FOR AN AUTONOMOUS VEHICLE, A MACHINE LEARNING-BASED DRIVING DECISION STRATEGY (DDS)

MS.K. PAVANI [1], M s.M.ANITHA[2], Mr.MUSIBOYINA. RAMAKRISHNA[3]

#1 Assistant Professor in the Master of Computer Applications in the SRK Institute of Technology, Enikepadu, Vijayawada, NTR District

#2 Assistant Professor & Head of Department of MCA, SRK Institute of Technology, Vijayawada, Enikepadu, Vijayawada, NTR District

#3 MCA Student in the Master of Computer Applications at SRK Institute of Technology, Enikepadu, Vijayawada, NTR District

Pavanicomputers2010@gmail.com[1], anitha3harshak@gmail.com[2] , , ramakrishnamusiboyina@gmail.com[3]

Abstract: These days, autonomous cars make decisions about how to drive only based on external variables like other people and the state of the road. The author offered a creative solution to these issues: "A Driving Decision Strategy (DDS) Based on Machine Learning for an Autonomous Vehicle," This determines the best solution by considering both internal and external factors. The DDS software, which uses genetic algorithms to choose optimal gene values for better prediction and decision-making, was introduced by the author. To choose the best value for a quicker forecast, the DDS algorithm receives sensor data and forwards it to a genetic algorithm. The performance of DDS using genetic algorithms is compared to that of Random Forest and MLP. imply that DDS outperforms MLP and random forest in predicting.

Keywords: Autonomous vehicles, Driving Decision Strategy (DDS), Machine learning, Genetic algorithm, Sensor data, Prediction accuracy, Random Forest, Multilayer Perceptron (MLP), Self-driving cars, Decision-making models.

INTRODUCTION

As self-driving car technology advances, vehicles are being equipped with a growing number of sensors to gather information about their surroundings. These sensors help in making real-time decisions but can also lead to system overload due to the massive amount of data being processed inside the vehicle. This computational burden can delay decision-making and affect the stability and safety of the autonomous vehicle. While some solutions offload the processing to the cloud, others develop specialized hardware for faster processing within the vehicle itself.

To overcome these issues, a Driving Decision Strategy (DDS) based on machine learning is proposed. This strategy aims to reduce in-vehicle computation by using cloud-based processing. DDS collects driving data from the vehicle and uses a genetic algorithm in the cloud to analyze historical and real-time data. Based on this, it generates an optimal driving strategy that ensures both efficiency and safety. By doing so, DDS effectively combines both internal vehicle data and external road/environmental factors to enhance decision-making for autonomous driving.

LITERATURE SURVEY

2.1 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

"An Integrated Self-diagnosis System (ISS) for an Autonomous Vehicle based on an Internet of Things (IoT) Gateway and Deep Learning" is presented in this article. It collects sensor data, uses Deep Learning to diagnose itself and its parts, and alerts the driver. There are three parts to the ISS. The first In-VGM collects media data from in-vehicle sensors, such as a black box, driving radar, and vehicle control messages, and transmits it to the on-board diagnostics (OBD) or actuators via the Controller Area Network (CAN), FlexRay, and Media Orientated Systems Transport (MOST) protocols. Data from driving media goes to MOST Various communications are converted into message types for the destination protocol. The ODLM creates the Training Dataset and calculates the risk of vehicle parts, consumables, and other elements using in-vehicle sensor data. The vehicle's overall condition risk is assessed. In-VGM simultaneous message transmission efficiency is raised by 15.25%, whereas ODLM reduces the learning error rate of neural network techniques by 5.5%. Thus, cutting down on the amount of time needed to properly replace autonomous driving car parts and provide self-diagnosis data lowers the number of fatalities and costs. "An Integrated Self-diagnosis System (ISS) for an Autonomous Vehicle based on an Internet of Things (IoT) Gateway and Deep Learning" is presented in this article. It collects sensor data, diagnoses itself and its parts, such as the driving radar, black box, and vehicle control messages, and transmits the information to the OBD or actuators using the CAN, FlexRay, and MOST protocols. In-car sensor data is sent to FlexRay or CAN, while driving media data is sent to MOST. Various communications are converted into different kinds of destination protocol messages. The efficiency of simultaneous message transmission is raised by 15.25% in-VGM. Additionally, this lowers total costs and fatalities by sharing self-diagnosis data and scheduling the safe replacement of auto parts in autonomous driving vehicles.

