Journal of Intelligent Systems and Internet of Things (JISIoT)
Vol. 09, No. 01, PP. 69-83, 2023
DOI: https://doi.org/10.54216/JISIoT.090105

Fuzzy-Based Clustering for Larger-Scale Deep Learning in Autonomous Systems Based on Fusion Data

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Abstract

Problems in autonomous systems may be tackled with the help of the attention-based siamese fully convolutional deep learning (AS-FC-DL) approach, which integrates autonomous fuzzy clustering and deep learning methods. The system can anticipate human behavior on crowded roadways by employing these techniques to recognize patterns and extract features from complicated unsupervised data. Each image point's membership value is associated with the cluster's epicenter using the fuzzy clustering methodology in the AS-FC-DL approach. Using least-squares methods, this approach finds the optimal position for each data point within a probability space, which may be anywhere among multiple clusters. Data points from an unlabeled dataset may be organized into distinct groups using a deep learning technique called cluster analysis. Data fusion from many sources, including sensor data and video data, can improve the AS-FC-DL method's precision and performance. The algorithm is able to deliver an all-encompassing and precise evaluation of human behavior on crowded roadways by fusing data from many sources. The AS-FC-DL approach may also be employed in autonomous vehicles (AV) to help them learn from their experiences and improve their performance. Using reinforcement learning, a model for AV driving may be constructed. The AS-FC-DL approach helps the self-driving car traverse the area with increased precision and efficiency by allowing it to recognize structures and extract features from complicated unsupervised data.

Received: January 25, 2023 Revised: April 13, 2023 Accepted: June 09, 2023

Keywords: Autonomous Vehicles; Fuzzy clustering; Deep Learning; Fusion Data; Large-scale DL

1. Introduction

Large-scale deep learning for fusion-based autonomous systems relies heavily on fuzzy-based clustering. It is challenging for autonomous systems to efficiently handle and analyze the massive volumes of data provided by their many sensors. The effective operation of autonomous systems relies heavily on the accurate grouping of data pieces, a task made easier by the use of fuzzy-based clustering. Fuzzy-based clustering is useful in autonomous systems for fusing data from many sources, such as sensors, cameras, and various other inputs, into a unified picture of the surrounding environment. This combined information aids in forming more informed judgments, and the precision with which the data are clustered is increased by the use of fuzzy-based clustering [1].

Autonomous vehicles (AV) can be used in various ways, including substituting users in dangerous locations, executing military operations, and carrying out mundane duties in the industry [2]. Human performance is dependable while operating ground vehicles, and sudden changes in a driver's surroundings are usually interpreted quickly [1]. One of the benefits of using fuzzy logic to operate a vehicle over other control methods is integrating human knowledge and experience into connections among the provided variables through language [3]. There are four key properties of intelligent autonomous systems. Self-aware and sensitive to their work environment, they can quickly adapt to new circumstances and are dependable, adhering to robust security [4] and privacy principles in their interactions with others and their data [5,6]. It is common to encounter classification issues while working in highly dynamic contexts with many classes [7]. It is only possible to sample or classify massive data streams to perform indirect analyses. Sampling can give skewed findings since the size and quantity of samples obtained from that data have a large role in its accuracy [8,9]. A good alternative for organizing and learning from massive volumes of data is clustering [10]. One of the most difficult problems in computer vision and large data processing is identifying thousands of visual data elements [11]. The standard one-versus-all multi-class paradigm is time- and space-intensive because of many classes [12]. Because the time complexity rises linearly with the number of categories, real-time practical applications like autonomous robots find it difficult to train and test [13]. These self-driving systems need high bandwidth and minimal latency [14].

Although AV have been used in various settings, their primary function is to travel from one location to another while avoiding collisions and identifying obstacles [15]. Obstacle recognition and collision avoidance are now the only issues remaining, which is why they are so difficult to solve at this point [16,17]. For an AV to go from one location to another, it must have a system to recognize its surroundings [18]. This necessitates the employment of visual technologies that allow the AV to recognize and avoid obstacles [19,20]. A vision system allows the robot to thrive better in an environment marked by uncertainties – an inherent characteristic of urban or rural settings – even though other means that require the use of model representation of the world are in place for obstacle-free path planning, as will be seen shortly [21].

In this paper, AVs have many possible uses, many critical. As an example, dangerous procedures or scenarios will use this technology. In part or whole, passenger car control is another common use for AV control. AV technology has the potential to revolutionize transportation fundamentally. This technology in autos and light vehicles will likely reduce crash pollution and congestion costs. The ever-increasing number of networked devices necessitates networking technologies in several sectors. AV control can reduce traffic congestion by eliminating the needless stop-and-go behavior caused by dense vehicle traffic or accident scenes. Binary bit vectors with a defined length are an effective approximation strategy for data items. Based on their hamming distance from one another, binary vectors are grouped in the FC approach using fuzzy matching, which is achieved by reversing error-correcting codes. The self-driving technology stack includes recurrent neural networks as one of its most important components. An onboard video feed assesses road signs, traffic lights, obstructions, and pedestrians. On the other hand, deep learning can make errors when identifying things in images.

- AVs have two primary goals: Reaching their destination and avoiding collisions. In addition, the controller must adjust the vehicle steering angle and speed to achieve these goals.
- Vehicle navigation control is a topic that has drawn the attention of several researchers. However, human performance in-ground vehicle navigation has been demonstrated to be trustworthy, and drivers react fast to abrupt changes in their surroundings.
- Even though other methods exist, fuzzy logic has shown to be a viable option for human control of a vehicle. Human knowledge and experience can be incorporated into fuzzy control by language to link variables.
- Optimum fuzzy logic can benefit control systems for a wide range of consumer devices. Researchers have recently considered fuzzy logic control as a possible solution to AV navigation.

