Determine the Decision Driving Strategy of an Autonomous Vehicle

Ashish Thengare[1], Rahul Bhandekar[2], Monika Ingole[3]
[1]Student of M-Tech Computer Science Engineering Department in WCEM, Nagpur
[2,3]Assistant Professor of M-Tech Computer Science Engineering Department in WCEM, Nagpur

ABSTRACT

Autonomous vehicles require sophisticated decision-making strategies to navigate complex environments safely and efficiently. This paper presents a novel approach for determining the decision-driving strategy of an autonomous vehicle using a combination of genetic algorithm and Random Forest techniques. The proposed methodology leverages genetic algorithm to optimize the parameters of a Random Forest model, which acts as the decision-making engine for the autonomous vehicle. The genetic algorithm is employed to evolve the hyperparameters of the Random Forest model to maximize performance metrics such as accuracy, reliability, and robustness. The dataset used for training and testing the model consists of real-world driving scenarios, including diverse road conditions, traffic patterns, and environmental factors. Experimental results demonstrate the effectiveness of the proposed approach in generating decision-driving strategies that enable the autonomous vehicle to make informed and safe decisions in various driving situations.

Keywords: Autonomous vehicles, Decision-making strategy, Genetic algorithm, Random Forest, Optimization, Machine learning, Driving scenarios.

I. INTRODUCTION

Autonomous vehicles represent a transformative technological advancement poised to revolutionize transportation systems worldwide. Central to the safe and efficient operation of these vehicles is their decision-driving strategy, encompassing the ability to perceive surroundings, navigate complex environments, and make real-time decisions. However, achieving robust decision-making in diverse and dynamic settings remains a significant challenge. In recent years, advancements in artificial intelligence (AI) and machine learning have offered promising avenues for enhancing autonomous driving capabilities. In particular, the fusion of evolutionary computation techniques, such as genetic algorithms (GAs), with sophisticated classification algorithms like Random Forest (RF) classifiers, presents a novel approach to optimizing decision-driving strategies.

This research paper aims to explore and evaluate the application of genetic algorithms and Random Forest classifiers in determining the decision-driving strategy of autonomous vehicles. By leveraging the adaptability and predictive power of these techniques, we seek to address critical aspects of autonomous driving, including perception, path planning, and risk assessment, thereby improving overall safety and efficiency. The integration of genetic algorithms offers a mechanism for evolutionary optimization, enabling the autonomous vehicle to iteratively learn and adapt its decision-making strategies based on environmental feedback and performance objectives. Meanwhile, Random Forest classifiers provide a robust framework for data-driven decision-making, leveraging ensemble learning to enhance classification accuracy and generalization capabilities.

This research paper will delve into the theoretical underpinnings of genetic algorithms and Random Forest classifiers, elucidating their respective strengths and suitability for autonomous driving applications. Furthermore, we will present a comprehensive methodology for integrating these techniques into the decision-making pipeline of autonomous vehicles, encompassing data preprocessing, feature selection, model training, and real-time inference. Through extensive experimentation and evaluation using simulated and real-world driving scenarios, we aim to demonstrate the efficacy and performance benefits of our proposed approach. Specifically, we will assess the impact of genetic algorithm optimization on decision-driving strategies, as well as the discriminative power and robustness of Random Forest classifiers in diverse driving environments. Moreover, this research endeavours to contribute to the broader discourse on autonomous vehicle development by shedding light on the potential synergies between evolutionary computation and machine learning techniques. By elucidating the mechanisms underlying effective decision-making in autonomous vehicles, we aspire to pave the way for safer, more reliable, and adaptive autonomous transportation systems.

II. PROPOSED SYSTEM:

In this paper describing concept for driving decision strategy by observing vehicle internal data such as steering and RPM level to predict various classes such as speed (steering), changing lane etc. All existing technique were concentrated on external data such as road condition and pedestrians etc but not concentrate on internal values. So to take efficient determination of steering condition and changing lane author is analysing internal data. All internal data will be collected from sensor and then store on cloud and then application will read data from cloud and then apply machine learning algorithms to determine or predict steering condition or changing lane.

