention. Machine learning techniques have been applied to various aspects of autonomous driving, such as sensory data integration, object detection, tracking, and decision-making.

[1]. Al-Tahmeesschi et al. (2020) proposed a machine learning-based system for autonomous driving that integrates sensory data, detects and tracks dynamic objects, and predicts their future movements. The system uses a combination of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to process sensory data and predict object movements

[2]. Guo et al. (2020) proposed a deep reinforcement learning-based autonomous driving algorithm that learns to drive in different scenarios, such as intersections and roundabouts, by interacting with the environment. The algorithm uses a combination of CNNs and long short-term memory (LSTM) networks to process sensory data and generate driving commands

[3]. Lee et al. (2020) conducted a survey of machine learning techniques for autonomous driving. They categorized the techniques into

six categories: object detection and tracking, behaviour prediction, motion planning, control, simulation, and validation. They discussed the advantages and limitations of each technique and highlighted some future research directions

[4]. Kumar et al. (2019) proposed a neural network-based approach for lane detection and vehicle tracking. The approach uses a CNN to detect lanes and a Kalman filter to track vehicles. The approach achieved high accuracy in lane detection and vehicle tracking

[5]. Liu et al. (2019) proposed a hybrid algorithm for an intelligent autonomous driving system that uses a support vector machine (SVM) and fuzzy logic controller (FLC). The algorithm processes sensory data, such as camera and lidar data, and generates driving commands. The FLC helps to make the driving commands smoother and more stable

[6]. Joo et al. (2020) proposed an urban autonomous driving system that uses a hierarchical decisionmaking framework. The system consists of three levels: perception, planning, and control. The perception level uses a deep learning-based object detection algorithm, and the planning level uses a rule-based algorithm. The control level generates driving commands based on the output of the planning level

In conclusion, machine learning techniques have shown great potential in various aspects of autonomous driving, such as object detection, tracking, decision-making, and control. The proposed approaches in the reviewed papers have achieved high accuracy and demonstrated good performance in different scenarios. However, more research is needed to address some of the challenges in autonomous driving, such as real-time processing, scalability, and safety

3. LIMITATIONS

Existing models comprise k-NN, RF, SVM, and Bayes. Although research has been done in the medical field using sophisticated data analysis and machine learning algorithms, the field of musculoskeletal disease prognosis is still in its infancy and needs more study to ensure effective avoidance and therapy. After digging two-levels-deep into the hidden states of past car paths, it selects Hidden Markov Model (HMM) parameters based on the collected evidence. In addition, a Viterbi method is employed to locate double-layer hidden state sequences that correspond to just-driven trajectory. In the final section of the article, a novel method for predicting car trajectories using a hidden Markov model with double levels of hidden states is proposed.

This model forecasts closest neighbour unit of location information for subsequent k phases.

Drawbacks :

1. reduced effectiveness and need for further investigation are required for prevention

4. PROPOSED SYSTEM

To discover the best course of action for an automated vehicle, we offer "A Driving Decision Strategy (DDS) based on Machine Learning for an autonomous car," which takes into account both the environment around and inside the car (consumable conditions, RPM levels etc.). DDS builds an evolutionary algorithm and produces the best driving strategy for an automated car based on data from automotive sensors saved in the cloud. In order to verify DDS, this study compares it to two other neural network models, the multilayer perceptron (MLP) and the recurrent fuzzy network (RF). When compared to conventional vehicle gates, DDS's loss rate was about 5% lower, and it was 40% quicker at determining RPM, speed, turning angle, and position shifts.