It is possible to arrange the remaining autonomous systems properly. The related research on AV is described in Section 2. The recommended study utilized to create this paper is described in Section 3 of the publication. A discussion and a summary of the simulation's findings may be found in Section 4. Section 5 then brings this investigation to a close by going into great detail about the observation and its results.

2. Related Works

Recently, the automobile business has been disrupted by developing autonomous system research. According to traffic statistics, 94% of road accidents are caused by driver-related problems, such as improper movements and inattentive driving. Automating automobiles can considerably decrease human errors since inebriated behavior, and attention is avoided. An accident resulting from a driver's inattention or error can be greatly reduced using AVs. In addition, cars can have the capability to execute precise maneuvers to avoid a collision. The existing methods related to AVs are listed below.

2.1. Linear parameter varying (LPV)

As AVs become more common, they are predicted to eliminate human errors and contribute to major advances in safety, mobility, and environmental impacts. Automation of roadways is possible thanks to advances in technology [22]. This analysis provided new modeling techniques for AV control system design. LPV was a control-oriented model in a predefined structure. There were machine-learning approaches used to choose the LPV model's scheduling variables. An optimization approach was used to construct the LPV model parameters, resulting in an accurate fit to the dataset. LPV-based vehicle models were utilized to govern AVs less in path analysis capability.

2.2. Human activity recognition (HAR)

A broad area of computer science research was focused on HAR. Improving HAR could provide breakthroughs in humanoid robotics, medical robots, and self-driving vehicles [23]. Safe and more sympathetic autonomous systems might be created by recognizing human action without mistakes or abnormalities. More than one way of estimating an action's direction was offered to improve the network and less in-vehicle cybersecurity.

2.3. Deep reinforcement learning (DRL)

The connected AV (CAV) connection component made vehicle-to-External communication, which makes it easier to provide traffic-related information to cars [24]. In this research, they offer a DRL-based system that fuses data acquired through sensing and connection capabilities of other vehicles around the CAV and those situated farther downstream and then utilize the fused data to guide lane change, a unique context of CAV operations. Implementing the algorithm in CAVs was intended to improve the safety and mobility of CAV driving operations and had high collision avoidance.

2.4. Winner determination problem (WDP)

As AVs become more widely available, car sharing and other forms of joint ownership will become more popular [25]. An auction market for fractional ownership of AVs that is both unique and combinatorial was examined in this research. The WDP should use bidders' location information to share a car to work. They develop the WDP, a key component of different auction designs and pricing methods, in discrete and continuous-time contexts with less stability ratio.

2.5. Virtual reality approach (VRA)

Game theory describes and governs AV pedestrian interactions to fight road space while avoiding accidents [26]. VRA scenarios with more realistic pedestrian behavior were used to test the realism of the simulators' pedestrian simulations. According to these results, virtual reality trials could be used to forecast the game-theoretic parameters that AVs will need to interact with pedestrians in the future. However, they were less accurate in estimating images. The suggested solution has solved the problems with the current model. It has been suggested that this work will improve vehicle stability, accuracy, path analysis, and collision avoidance.

2.5.1. Proposed method: Autonomous system- fuzzy clustering-deep learning

Intelligent Transportation Systems (ITS) have recently developed automated systems that have increased safety and comfort for drivers. Cruise control and adaptive cruise control and emergency braking systems with active suspension help, automated parking, and detection of vehicles to the rear using vision systems are currently standard features in commercial vehicles. The ultimate objective of automotive technology is the development of self-driving automobiles. An experienced driver's knowledge and skill are essential while operating a vehicle. The benefit of using fuzzy logic-based methods to handle complicated and nonlinear systems like autonomous driving is that they can represent expert knowledge. Particularly in ITS, fuzzy logic has become a popular tool. Fuzzy controllers effectively control an AV, allowing for a comfortable and secure ride.

Figure 1 shows the development and implementation of an AV. The driver does not have to be involved in the operation of an automated vehicle. A wide range of modern technologies is required to make these vehicles work properly. Actuators, obstacle detectors, and central control devices are all included in the automation process. A further peek at the underlying architecture of the self-driving automobile system is provided now. Self-driving cars need to detect danger and maneuver the vehicle, respectively. Road traffic assistance and adaptive cruise control are included in

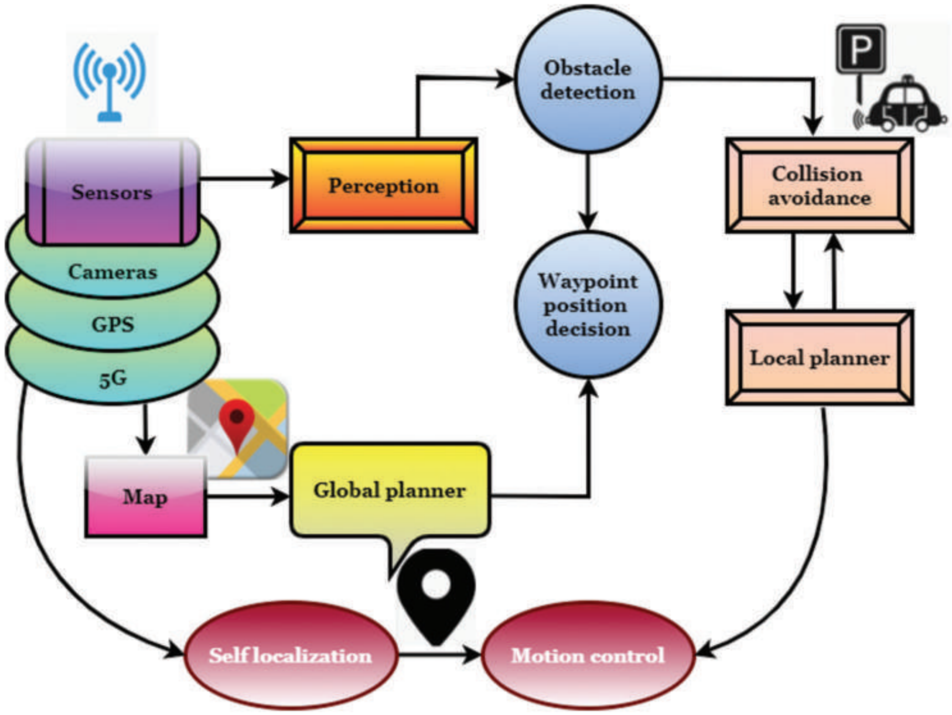

Figure 1: Develop and implement autonomous vehicle based on fusion data.

