Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8, 179-196
2025
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v9i8.9251

Decision-making and safety enhancement in next-generation autonomous vehicles: A comparative analysis with deep learning

C. Joe Arun, SJ[1*], Kishore Kunal[2], P. Kumari[3], M. Manikandan[4], Pillalamarri Lavanya[5], Vairavel Madeshwaren[6]

[1]Loyola Institute of Business Administration (LIBA), Chennai, Tamil Nadu, India; director@liba.edu (C.J.A.).
[2]Department of Business Analytics, Loyola Institute of Business Administration (LIBA), Chennai, Tamil Nadu, India, kishore81.research@gmail.com (K.K.).
[3]Department of Computer Science and Engineering, Excel Engineering College, Komarapalayam, Tamil Nadu, India.
[4]Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Thandalam, Chennai-602105, India; manikandanm10@gmail.com (M.M.).
[5]Department of Physics & Electronics, Bhavan's Vivekananda College of Science, Humanities and Commerce, Hyderabad, Telangana, India, lavanya.elec@bhavansvc.ac.in (P.L.).
[6]Department of Agriculture Engineering, Dhanalakshmi Srinivasan College of Engineering, Coimbatore, Tamil Nadu, India, phdannauniv2020@gmail.com (V.M.)

Abstract: The rapid evolution of Artificial Intelligence (AI) is reshaping autonomous vehicle (AV) systems, enhancing decision-making, navigation, and vehicular safety. However, real-time responsiveness, reliable object detection, adaptive path planning, and resilience to adversarial threats remain significant challenges. This study aims to improve AV safety, adaptability, and performance by integrating advanced AI techniques and benchmarking them against conventional rule-based methods to highlight strengths and limitations. The study utilized a multi-phase analytical and experimental framework that integrated reinforcement learning-based navigation through simulation environments with deep learning perception models. Robust environmental modeling was achieved by integrating LiDAR, radar, and camera data using hybrid sensor fusion techniques. The latency and predictive accuracy were evaluated using real-time computing systems. Long Short-Term Memory (LSTM) networks for trajectory prediction, Deep Neural Networks (DNNs), and Convolutional Neural Networks (CNNs) for object detection, and Reinforcement Learning (RL) for adaptive decision-making in dynamic situations were important AI techniques. While hybrid sensor fusion enhanced perception of the surroundings, neuromorphic computing was investigated for low-latency, energy-efficient processing. The study supports future directions for safe, scalable, and morally sound autonomous mobility systems while confirming AI's ability to handle functional AV challenges.

Keywords: *Artificial intelligence, Autonomous vehicles, Deep learning, Neuromorphic computing, Object detection, Reinforcement learning, Sensor fusion.*

1. Introduction

The future of autonomous vehicles (AVs) is being profoundly altered by the quick developments in artificial intelligence (AI) which are changing how these vehicles see comprehend and engage with their surroundings. But even with AIs' bright future in AVs several issues still need to be resolved such as adaptive navigation robust object detection real-time decision-making and resistance to hostile interference. Additionally, as AI develops further it becomes more and more necessary to integrate various AI paradigms effectively to guarantee scalability high performance and deployment ethics. This study investigates cutting-edge AI strategies meant to enhance autonomous vehicles performance safety and adaptability. To get around current constraints it suggests incorporating cutting-edge AI

History: Received: 23 May 2025; Revised: 10 July2025; Accepted: 14 July 2025; Published: 4 August 2025
* Correspondence: director@liba.edu

techniques like deep learning reinforcement learning and hybrid sensor fusion. Utilizing experimental comparisons with traditional techniques this study aims to assess how AI might improve AV performance in a variety of driving situations. It also explores novel neuromorphic computing approaches that may provide AV systems with low latency and energy-efficient solutions (Figure 1).