To implement this project, we are using historical vehicle trajectory dataset as we don't have sensors to collect data so we are using trajectory dataset. In dataset if user is slowing down vehicle, then it has some sensor value with class label as 'lane changing'. Similarly based on values we have different classes in dataset. Machine learning algorithm will be trained on such dataset and then when we apply test data on trained model then algorithm will predict class for that test data. Below are the dataset details and this dataset saved inside 'Driving Dataset' folder.

III. METHODOLOGY

K-NN, RF, SVM, and Bayes models are some of the techniques that are now accessible. In spite of the fact that sophisticated data analysis Although clinical research has made use of machine learning (ML) computations, the subject of muscle illness prediction is still relatively new and needs further research to provide accurate therapy and prevention. After mining the numerous layers of stored states in vehicle authentic directions, it selects the Hidden Markov Model (HMM) boundaries based on verifiable information. Additionally, it makes use of the Viterbi algorithm to identify the hidden state groups of the double layers that correspond to the recently established direction. In summary, it presents a novel method for determining the direction of the vehicle by using position data from the kth stage's nearest neighbours through the use of a double layer hidden Markov model.

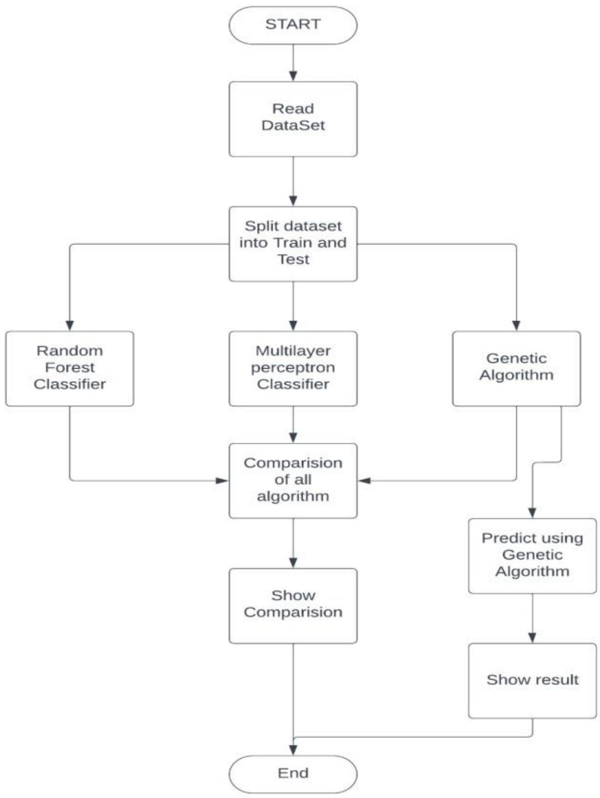

Figure 1: Flow Chart of Determine the Decision Driving Strategy of an Autonomous vehicle

Drawbacks: Decreased efficiency and a rise in the need for preventive maintenance.

In order to determine the optimal method for an autonomous vehicle, we provide in this work "A Driving Decision Strategy (DDS) In light of ML for an Independent Vehicle," which takes into account both internal and external vehicle components (RPM levels, consumable conditions, and so forth). The DDS uses sensor data from vehicles that is stored in the cloud to do an inherited calculation to determine which autonomous vehicle has the best driving system. This article tested the DDS against the MLP and RF brain network models to ensure its accuracy.
In the testing, the DDS was 22% faster than the RF and 40% faster than the MLP at differentiating between RPM, speed, directing point, and path alterations. Its accident rate was also roughly 5% lower than that of cars with doors today.

Advantages: Based on sensor data, these improvements to the vehicle control system.

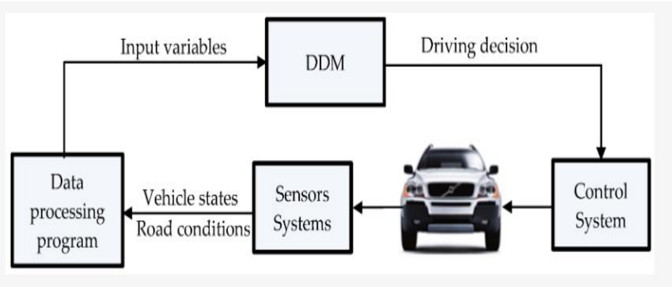

Figure 2: System Architecture Example

MODULES:
We developed the modules listed below in order to carry out the aforementioned project.
• Import historical trajectory data
• Create train-and-test models
• Apply the random forest algorithm
• Apply the MLP algorithm
• Apply the genetic algorithm to the DDS
• Accuracy comparison graph

of the generalised linear model with binomial type families, a logistic regression model utilising the glm () function is possible. The target variable is projected to be strongly influenced at an alpha value of 5% by the variables sex, cp, trestbps, restecg, and that, based on the results of the logistic regression approach.