the package, and lane departure and speed limit warnings are included. In recent years, fuzzy logic technology has advanced substantially, allowing self-driving cars in smart cities to become a reality sooner.

At present, self-driving vehicles lack the accuracy and reliability needed to compete with human drivers in these areas. Due to existing deep learning technology limits, the sensor deployed cannot receive and evaluate information simultaneously as humans gather data about the vehicle system. It is no surprise that fuzzy logic technology is getting much attention since it is essential for gathering and analyzing data. Since it has low latency and large bandwidth, fuzzy is suitable for providing people with real-time wireless network data and location identification [27].

Large data streams F can only be processed in indirect ways, such as by sampling N_k and grouping them into clusters E_l are defined as

$$F = \left(N_k, E_l, G_d\right)$$

$$|F|\sum_{j=0}^{f}\binom{N_k}{j} \geq 2^{N_k} \quad (1)$$

As revealed in equation (1), real-time practical technologies G_d including autonomous robots, f find it difficult to train and test due to the increasing time complexity j that rises linearly with the number of classifications.

Data are labeled using a hashing mechanism in the proposed, Fuzzy-based Clustering technique's close matching process k is described as,

$$R(z) = k_{11}z^{11} + \ldots + k_{22}z^{22} \quad (2)$$

As revealed in equation (2), R (z) should be used as the label, z denotes an expression for the data labeling polynomial.

A 12-bit binary vector with 11 parity check bits D (z) should be used to encode the data item is stated as,

$$D(z) = k_0 + k_1 z - k_2 z^2 + \ldots + k_{10} z^{10} \quad (3)$$

As revealed in equation (3), polynomials k can be generated rather than parity checks to reduce the z complexity of the implementation.

Fuzzy matching *H* (*z*) is an approximation method similar to the one suggested in-vehicle cybersecurity, which gives phonetically comparable words a decreased dimensionality is given as,

$$H(z) = R(z) - D(z) \tag{4}$$

As revealed in equation (4), a data item's label vector *R* (*z*) has to be a multiple of the generating polynomial's coefficients *D* (*z*).

Network networks can rapidly and accurately analyze autonomous car sensors using fuzzy logic. Modern computers and deep learning can be used long-term to create self-driving automobiles. Driver assistance systems (DAS) aim to prevent or minimize an accident's severity even before it occurs. These gadgets can alert the driver by sound or light if a collision is detected. For humans and AVs, self-localization is essential since it provides the basis for spatial configuration and route planning.

Figure 2 shows the fundamentals of the Steering Fuzzy Controller. Fuzzy controllers are built for each driving duty to integrate human skills and experience into the controller design as quickly as possible. The primary responsibilities are to steer the vehicle in the desired direction while avoiding collisions with other objects. They have an advanced Collision Avoidance System with Fuzzy Target Steering. The Fuzzy Steering module is designed to meet these two objectives. The next section uses two more modules to accommodate more complex setups or needs: Two fuzzy modules, one for target steering and the other for collision avoidance. The sum of two fuzzy module outputs gives the overall steering angle. Due to the higher weight given to the collision avoidance steering fuzzy module output, a significant impact on the vehicle's behavior can be seen in a very short period due to this collision avoidance steering fuzzy controller.

The dissertation's fuzzy modules use a mixture of sigmoid membership functions. Sigmoid membership *h* (*z*) is stated as follows:

$$h(z) = \frac{1}{1 - e^{d(z-b)}} \tag{5}$$

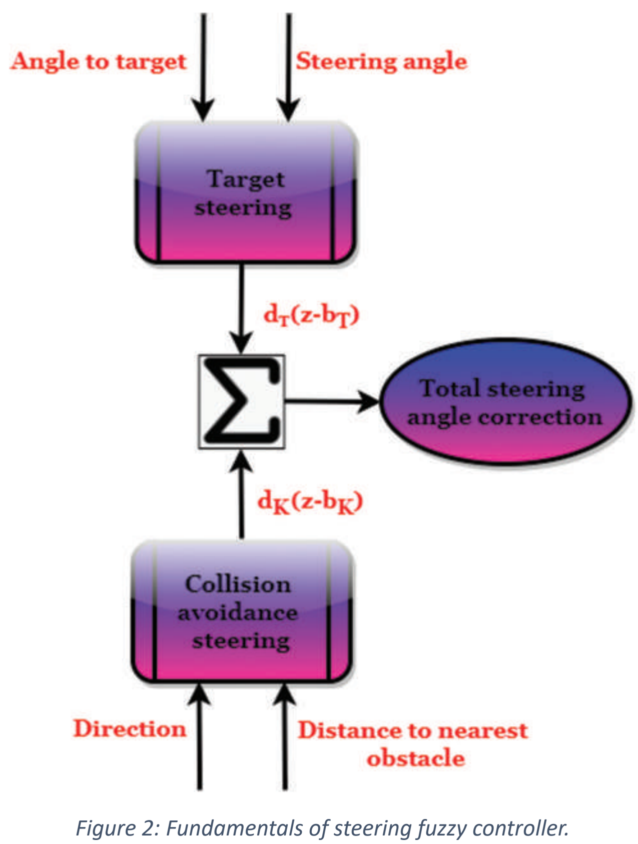

Figure 2: Fundamentals of steering fuzzy controller.