Benefits:

1. These enhancements Control system for a vehicle based on sensor data.

5. SYSTEMDESIGN

5.1 SYSTEM ARCHITECTURE

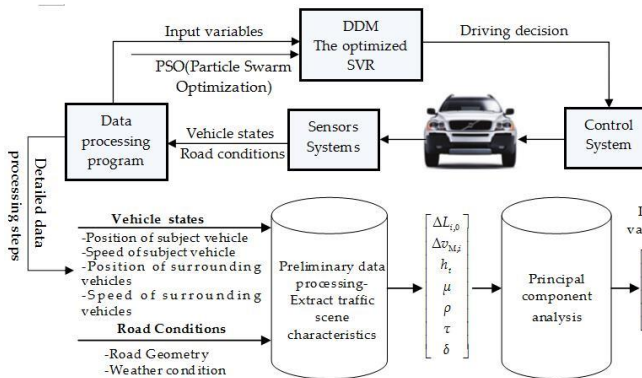
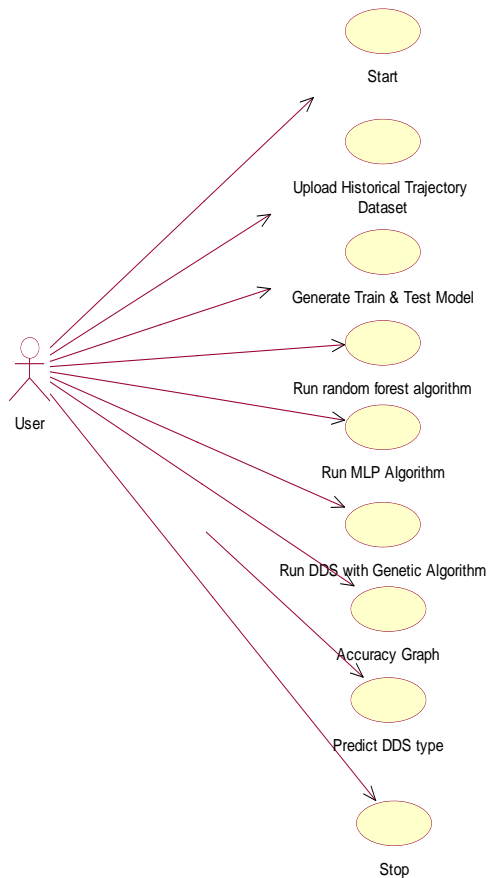


Fig 1: System architecture

Fig 2: Use Case Diagram

As a type of behavioural diagram, use-case diagrams in the Unified Modelling Language (UML) are defined and produced from a Use-case analysis. The reason for this chart is to give a realistic outline of the framework's powers with regards to members, their goals (addressed as use cases), and any associations between the utilization cases. The primary goal of a use case illustration is to illustrate the interaction between various actors and the system. Each participant's part in the system can be represented graphically.

5.2 USE CASE DIAGRAM



5.3 FLOW CHART:

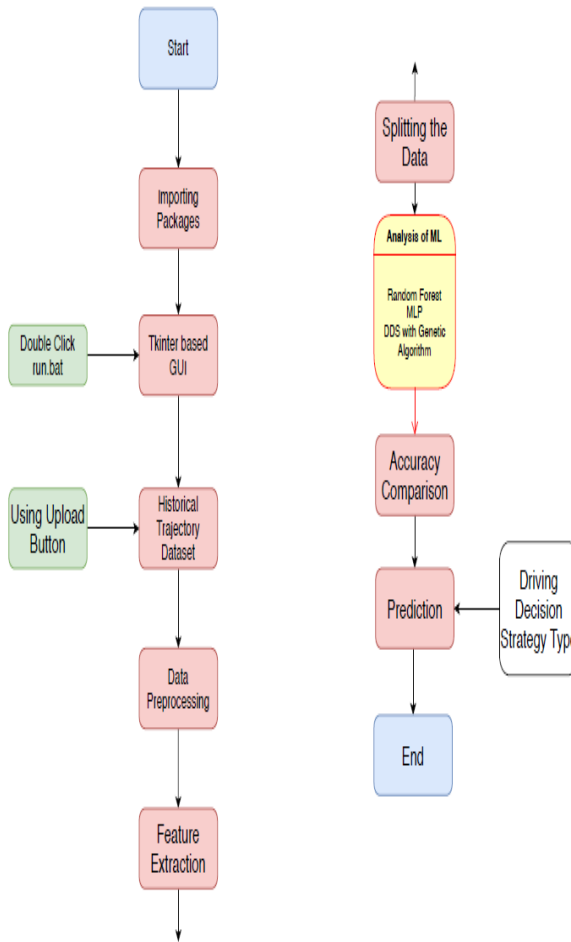


Fig 3: Flow chart

5.4 DATA FLOW DIAGRAM:

1. The DFD is also known as a bubble graphic. It's a simple pictorial model for representing a system in terms of the inputs it receives, the processes that can be applied to that input, and the outputs it generates.
2. The data flow map is a vital modelling instrument, and it is one of the most fundamental (DFD). Useful for modelling individual components of a system. These elements include things like the system's process, the data used by the process, any

external entity's interaction with the system, and the flow of information within the system.