2.2 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.

This article divides a 3D point cloud into planar surfaces using current discrete-geometry discoveries. Discrete geometry defines a discrete plane as a collection of grid points that span two parallel planes with a little amount of thickness. Discrete planes feature fewer local geometric patterns (LGPs) than continuous planes. Instead of having a single normal vector, such an LGP has several. The LGP properties allow us to eliminate non-linear points from a point cloud and categorise non-rejected points with common normal vectors into a planar-surface-point set. Discrete plane parameters can be computed by minimising the thickness of each segmented point set.

2.3 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.

ITS, logistics distribution, and mobile e-commerce all benefit from reliable, precise, and real-time vehicle trajectory prediction. Vehicle trajectory prediction may provide precise location-based services, track and anticipate traffic, and recommend the best route for customers. In this study, offer HMM (hidden Markov model) parameters based on historical data. Second, we find double-layer hidden state sequences for the driven trajectory using the Viterbi approach. In order to forecast the trajectory of the vehicle and the nearest neighbour unit of position data for the upcoming k stages, we ultimately propose DHMTP. The experimental results show that the proposed algorithm predicts the trajectories of the next k phases 18.3% better than the TPMO method and 23.1% better than the Naive algorithm, especially under higher traffic flow, such as weekday morning to evening. The DHMTP method outperforms TPMO in terms of time.

2.4 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

Real-time, precise assessments of effluent quality contribute to lower energy use and increased efficacy of wastewater treatment. due to the fact that traditional effluent quality assessments are inaccurate and unreliable estimates. The extreme learning machine approach is used as a component model in a selected ensemble frame since it is quicker and more generalisable than other common methods. Single model simulation trial variances are outperformed by ensemble extreme learning machine models. The selective ensemble, which is based on evolutionary algorithms, reduces computing complexity and enhances generalisation performance by removing undesirable components from all ensembles. The suggested approach is supported by data from an industrial wastewater treatment plant in Shenyang, China. The suggested approach outperforms partial least square, neural network partial least square, single extreme learning machine, and ensemble extreme learning machine models in terms of generality and accuracy, according to experimental data.

2.5 D. S. Lee, C. O. Jeon, J. M. Park, K. S. Chang. Hybrid neural network modeling of a full-scale industrial wastewater treatment process. Biotechnology and Bioengineering, vol. 78, no. 6, pp. 670–682, 2002.

These methods can improve process dynamics forecasts by combining neural network and mechanical models to account for the nonlinear and unpredictable aspects of the mechanical model. This project replicated a full-scale wastewater treatment process at a coke refinery. Data analysis on operational data was initially processed using principal component analysis. The coke-plant wastewater treatment system's operational data and process expertise were used to create a simplified mechanistic model and a neural network model. Finally, both serial and parallel neural network topologies were included in the mechanistic model. According to simulation results, the parallel hybrid modelling technique outperformed the other modelling approaches in terms of prediction accuracy and extrapolation characteristics, especially when it came to process disruption brought on by hazardous chemical shock loading. In the absence of alternative reasonably accurate process models, our results suggest that the parallel hybrid neural modelling technique may accurately and economically describe biochemical processes.

3. METHODOLOGY

a) Proposed Work:

In this work, we propose a novel approach titled "A Driving Decision Strategy (DDS) Based on Machine Learning for an Autonomous Vehicle". Unlike traditional systems that mainly focus on external environmental factors, DDS considers both external conditions (such as road and traffic) and internal vehicle factors (such as RPM levels, steering angle, and consumable status). This comprehensive analysis enables the autonomous vehicle to determine the most effective and context-aware driving strategy. The DDS model utilizes a Genetic Algorithm (GA), trained using large-scale sensor data stored in the cloud, to make real-time decisions that enhance both performance and safety.