As revealed in equation (5), simple logic *d* and observations of drivers' behavior, and a description of the factors in play, inform the report's usage of membership functions *z–b* and controlling module rules.

It is possible to acquire the sum of two sigmoid membership functions ϑ (*z*) by multiplying them together d_T is given as

$$\vartheta(z) = \frac{1}{1-e^{d_K(z-b_K)}} \frac{1}{1-e^{d_T(z-b_T)}} \tag{6}$$

As revealed in equation (6), the intention of this module d_K is to direct the vehicle b_K in the direction b_T of a certain destination *z*.

Figure 3 shows the fuzzy logic clustering in an autonomous system. Driving issues occur into a category that depends on the underlying system to make sense of and cope with ambiguity. All human cognition and behavior components must be integrated into environmental perception and driving duties if a car drives like a human. Physical components can be used to alter the attributes of another physical system using a fuzzy logic control system. Both open and closed control systems are used in various applications. In closed-loop control, the efficiency of the physical system has no bearing on the input control impact.

In contrast, in a closed-loop control system, the impact of input control relies on the physical system's performance. Measurement is the initial step in controlling physical variables, and the sensor detects the regulated signal. Plant physical systems are under the direct supervision of the system's controllers. Consequently, a system's output characteristics define its input power signal in closed-loop control. The physical system in question can produce a certain output, and the discrepancy between the anticipated and actual responses indicates a problem using an error signal. Closed-loop control can benefit from additional positive feedback and performance from a compensator or regulator system. Fuzzy rules have been used to keep the car in the middle of the right lane using AVs and Real-time lane detection and tracking. According to vehicle speed and road lane centering, a fuzzy controller produces a steering angle in response to the vehicle's direction of travel.

2.5.2. Path analysis

An AV's control settings are first determined by processing a local reference route. The lateral offset, heading angle error, and distance to the first curve are all retrieved from the route data.

It is required that the angle between the existing vehicle heading and a reference path's J_B Near-matching direction is smaller than a predetermined threshold.

$$J_B = \left\{ arctan\left(\frac{z_{j-1}+z_j}{x_{j-1}+x_j}\right) < R_{fg}, j \in J \right\} \tag{7}$$

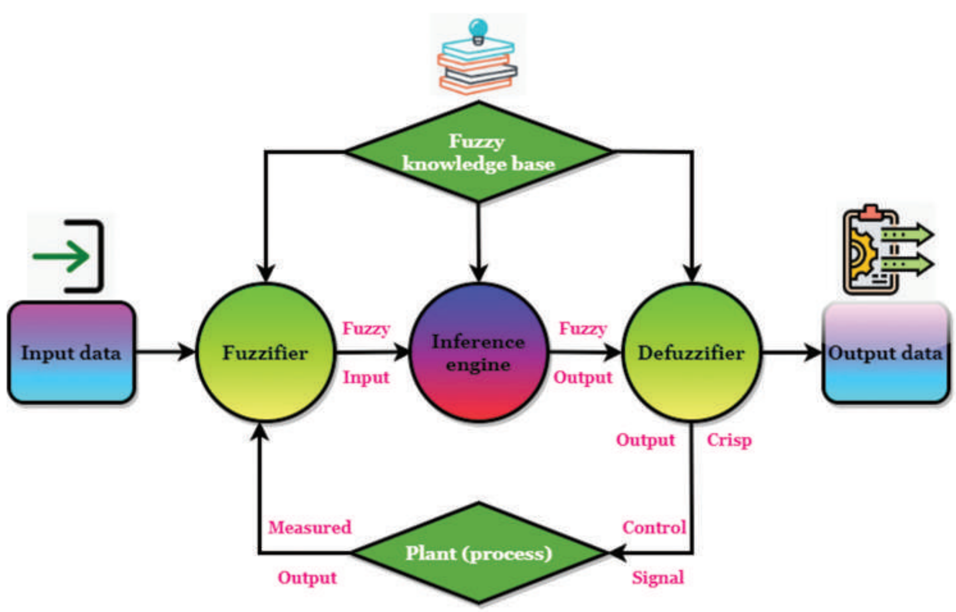

Figure 3: Fuzzy logic clustering an autonomous system.

As revealed in equation (7), where z_j and x_j are the variables of the location on the standard path, which are specified under the R_{fg} coordinates of the vehicle body.

2.5.3. Conditions of stability

The fuzzy inference surface *cotv* can be designed under the system stability criteria. Because they have distinct fuzzy inference surfaces, the stability of the heading angle error and lateral offset *h* is examined independently in the system dynamics *K* provided.

$$\{z_1 = \frac{z_2 cotv}{K} = h_1(z)z_2 = 0 = h_2(z) \quad (8)$$

As revealed in equation (8), feedback linearization theory *z* is used for the lateral control system stability study.

There are three types of steering modules: the driver's task, which includes target steering and obstacle detection guiding; the bug steering module, which deals with issues like trapping and drifting; and the vehicle orientation controller, which uses appropriate inputs and fuzzifies them to produce a rectified steering angle. The Fuzzifier's job is to smooth down the sharp input data, and the input specifies the input and output variables for the fuzzy rule base and the plant under management. Defuzzification is the process of converting a fuzzy collection into a single integer. The center of gravity defuzzification approach defuzzifies the output of each behavioral controller. The center of area approach (COA), the centroid method, is the most often used defuzzification technique. This function returns the crisp value corresponding to the area's fuzzy set's center.