3. DFD demonstrates how information undergoes transformations across a system as it travels through it. It's a visual representation of the transformations and transfers that take place in the passage of data from its intake to its final output.

4. Moreover, a DFD can be used to describe a system at any level of complexity. DFD has levels that correlate to the increasing intricacy of functions and the amount of data being transferred between them.

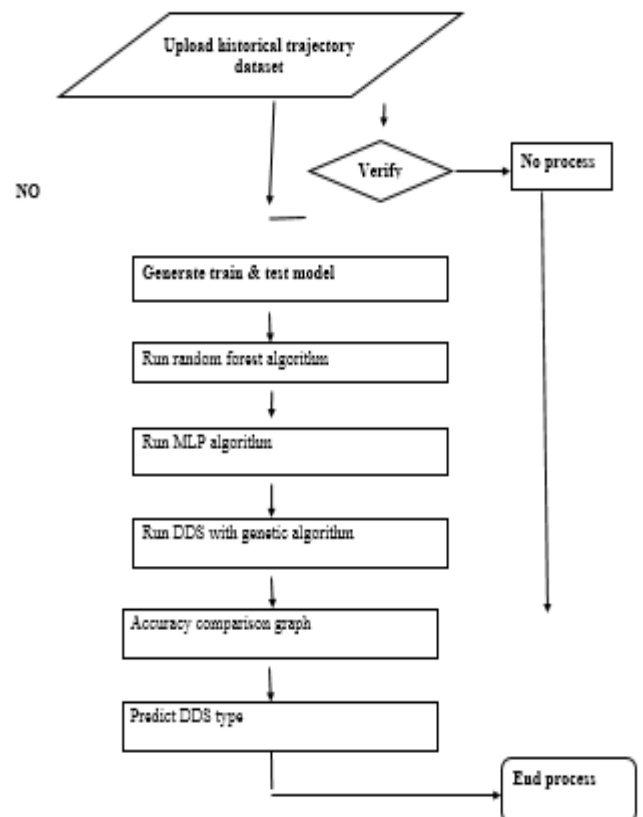


Fig: Data flow diagram

6. DATA-SET AND DATA PREPROCESSING

we are utilizing a historical vehicle trajectory dataset since we do not have sensors to gather data. The trajectory dataset contains sensor values with corresponding class labels, such as "lane changing," when the user slows down the vehicle. The dataset is comprised of various classes based on the values. The machine learning algorithm will be trained on this dataset, and when we apply test data.

trajectory_id	start_time	end_time	rpm_aver	rpm_med	rpm_max	rpm_std	speed_aver	speed_med	speed_max	speed_std
2.01E+13	2007-11-08T01:05:36.000000000	2007-11-08T01:12:14.000000000	3.561229	4.237586	4.702	1.428515	-0.00985	-0.00271	0.135384	0.091201
2.01E+13	2008-06-18T09:22:10.000000000	2008-06-18T09:22:45.000000000	21.70835	18.1923	54.6717	15.65798	3.123229	1.868308	16.83847	7.667033
2.01E+13	2008-06-18T09:53:17.000000000	2008-06-18T10:01:31.000000000	1.384173	1.30718	7.172	0.842763	0.016952	0.020387	2.082622	0.361382
2.01E+13	2008-06-19T11:57:02.000000000	2008-06-19T12:01:50.000000000	3.217921	2.19409	12.54107	2.79383	-0.03803	-0.02231	2.400153	0.712168
2.01E+13	2008-06-19T23:47:07.000000000	2008-06-20T01:10:51.000000000	1.509991	1.05224	29.80859	1.957342	0.002243	0.001583	3.059844	0.365482
2.01E+13	2008-06-20T02:45:28.000000000	2008-06-20T03:12:05.000000000	2.87243	2.220617	13.68806	2.47965	-0.01625	0.002861	2.864375	0.596121
2.01E+13	2008-06-20T04:21:40.000000000	2008-06-20T05:05:47.000000000	6.190253	6.050348	24.4936	4.017136	-0.03948	0.016615	7.599066	0.810596

Table 1: Sample Data-Set

7. PROPOSED SYSTEM APPROACH:

Random Forest is a popular machine learning algorithm that belongs to the family of ensemble methods. It is used for both classification and regression tasks.