To validate its performance, DDS was compared with well-known machine learning models such as Multilayer Perceptron (MLP) and Random Forest (RF). The results showed that DDS outperformed both models in terms of speed and accuracy. Specifically, DDS reduced the loss rate by approximately 5% compared to existing vehicle gateway systems. It also generated driving decisions—such as speed control, RPM adjustment, steering angle, and lane switching—40% faster than the MLP and 22% faster than the RF model. These results demonstrate the effectiveness of DDS in real-time autonomous driving applications.

b) System Architecture:

The system architecture of the proposed Driving Decision Strategy (DDS) consists of three main layers: data collection, cloud-based processing, and decision execution. In the data collection layer, various sensors embedded in the autonomous vehicle gather real-time internal and external data, including RPM, speed, road curvature, and vehicle conditions. This data is transmitted to the cloud, where the processing layer utilizes a Genetic Algorithm to analyze historical and current sensor inputs. The algorithm identifies optimal driving strategies by learning from patterns and trends stored in the cloud database. Finally, the decision execution layer sends the computed strategy back to the vehicle for real-time implementation, enabling dynamic control over speed, direction, and other driving parameters. This architecture ensures faster, smarter, and more stable autonomous driving decisions.

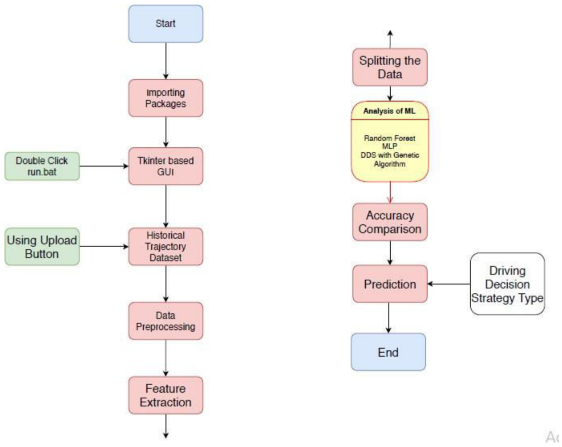


Fig: proposed architecture

c) Modules:

i. Sensor Data Collection Module

Collects real-time data from GPS, camera, radar, and internal vehicle sensors (RPM, speed, consumable status, etc.).

ii. Data Transmission Module

Transmits the collected sensor data securely to the cloud for processing.

iii. Cloud Data Storage Module

Stores historical and real-time vehicle data for training and future decision-making.

iv. Genetic Algorithm Processing Module

Uses historical and current data to determine the optimal driving strategy by evaluating various gene values.

v. Driving Decision Module (DDS Core)

Integrates the genetic algorithm's output to select actions like speed adjustment, steering angle, and lane change.

vi. Comparison & Evaluation Module

Compares DDS performance with existing models (MLP, RF) to assess efficiency and accuracy.

vii. Control Execution Module

Sends back the final driving strategy to the vehicle for real-time implementation.

e) Algorithms:

i. Random Forest Algorithm

- Used as a benchmark model to predict driving strategies based on vehicle sensor data.
- It combines multiple decision trees to improve prediction accuracy.
- Used here for comparison with the DDS system in terms of speed and efficiency.

ii. Multilayer Perceptron (MLP) Algorithm

- A type of feedforward neural network used for classification and prediction tasks.
- Trained on sensor data to generate driving decisions.
- Compared with DDS to evaluate performance and accuracy.

iii. Genetic Algorithm (Used in DDS)

- A population-based optimization algorithm that simulates the process of natural selection.
- It selects the optimal gene values (e.g., RPM, speed, steering) based on fitness evaluation.
- Forms the core of DDS to determine the best driving decision from historical and real-time data.