Figure 4 shows the strategy of recurrent neural networks. There are a variety of onboard sensors, including cameras, radars, LiDARs, ultrasonic sensors, and GPS units in self-driving vehicles. They use this information to make autonomous decisions based on a data stream. The computer in the vehicle makes driving decisions based on these

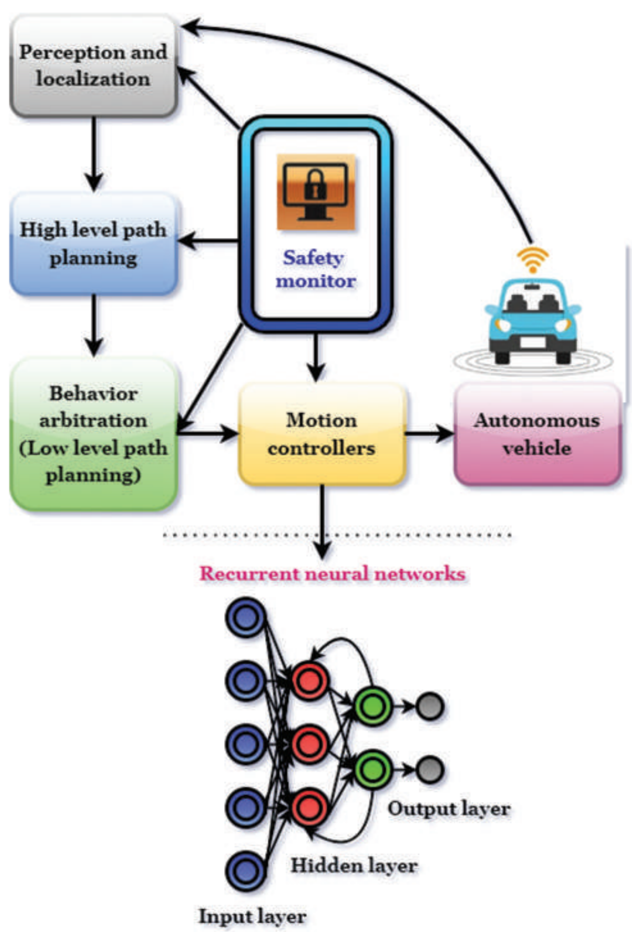

Figure 4: Strategy of recurrent neural networks.

observations. Perception, planning, and action can all be accomplished through a single pipeline. The modular pipeline's constituents can be created potentially utilizing deep learning technologies. A safety monitor monitors each module's safety.

One option is to use an action-oriented pipeline of perception-planning-action to implement the architecture. Deep learning can be used to create the components of a sequential pipeline. A safety monitor normally ensures each module's safety. Behavior arbitration, high-level path planning, perception and localization, and motion controllers are four high-level components to consider when grouping deep learning articles covering AV system methodologies. RNN addressing safety, data sources, and hardware considerations for creating deep learning modules for self-driving vehicles are included in this collection.

It is possible to approximate the temporal dynamics of sequence data with accuracy d_v using classifier W_v and the input layer of RNN $\Delta_v^{\langle r\rangle}$ is described as

$$\Delta_v^{\langle r\rangle} = \tau\left(U_v t^{\langle r\rangle} - W_v g^{\langle r-1\rangle} + d_v\right) \tag{9}$$

As revealed in equation (9), the gradient signal U_v can be amplified τ as many times as the period ranging $U_v t^{\langle r\rangle}$.

Neural architectures $d(r)$ and its hidden layer $\Delta_v^{\langle r\rangle}$ are learned using recurrent layers, which utilize temporal correlations of sequence data *secg* is given as,

$$d(r) = \Delta_v^{\langle r\rangle} * secg\left(U_d t^{\langle r\rangle} - W_d g^{\langle r-1\rangle} + e_d\right) + \Delta_g * d(r+1) \tag{10}$$

As revealed in equation (10), the activation weights are denoted by $U_d t^{\langle r\rangle}$, while the bias values are represented by $W_d g^{\langle r-1\rangle}$. Δ_g and e_d stands for element-by-element multiplication.

Gradient vanishing leads the weights in the network to stop updating properly; resulting in a very low weighting factor and the output layer of RNN *h* (*r*) is defined as

$$h(r) = \Delta_v^{\langle r\rangle} * secg\left(d(r)\right) \tag{11}$$

As revealed in equation (11), the weights of network gates and memory cells are combined by the input layer $\Delta_v^{\langle r\rangle}$ and *secg* (*d* (*r*)) hidden layer.

An autonomous car's first challenge is comprehending and locating itself in the surrounding environment, given a predetermined path through the road network. The vehicle's further activities are guided by the arbitration mechanism shown in this illustration. An automated motion control device responds to errors that occur during movement. An overview of deep learning for AV s will be provided in the following sections, along with a look at the various design techniques used to create this hierarchical decision-making process.

Figure 5 shows ensuring safety and security using deep learning. To determine the distance between nearby objects, an AVh_i is expected to include a camera, a smart radar scanner, and a transmitter for communicating vital acceleration speed position (AVP) beacon with closer AVh_i, among other sensors, all built into the device. Sensor data and beacon data can be used to control better AVh_i in the Intelligent Transportation System (ITS) to ensure the best possible traffic flow. If an attacker is present, it is possible that their actions can cause the system to malfunction, increasing the risk of an accident or a decrease in traffic flow. A malicious opponent might inject inaccurate data into the AVh_i system using sensor readings and beacons; therefore, the system needs more than just improved road control and administration.