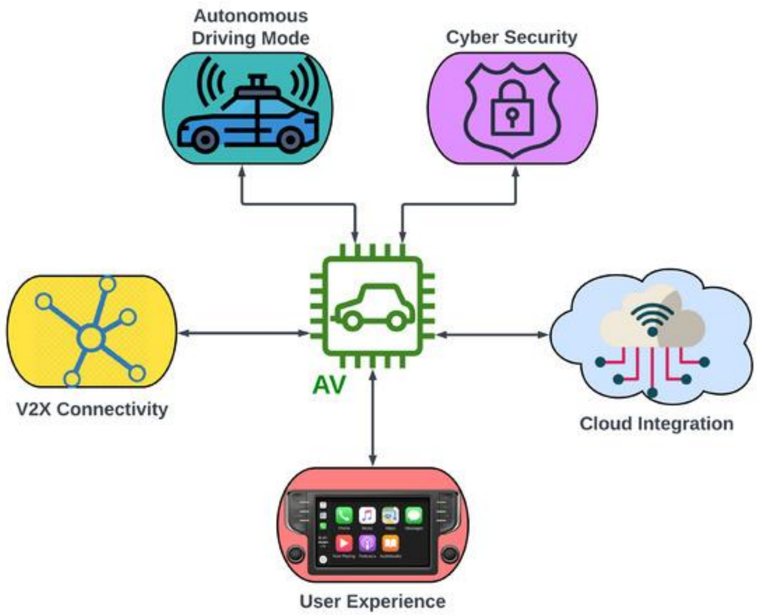


Figure 1.
Autonomous vehicle applications.

The field of autonomous vehicles (AVs) has advanced significantly in a number of areas such as safety assessment decision-making procedures and risk prediction. Using deep learning and machine learning methods together to improve the effectiveness and functionality of AVs is a major area of focus. AutoML approaches for example have been investigated for risk prediction supporting AV decision-making and enhancing their safety performance [1]. Furthermore a thorough analysis of autonomous vehicle decision-making safety assessment techniques emphasizes the significance of comprehending and reducing risks in AV operation using a variety of approaches [2]. Using sensor-fused data adaptive approaches for obstacle detection have also been investigated in research to improve AVs real-time decision-making capabilities [3]. Two other important aspects of AV research are guiding decision-making and maximizing safety planning. Machine learning-based methods that recommend the best driving practices in complex traffic situations have been used to model safety for multiple autonomous vehicles [4]. Numerous reviews of motion planning and end-to-end learning strategies particularly those based on deep learning have been carried out providing insight into how these tactics impact the overall efficacy of AVs [5]. Deep learning and reinforcement learning techniques are also increasingly being used to address autonomous driving issues particularly when making decisions in uncertain circumstances [6]. Wireless technology and sensor fusion are critical to AV connectivity and operation. According to research these technologies improve next-generation autonomous vehicles safety and communication capabilities [7]. Autonomous vehicle navigation traffic management and general transportation network optimization are further uses for these models according to surveys on machine learning applications in intelligent transportation systems [8]. By enhancing trajectory planning and mimicking actual driving conditions deep learning models in particular have demonstrated promise in enhancing AV decision-making applications [9]. Deep learning algorithms have also been investigated for their potential to predict and optimize autonomous driving behaviors through simulations that take into account temporal information and prior knowledge in order to enhance decision-making in dynamic environments [9]. Recent developments have focused on enhancing AVs safety and responsiveness as well as accelerating the efficiency of traffic safety decisions through the use of DNN-APF techniques [10]. Researchers have also examined the weaknesses and proposed fixes for robust security frameworks in the future underscoring the growing concern about defending autonomous and connected cars against hostile machine learning attacks [11]. The usefulness of comparative research in understanding the operation and potential for improvement in smart driving systems has been shown by analysis of the integration of IoT protocols into AVs [12]. Reinforcement learning sensor fusion and path planning algorithms are particularly useful for increasing the logistics efficiency of autonomous vehicles mainly because they ensure that AVs can make the best decisions and navigate difficult environments [13]. Current studies have looked into increasing autonomy through integrated perception platforms that use cutting-edge algorithms like DeepLabV3 and Faster R-CNN for advanced self-driving cars which enable more accurate and reliable environment recognition [14]. In AVs large language models (LLMs) have also been employed for reasoning and decision-making offering novel techniques for information interpretation and decision-making from spoken instructions [15]. Machine learning paradigms are being incorporated into next-generation wireless networks which provide the infrastructure needed to ensure high vehicle-to-vehicle communication efficiency and enable autonomous driving in future smart cities [8, 16, 17]. Explainable AI has emerged as a key instrument for increasing transparency in autonomous driving systems by offering insights into decision-making procedures and boosting trust in AV operations [18]. A lot of work has also been done on machine learning-based vehicle intention trajectory recognition and prediction to predict and enhance AVs ability to adapt to changing driving conditions providing crucial data for safe navigation and decision-making [19]. Finally in order to ensure that AVs are successfully integrated into the broader transportation system a human-centered approach to the design of transportation infrastructure is required. This means considering how automated and connected vehicles impact system efficiency and user experience ergonomics [20]. The social decision-making aspect of AVs which includes interaction orientation identification and mixed-strategy game approaches is also gaining more attention in an effort to enhance their ability to adapt to complex human-centered contexts [21]. The multidisciplinary efforts being made to develop autonomous driving technology are highlighted by these innovations taken together.