4. EXPERIMENTAL RESULTS

The experimental results demonstrate the effectiveness of the proposed Driving Decision Strategy (DDS) compared to traditional models like Random Forest (RF) and Multilayer Perceptron (MLP). By using a Genetic Algorithm to process both historical and real-time sensor data in the cloud, DDS achieved a more accurate and faster decision-making process. Specifically, DDS reduced the decision-making time by 40% compared to MLP and by 22% compared to RF, while also showing a 5% lower loss rate than conventional vehicle gateways. These results confirm that DDS offers superior performance in predicting optimal driving strategies for autonomous vehicles.

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. The formula is used to calculate precision:

Precision = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: The ability of a model to identify all pertinent instances of a class is assessed by machine learning recall. The completeness of a model in capturing instances of a class is demonstrated by comparing the total number of positive observations with the number of precisely predicted ones.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$F1 - Score = 2 * \frac{(\text{Precision} \ * \ \text{Recall})}{((\text{Precision} \ + \ \text{Recall})\ )}$$

mAP: Assessing the level of quality Precision on Average (MAP). The position on the list and the number of pertinent recommendations are taken into account. The Mean Absolute Precision (MAP) at K is the sum of all users' or enquiries' Average Precision (AP) at K.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \ the\ AP\ of\ class\ k$$