They want to provide a dynamic system that can accurately estimate how far apart AVh_i are in connection to each other. Acquiring and processing information about the vehicle's velocity, location, and, most critically, its distance from the surrounding vehicles or objects and their velocities is essential for any AV (AVh_i). Focused on the automobile following model for this project. AVh_i must be familiar with the AVh_i essential parameters to function properly. It is possible to describe AVh_i updated speed as an expression of how fast its lead vehicle moves without collision avoidance.

$$\mu_i^{'}(r) = \rho\left(\hat{\mu}_{i-1}(r) + \mu_i(r)\right) \tag{12}$$

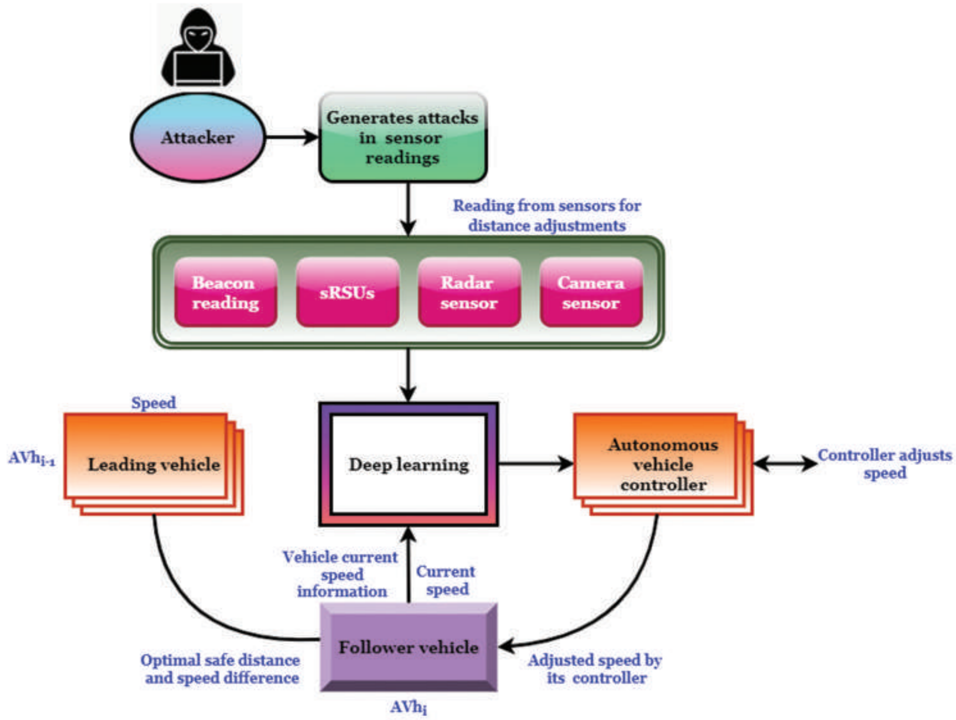

Figure 5: Ensuring safety and security using deep learning.

As revealed in equation (12), AVh_i indicates an AV, $\mu_i^{'}(r)$'s predicted velocity, and ρ the response factor. AVh_i must constantly monitor to make adjustments to their spacing and prevent an accident $\mu_i\,(r)$ from occurring. As the next AV moves forward, each AVh_i can use its onboard sensors $\hat{\mu}_{i-1}(r)$, including cameras and radar, as well as beacon signals from AVh_i and data from Smart Roadside Units to estimate their speed (sRSU). Autonomous decision-making systems are at the core of self-driving vehicles. They can handle data streams from various cameras or inertia sensors. Deep learning algorithms are used to model this data, and the resulting models make decisions that are appropriate to the current situation the vehicle is in. Vehicles must change and develop to the ever-changing behavior of other vehicles around them. AVs with deep learning can make judgments at the moment. This improves the safety and dependability of AVs.

Figure 6 shows the predictive control block diagram for an AV. In recent decades, the fast advancement of technology has resulted in a wide range of new solutions that make life easier and more secure for users. The long-term aim of the robotics industry is to reduce the amount of manual labor performed daily by humans while increasing the precision, speed, and power required for any operation. The main areas of robotics applications that have advanced the most are automated systems and small autonomous robotic vehicles that move autonomously and communicate data to a central control station over a local or global network. Recent advancements in autonomous robotic vehicle remote control and monitoring have been remarkable. User mechatronics, deep learning, and multi-agent systems are a few technologies used in the robotic vehicle sector to help with the automotive operation. A driver's state is a classification of the driver's conduct into a set number of states. A vehicle must have some traits to qualify as intelligent or smart. An action engine can characterize a semi-automatic vehicle as utilizing automation for challenging activities, such as navigation.

Autonomous or robotic vehicles, on the other hand, rely only on automation technologies. Since the invention of the integrated circuit, the complexity of automation systems has increased. Following that, researchers and automakers created a wide range of automated functions, mostly for use in autos. V2V and V2I protocols enable communication between infrastructure and vehicles to support services such as navigation, entertainment, and traffic safety. Autonomous operation is commonly defined as the ability of a vehicle to regulate its environment and maneuver around it without human intervention. Radar, LIDAR (Light Detection and Ranging), GPS, Odometry, and 3D scanning are technologies used by AVs to gather their surroundings. Advanced control systems collect and interpret data from the sensors to determine acceptable routes, impediments, and important markers and then use this knowledge to make decisions.