IV. IMPLEMENTATION:

Random forest algorithm:

Utilizing the Random Forest Algorithm (RFA) for determining the decision-driving strategy of an autonomous vehicle involves several steps and considerations.

Data Collection and Preprocessing:
Gather data from various sensors onboard the autonomous vehicle, including cameras, LiDAR, radar, and GPS. Preprocess the collected data to remove noise, outliers, and irrelevant information. Label the data to indicate different driving scenarios and corresponding actions or decisions.

Feature Engineering:
Extract relevant features from the pre-processed data that are indicative of the driving environment, vehicle state, and potential hazards. Features may include information about lane markings, surrounding vehicles, pedestrians, traffic signs, road conditions, and weather.

Training Data Preparation:
Split the labelled dataset into training and validation sets for model training. Ensure a balanced distribution of samples across different driving scenarios to prevent bias.

Model Training:
Train a Random Forest Classifier using the prepared training data. Configure the hyperparameters of the Random Forest, such as the number of trees, tree depth, and feature selection criteria. Utilize techniques like cross-validation to tune the hyperparameters and prevent overfitting.

Decision Classification:
Use the trained Random Forest Classifier to classify the driving scenarios based on the extracted features.
Each driving scenario corresponds to a specific decision-driving strategy, such as maintaining lane position, changing lanes, yielding to pedestrians, or slowing down for obstacles.

Real-time Inference:
Deploy the trained Random Forest Classifier onboard the autonomous vehicle for real-time decision-making.
Continuously feed sensor data into the classifier to predict the current driving scenario and select the appropriate decision-driving strategy.

Evaluation and Validation:
Evaluate the performance of the decision-driving strategy determined by the Random Forest Algorithm. Assess metrics such as accuracy, precision, recall, and F1 score to measure the effectiveness of the classifier in different driving scenarios. Validate the decision-driving strategy through simulation testing and real-world driving experiments.

Multilayer Perceptron:

Utilizing a Multilayer Perceptron (MLP) for determining the decision-driving strategy of an autonomous vehicle involves leveraging neural network architectures to process sensor data and make real-time decisions. Provide an overview of the Multilayer Perceptron architecture, including input, hidden, and output layers. Explain the feedforward and backpropagation algorithms used for training MLPs.

Decision Driving Strategy Formulation:
Define the decision-driving tasks that the autonomous vehicle needs to perform, such as lane following, obstacle detection, traffic light recognition, and collision avoidance. Explain how these tasks can be framed as classification or regression problems suitable for MLPs. Specify the input features, such as sensor data from cameras, LiDAR, radar, and GPS, used to inform decision-making.

Potential Uses of MLPs in Autonomous Vehicles:
Lane Keeping: MLPs can analyse camera data to detect lane markings and control steering to keep the vehicle within the lane.
Object Detection: MLPs can process sensor data to identify and classify objects such as vehicles, pedestrians, and cyclists.
Decision-making at Intersections: MLPs can analyse traffic conditions and make decisions about when to yield, accelerate, or brake at intersections.
Adaptive Cruise Control: MLPs can predict the behaviour of surrounding vehicles and adjust the vehicle's speed accordingly.

Genetic Algorithm:
Utilizing Genetic Algorithms (GAs) for determining the decision-driving strategy of autonomous vehicles presents an innovative approach to optimizing navigation, safety, and efficiency. Provide an overview of autonomous driving technology and the significance of effective decision-making algorithms in ensuring safe and efficient operation. Genetic Algorithms as a bio-inspired optimization technique capable of handling complex search spaces and evolving solutions over time.