$$n = \ the\ number\ of\ classes$$

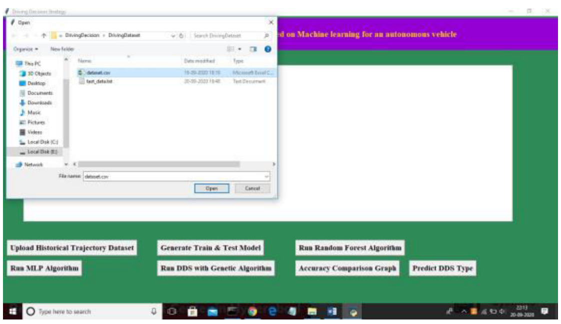


Fig.2 upload dataset

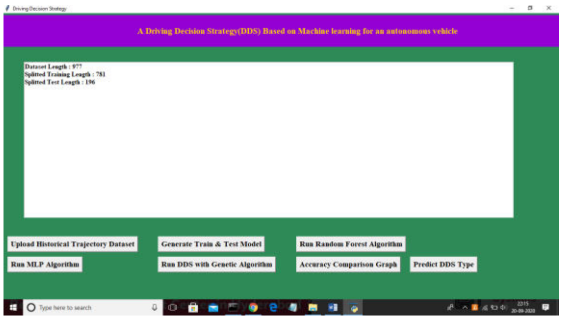


Fig.3. preprocess dataset

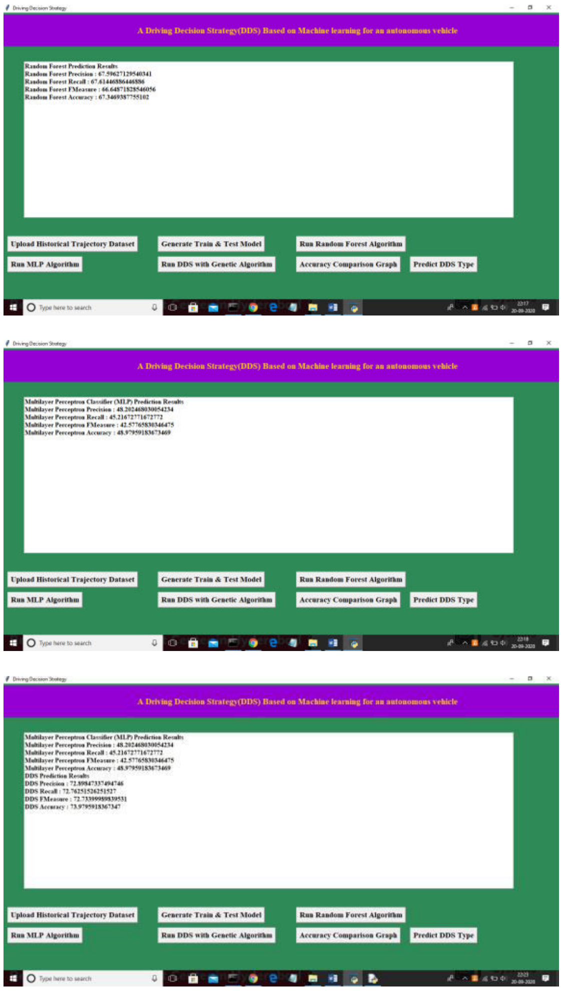


Fig.4. Train Algorithms

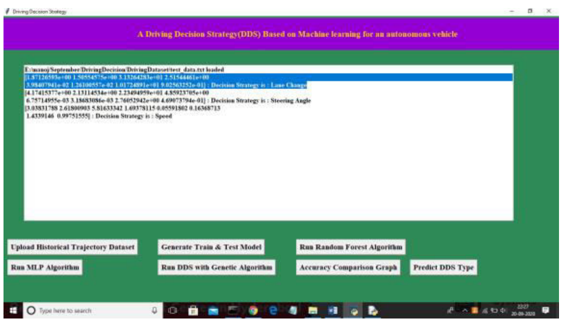
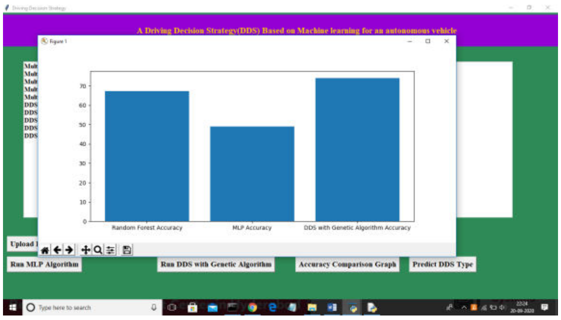


Fig.4. predicted Result



Graph 1: Accuracy graph

5. CONCLUSION

The proposed Driving Decision Strategy (DDS) based on machine learning and genetic algorithms significantly enhances the decision-making process of autonomous vehicles. By analyzing both internal and external vehicle data in the cloud, DDS determines the optimal driving strategy with higher accuracy and faster response time compared to existing models like Random Forest and MLP. The experimental results confirm that DDS improves vehicle control efficiency and reduces computational load within the vehicle, making it a reliable and intelligent solution for future self-driving systems.

6. FUTURE SCOPE

In the future, the Driving Decision Strategy (DDS) can be extended by incorporating more advanced deep learning models to further improve accuracy and adaptability in complex driving environments. Real-time integration with V2X (Vehicle-to-Everything) communication can enhance situational awareness and decision-making. Additionally, implementing DDS across a wider range of autonomous vehicle models and testing it in diverse real-world conditions will help refine its performance. Cloud-edge hybrid processing can also be explored to reduce latency and improve real-time responsiveness.

REFERENCES

BIBLIOGRAPHY

[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, “Vehicle trajectory prediction based on Hidden Markov Model, ” The KSII Transactions on Internet and Information Systems, Vol. 10, No. 7, 2017.

[4] 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.

Ms.K.Pavani working as Assistant professor in the department of MCA in SRK Institute of technology, Enikepadu, NTR District,Vijayawada. She has done M.tech and MCA from JNTUK and BCA from Andhra University . She has 9 years of teaching experience in SRK Institute of technology. Her area of interest includes Machine Learning with Python, DWDM.

Ms.M.Anitha Working as Assistant & Head of Department of MCA ,in SRK Institute of technology in Vijayawada. She done with B .tech, MCA ,M. Tech in Computer Science .She has 14 years of Teaching experience in SRK Institute of technology, Enikepadu, Vijayawada, NTR District. Her area of interest includes Machine Learning with Python and DBMS.

Mr.M.Ramakrishna is an MCA Student in the department of Computer Application at SRK Institute of technology, Enikepadu, NTR District, Vijayawada. He has Completed Degree in B.Sc.(Computers) from PB Siddhartha college of arts and science Vijayawada. His area of interest are DBMS and Machine Learning with Python