2. Materials and Methods

This section examines the main experimental setup instruments and technical strategies used in this study. After describing the problem context, the section goes on to discuss the datasets used sensor tools deployed and the comprehensive methodology used to address the difficulties in autonomous vehicle decision-making and safety improvement. Particular attention is paid to the suggested methods wherein the computational flow and mathematical expressions of every model are thoroughly examined. Finally, the performance metrics used to evaluate the proposed system are outlined to establish a clear basis for comparative analysis.

2.1. Problem Description

The accelerating evolution of autonomous vehicles (AVs) has unlocked remarkable mobility, safety, and operational efficiency opportunities. However autonomous driving systems still face a number of unsolved issues in spite of the significant progress made in artificial intelligence (AI) applications. These challenges include but are not restricted to adaptive trajectory prediction in uncertain situations real-time object detection in complex environments optimal navigation in dynamic traffic systems and defense mechanisms against hostile disturbances. Furthermore, to guarantee the sustainable deployment of these systems in practical situations it is imperative to strike a balance between high-performance computing and low energy consumption. Thus, this research offers a thorough AI-driven framework

ISSN: 2576-8484
Vol. 9, No. 8: 179-196, 2025
DOI: 10.55214/2576-8484.v9i8.9251

that not only tackles these current issues but also establishes the groundwork for improving the resilience security and judgment of next-generation autonomous cars.

2.2. Data Collection / Dataset

Any AI-powered autonomous car systems ability to function depends critically on the caliber and variety of the datasets used to train and validate the models. Several benchmark datasets were used for this study all of which were created especially to capture the complexities of autonomous driving situations. To create the main data sources the Cityscapes Dataset nuScenes Dataset and KITTI Vision Benchmark Suite were combined. Real-world photos LiDAR point clouds annotated 3D bounding boxes object labels and trajectory data from urban suburban and highway driving scenarios are just a few of the many resources available in these datasets. Below Table 1 displays a combined view of the datasets.

Table 1.
Dataset.

Dataset Name	Data Type	No. of Samples	Key Features
KITTI	Images, LiDAR, GPS	14,999	Object Detection, Stereo Vision, Optical Flow, SLAM scenarios
Cityscapes	Urban Street Images	5,000	Pixel-Level Semantic Segmentation
nuScenes	LiDAR, Radar, Camera	40,000+ scenes	Multi-Sensor Fusion, 3D Object Detection, Tracking

The combination of these datasets ensures that the models are exposed to varied driving scenarios, lighting conditions, weather disturbances, and unpredictable object movements, making them robust and generalizable for real-world deployment.

2.3. IoT Sensor Tools

The reliable functioning of autonomous vehicles hinges on their ability to perceive and interpret real-world stimuli, which is made possible through a robust network of Internet of Things (IoT) sensor tools given in Figure 2. In this study, a hybrid sensory setup composed of LiDAR scanners, high-definition RGB cameras, radar systems, ultrasonic proximity detectors, and GPS-IMU fusion units was employed.

Figure 2.
IoT sensor tools used for this research.