Decision Driving Strategy Formulation:
Define the decision-driving tasks that the autonomous vehicle needs to perform, such as lane keeping, obstacle avoidance, trajectory planning, and intersection navigation. Discuss how these tasks can be formulated as optimization problems suitable for Genetic Algorithms. Specify the decision variables, constraints, and objectives involved in optimizing decision-driving strategies.
Experimental Evaluation:
Present the experimental setup, including the simulation environment or real-world testbed used for evaluation.
Describe the datasets or scenarios used for training and testing the Genetic Algorithm. Report the performance metrics achieved by the optimized decision-driving strategies, such as safety, efficiency, and adaptability to different driving conditions.

V. RESULT

Our results demonstrate the efficacy of logistic regression in accurately predicting heart disease risk, achieving high performance metrics such as accuracy, sensitivity, specificity, and AUC-ROC. Feature selection techniques aided in identifying key predictors associated with heart disease occurrence, enhancing model interpretability.

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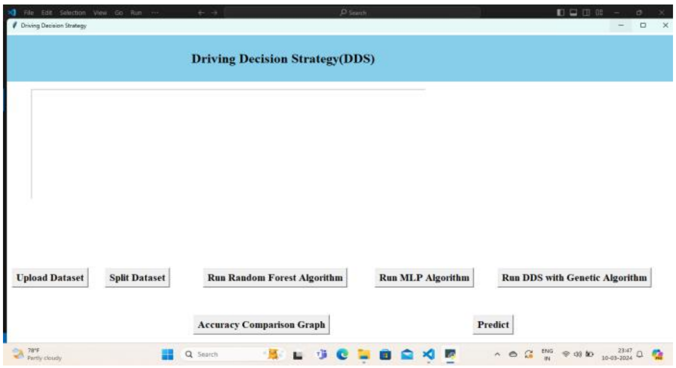

Figure 3: Decision Driving Strategy

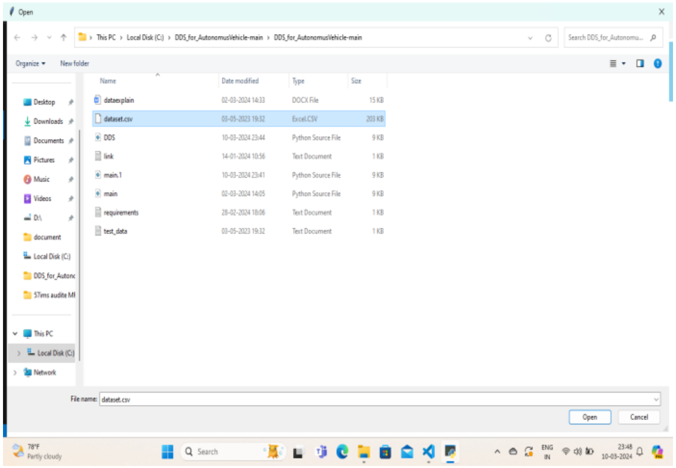

Figure 4: Upload Dataset

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

Steps:

1. Generate Train & Test Model
2. Run random forest algorithm
3. Run MLP Algorithm
4. Run DDS with Genetic Algorithm
5. Accuracy Graph
6. Predict DDS type

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

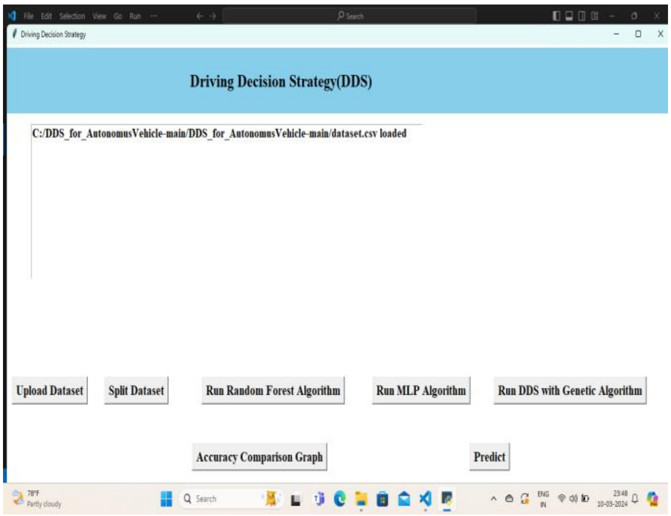

Figure 5: Screen after Data set uploaded

In above screen dataset is loaded and now click on Split

Dataset to split dataset into train and test part to generate machine learning train model