In a Random Forest, a large number of decision trees are created using a random

subset of the available data and features. Each tree independently makes a prediction, and the final prediction is made by taking the average (in regression) or majority vote (in classification) of the predictions of all the trees.

Multi-layer Perceptron (MLP) algorithm is a type of artificial neural network that is widely used in machine learning for both regression and classification tasks.

It consists of multiple layers of interconnected nodes or neurons, with each node performing a weighted sum of its inputs and applying an activation function to produce its output. The outputs of one layer are used as inputs to the next layer, and the process is repeated until the final output is obtained. MLPs can be prone to overfitting and can require a large amount of data to achieve good performance. They can also be sensitive to the choice of hyperparameters, such as the number of layers, the number of nodes per layer, and the choice of activation functions.

Stacking Approach also called as a stacked generalization, is a machine learning ensemble method that combines multiple models to improve predictive performance. In stacking, the predictions from several models are used as inputs to a meta-model, which then generates the final prediction.

8. Results and Analysis:

Driving Decision Strategy that utilizes trajectory data more accurately than previous models. Our approach involves a Stacking algorithm that combines MLP and RANDOM FOREST algorithms to analyse the internal data of the vehicle, including steering and RPM levels, to make predictions about various actions such as speed and lane changes.

Algo rithm	Preci sion	Rec all	FMe asure	Accu racy
MLP	48.20 24680	45.2 1672	42.57 76	48.9 7959
Rando m Forest	67.59 627	67.6 1776	66.64 871	67.3 4683
Stacki ng	72.89 847	72.7 6251	72.73 399	73.9 5979

Table 2 : Performance Metrics Comparison

9. CONCLUSION

A Moving Choice Method was suggested as a result of this research. It uses a genetic algorithm trained on historical data to identify the best course of action for a given vehicle, taking into account the grade and curve of the route it is travelling on, and then displays this information to the driver via a dashboard dashboard. Data from an automated vehicle was used to perform experiments on DDS in order to select the best operating strategy. DDS and MLP are equally accurate, but DDS is 40% quicker at determining the optimal driving strategy. DDS is also 20% quicker at finding the best driving strategy than RF and 22% more precise. Since determining the best course of action while driving is a highly precise and dynamic process, DDS is perfectly adapted for the task. DDS's faster calculation of the optimum driving strategy for a vehicle

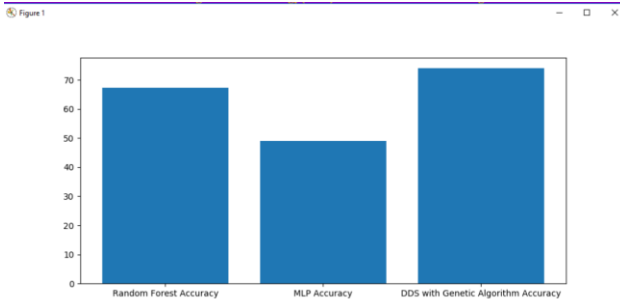


Fig 4 : Accuracy Comparison Graph

The graph above depicts the accuracy of different algorithms used in predicting vehicle behaviour, with the x-axis indicating the algorithm names and the y-axis indicating the corresponding accuracy. Based on the graph, it can be inferred that the STACKING algorithm is outperforming the other two algorithms in terms of accuracy.

is made possible by the fact that it sends only the data that is absolutely essential for identifying the best strategy for driving a vehicle to the cloud, where it is analysed using a genetic algorithm. While DDS testing was done, it was in a simulated Computer setting with limited viewing tools.

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