2.4. Cameras

Since cameras are the most effective way to gather data about the objects and surroundings of an autonomous vehicle they must be installed in all of them. Monocular cameras can provide the shape and texture information required to identify and categorize the color and shape of the lanes (e. g. A. traffic sign recognition traffic light color classification broken white or double yellow) and other object detection and classification tasks. Nevertheless this kind of camera is unable to supply the depth data required to determine the size and location of the detected object. As a result, stereo cameras are able to determine each points relative depth. Figure 3 shows the sensor's operation.

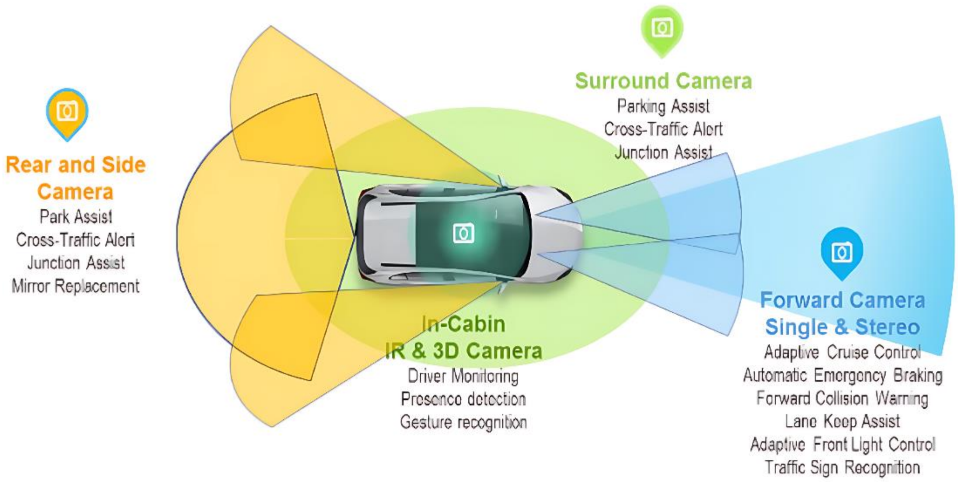


Figure 3.
Process of sensors.

2.5. LiDAR

Light Detection and Ranging (LiDAR) sensors send out laser pulses and receivers pick up the pulses that are returned. In order to detect and identify the objects class and precisely measure its distance and location regardless of the lighting and weather conditions this sensor is frequently utilized in autonomous vehicles

2.6. RADAR

Radar sensors—also known as radio detection and ranging sensors—have an antenna that emits a radio signal in a specific direction and a receiver that detects the signal after it has reflected off of objects in the area. The distance between the antenna and the object is determined using the time it takes for radio signals to and from the object. In bad weather conditions like snow fog and rain radars outperform other sensors and can identify the car in front of you.

3. Proposed Methodology

The methodology devised for this study followed a step-by-step process that progressively combined perception, prediction, decision-making, and control — forming a closed-loop autonomous driving architecture. Subsequently, object detection was performed using deep learning-based perception models, such as YOLOv8 and ResNet-50, which extracted semantic and positional information about surrounding objects (Figure 4).

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8: 179-196, 2025
DOI: 10.55214/2576-8484.v9i8.9251