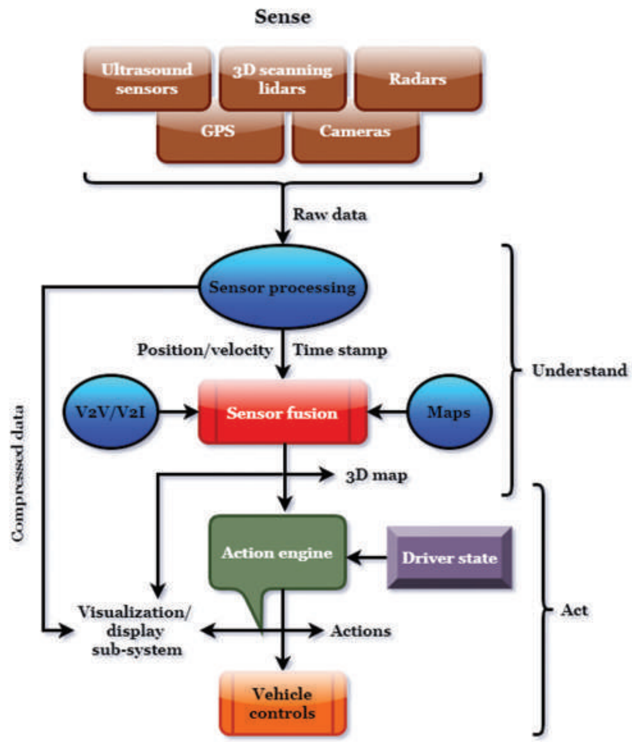

Figure 6: A predictive control block diagram for an autonomous vehicle.

Multiple radars, lidars, and cameras can be combined into a single model or image to perform sensor fusion. The balanced strengths of the various sensors result in a more accurate model.

Autonomous automobiles include control systems that can evaluate sensor data to discriminate between various vehicles on the road to design a route to the intended destination. The vehicle will be able to control itself under the phase autonomously. Many historical research initiatives on vehicle autonomy depend largely on artificial parts of their surroundings, such as magnetic tapes, for their automation. There must be a long-term capacity to function well in severe environmental uncertainty and compensate for possible system damage without external intervention. As can be observed from several initiatives, it is regularly suggested to enhance the capabilities of the AV by implementing communication networks with both nearby vehicles (Collision Avoidance) and long-distance vehicles. Some now consider the vehicle's behavior or potential autonomy with two more outside inputs. The proposed method enhances vehicle cybersecurity, stability, accuracy, path analysis, and collision avoidance.

3. Results and Discussion

When AVs are used, human error will be eliminated, allowing greater mobility, safety, and sustainability. AVs have already started to emerge on highways across the globe. Diverse public and commercial institutions have taken the technology through its paces before. The three essential components of the self-driving system are orientation, visibility, and decision-making. There are several duties that each element is responsible for utilizing a variety of technologies. This technology's reliability and accuracy are improved due to the inclusion of cameras and internal measurement equipment. Perception is another word for AV's visibility, used to identify infrastructure and traffic. These maps allow the vehicle to comprehend its immediate surroundings and prepare for turns and junctions outside the range of view of its sensor systems. The proposed method analyzes vehicle cybersecurity, stability, accuracy, path analysis, and collision avoidance.

Table 1 shows the vehicle cybersecurity ratio. AVs can use deep learning to identify aberrant network traffic patterns caused by malware. The invasion detection module necessitates using recognition architecture to identify and halt malware attacks on the vehicle through a smartphone. AV decision-making can be improved using an RNN. Initial forecasting of nearby vehicle movements is made probabilistically based on assessing the potential danger. For each state, a quantitative and accurate risk assessment function synthesizes the current Time-To-Collision TTC and Time-Headway TH, and the originals created by the coherent threat estimate tool are applied to analyze the danger in every state quantitatively and properly. Thus, the safest route can be constructed by the best search. AVs are more vulnerable to hacks because of the increased reliance on digital technology. Malicious hackers can access automated vehicles and infrastructure remotely through the communication networks installed in such infrastructure elements. As a result, a model for classifying cyber threats can be utilized that considers the vulnerabilities found in software. Cyber-risk can be represented using an RNN model, prefaced by the variables. The proposed method enhances cybersecurity by 95.2% compared to the existing methods.

Table 2 shows the stability ratio. Stability is the capacity to absorb external forces, which applies to the vehicle. If the vehicle travels in a straight path at an even speed, it is at its most stable point. Vehicle speed, lateral forces, tyre cornering characteristics, steering system stiffness, steering transmission ratio, and the vertical axis of inertia moments, to name a few, are additional factors that affect vehicle handling and driving stability. The advantages of self-driving cars are clearly exciting, but the path to complete transportation autonomy is likely to be difficult and uncertain. When managing an AV, these systems add complexity because various control systems are engaged based on the FC. They all have to operate together, offering stability guarantees and withstanding structural and environmental changes in a dynamic environment. The proposed method enhances the stability ratio by 96.8% compared to the existing methods.

Table 3 shows the accuracy ratio. A car must constantly learn and adapt to keep up with the ever-changing driving habits of other vehicles. Self-driving cars can make choices in real time due to deep learning. This improves the safety

Table 1: Vehicle cybersecurity ratio

Number of vehicles	LPV	VRA	AS-FC-DL
10	44.9	64	78.5
20	54.5	67	84
30	55	64	79
40	58	70.8	91
50	50.1	61.3	76
60	56	63.7	85.7
70	59	66	79
80	57	68.4	80
90	53	59	85
100	52.8	69	95.2

VRA: Virtual reality approach, LPV: Linear parameter varying

Table 2: Stability ratio

Number of vehicles	LPV	VRA	AS-FC-DL
10	57	72	79
20	51.3	61.6	85
30	45	73	76.3
40	56	75	91
50	48.4	65	83
60	54	67	94.4
70	52	69.1	77
80	46	63	93
90	53.9	68	88.9
100	49	70.5	96.8

VRA: Virtual reality approach, LPV: Linear parameter varying and trustworthiness of self-driving vehicles. DL helps AVs in several ways, including processing and interpreting vast volumes of data supplied by the vehicle's cameras and sensors fast and helping to enhance vehicle fuel economy and safety. Images or objects can be classified using RNNs because the network predicts a label or number for each image (the input and the output are both known). The network is utilized to lower the error rate since the images' labels are known. It is utilized by a huge number of self-driving cars to navigate in real time. With astonishingly precise depth perception, LiDAR can measure an object's distance from as far away as 60 m away. The suggested technique improves accuracy by 98.4% over the currently used approaches.