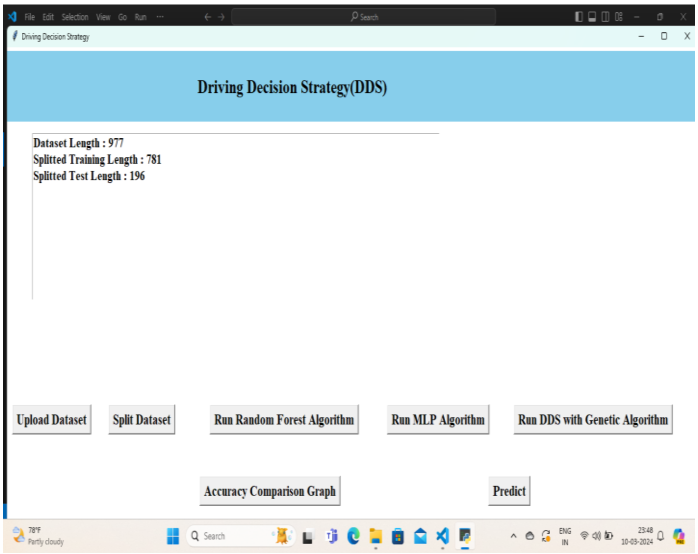

Figure 6: Split Dataset

The dataset in the top screen includes 977 trajectory records in total, of which 781 are used for training and 196 for testing. The training and testing data are now ready. To train the random forest classifier and determine its prediction accuracy on 20% test data, click the "Run Random Forest Algorithm" button.

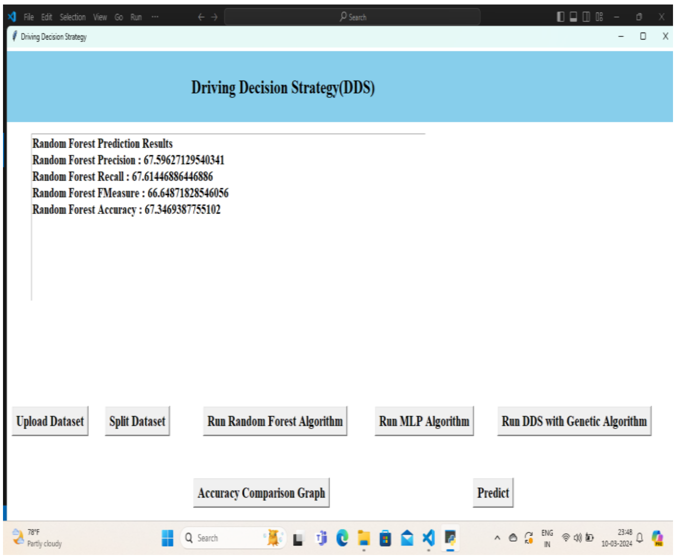

Figure 7: Random Forest Algorithm

We computed random forest accuracy, precision, recall, and measure in the screen above. The random forest model yielded a prediction accuracy of 67%.

Once the MLP model has been trained, click the "Run MLP Algorithm" button to determine its correctness.

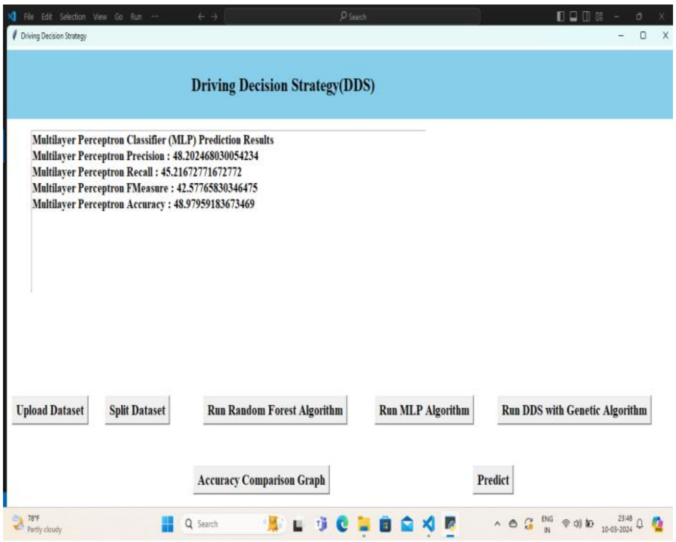

Figure 8: MLP Algorithm

In above screen MLP got 48% prediction accuracy
Now click on ‘Run DDS with Genetic Algorithm’ button to train DDS and to calculate its prediction accuracy