Figure 7 shows the path analysis ratio. Path planning allows an AV to identify the safest, most feasible, and cost-effective route between two sites. The predictive control method solves a nonlinear optimization problem for a finite-time and time-constrained optimum control issue. Route planning and control are utilized to overtake two-lane roadways using nonlinear PCM. There are two techniques to map out a route (hierarchical and parallel). Designing long-term missions for AVs takes a fraction of the time and effort it used to. The higher-level objective is broken down into smaller tasks and reassembled at each subsequent level. Complex problems are easier to solve when using the hierarchical approach; however, fine motor skills are hampered because of their impact on vehicle performance. The parallel technique allows many tasks to be accomplished at the same time. Each controller has its unique sensors and actuators. Due to the high frequency of their operation, control systems provide a high degree of fluidity and performance. Complex motion planning technologies are not required. Path planning is improved by 91.8% using the AS-FC-DL approach instead of the previous methods.

Figure 8 shows the collision avoidance ratio. Collision avoidance systems warn, alert, or assist them in some way to help drivers avoid crashes. Different technologies and sensors are used in collision avoidance systems, including radar, lasers, cameras, GPS, and Deep learning. Fuzzy logic with RNN-based methods is used to address the navigation

Table 3: Accuracy ratio

Number of vehicles	LPV	VRA	AS-FC-DL
10	49.7	64	76.5
20	48	63.5	82
30	57	67	78.9
40	60.5	72	84
50	47	63	77
60	52	61.7	92
70	55	65.5	90
80	45	73	94
90	51	71	89
100	53	74	98.4

VRA: Virtual reality approach, LPV: Linear parameter varying

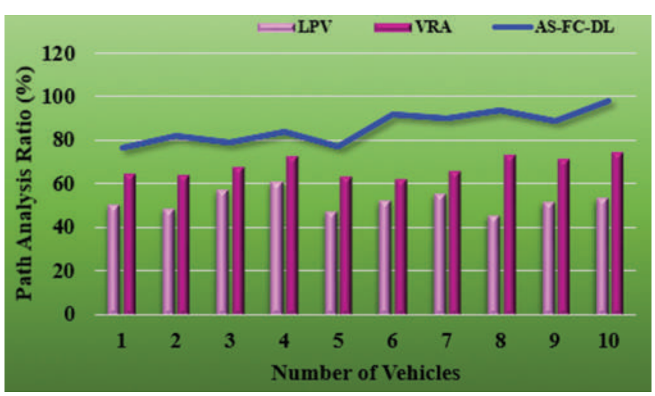

Figure 7: Path analysis ratio.

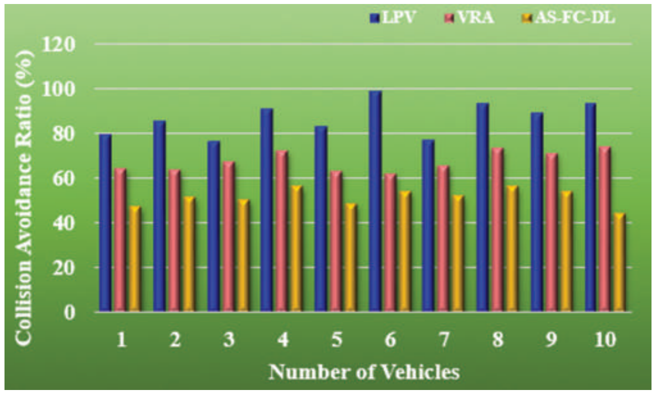

Figure 8: Collision avoidance ratio.

control issue. Interested readers should consult to learn more about the FC-based approach to collision avoidance methods. Fuzzy logic and RNN reactive have been coupled to provide fine, resilient, and adaptable control; however, fuzzy logic can be used alone to provide quick and noticeably smooth control. It is not easy to classify mobile robots' navigation process under any subsections, while autonomous robots' categorization must have some audience. The robot keeps a copy of the world's model for obstacle-free route planning in a DL-based approach. This technique focuses solely on using sensor data from the surroundings to make navigational decisions. Systems employ sensor data for autonomous navigation. This idea expands the paradigm to encompass both goal- and target-oriented approaches instead of just the environment's map. Comparing the proposed strategy to the current approaches, collision avoidance is reduced by 44.1%. The proposed method assessed the vehicle's stability, accuracy, path analysis, and collision avoidance.

4. Conclusion

Fuzzy-based clustering for large-scale deep learning has been shown in this study employing autonomous systems. The steering angle and vehicle velocity are controlled by both controllers, which receive as input the longitudinally, lateral, and direction errors. Current deep-learning approaches are either being utilized or considered to create several components for self-driving vehicles. The game-theoretic technique assesses the interaction between the attacker and the AV. Reduce the implementation time in various systems using deep learning to build fuzzy rules and fine-tune variables of a vehicle's fuzzy logic controllers. The effectiveness of AV methods will likely be shown through simulations. The underlying environmental components should form the basis for all viable combinations of autonomous and human-driven vehicles. The strategy becomes more complicated because the AVs will operate on an unstable road full of human-driven vehicles. Multiple models with force computations for each tyre are needed to calculate the steering angle while driving. Future research is anticipated to employ the fuzzy logic controllers suggested in this study to control autonomous underwater and aerial vehicles. The proposed approach boosts vehicle cybersecurity (95.2%), stability (96.8%), accuracy (98.4%), path analysis (91.8%), and collision avoidance (44.1%), according to the numerical results.

5. Funding

"This research received no external funding."

6. Conflicts of Interest

"The authors declare no conflicts of interest."

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