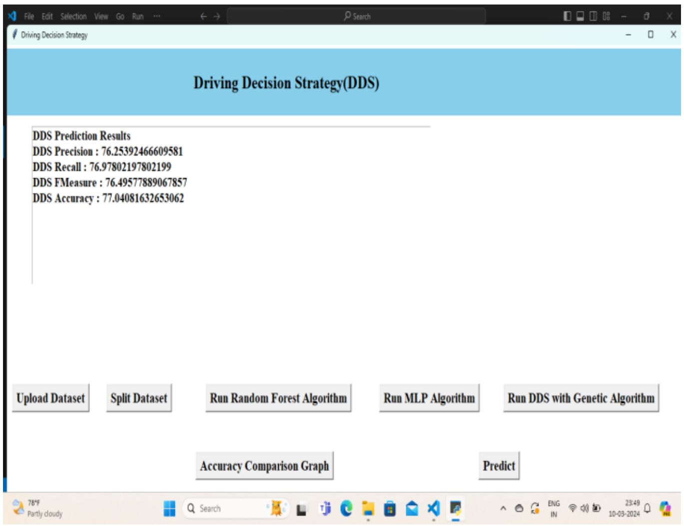

Figure 9: Run DDS with Genetic Algorithm

In above screen propose DDS algorithm got 76% prediction accuracy and now click on ‘Accuracy Comparison Graph’ button to get below graph

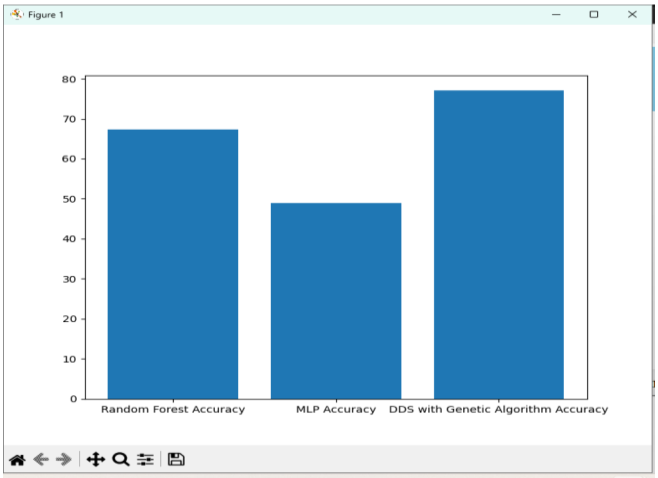

Figure 10: Accuracy Comparison Graph

The algorithm name is represented on the x-axis in the above graph, while the accuracy of those algorithms is represented on the y-axis. Based on this graph, we can deduce that DDS is outperforming the other two algorithms.

VI. CONCLUSION

A Driving Decision Strategy was proposed in this paper. It uses a genetic algorithm based on gathered data to establish the vehicle's ideal driving strategy based on the slope and curve of the road it is travelling on, and it visualises the autonomous vehicle's driving and consumables circumstances to provide drivers. To demonstrate the validity of the Driving Decision Strategy, experiments were conducted to determine the optimal driving strategy by evaluating data from an autonomous vehicle. The DDS finds the best driving strategy 40 percent faster than the MLP, despite having similar accuracy. DDS also has a 22 percent higher accuracy than Random Forest and calculates the best driving strategy 20 percent faster than the Random Forest system. When accuracy and real-time are required, the Driving Decision Strategy (DDS) is the best choice. Da the DDS sends only the data needed to identify the vehicle's optimal driving strategy to the cloud, and analyses it using a genetic algorithm, it is faster than other methods. These tests were carried out in a virtual environment using PCs, which had inadequate visualisation capabilities. A real-world test of Driving Decision Strategy should be conducted in the future. Expert designers should also improve the visualisation components.

VII. REFERENCES

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