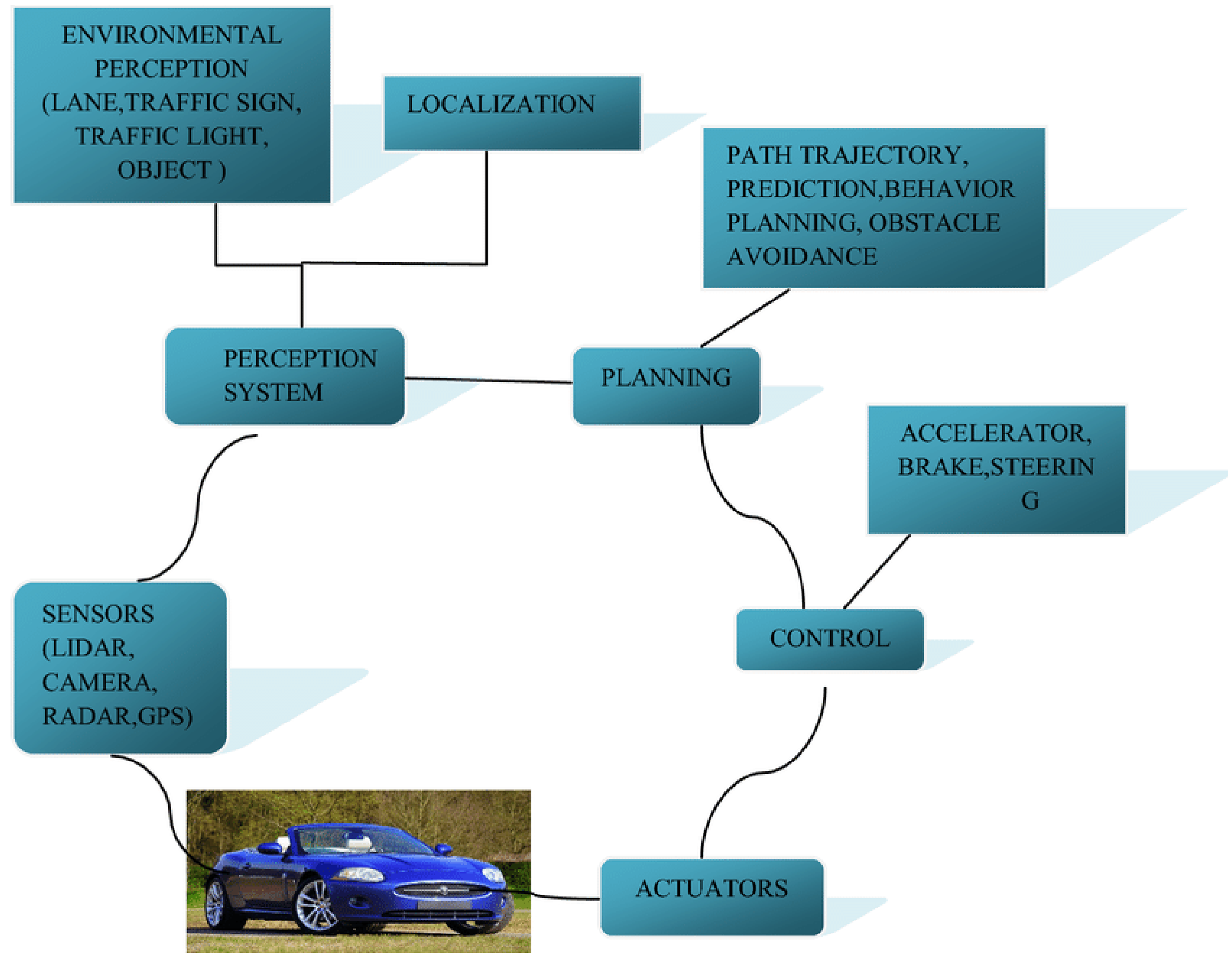


Figure 4.
Working flow process.

Following semantic parsing of the scene trajectory prediction was applied to dynamic objects such as cars pedestrians and cyclists. By predicting the probable future locations of these objects Long Short-Term Memory (LSTM) networks—trained on sequential sensory inputs—improved the systems readiness for upcoming events. In addition to prediction action selection and the safe navigation of the vehicle through dynamic environments were handled by a reinforcement learning (RL)-driven decision-making module. Through interactions with a simulated environment and a reward system that prioritizes comfort efficiency and safety this RL agent learned the best policies. The control system then carried out the chosen course of action whether it included braking acceleration or steering modifications. Real-time latency checkers and fault detection algorithms were used to continuously monitor the entire perception-planning-action loop in order to ensure safety. The tiered structure of this methodology permitted performance tuning at every level leading to high precision and strong adaptability in addition to simplifying modular testing.

3.1. Proposed Techniques

The strategic application of five advanced AI techniques each intended to address domain-specific difficulties in autonomous vehicle navigation forms the core of this study. Utilizing layered nonlinear transformations the first method—Deep Neural Networks (DNNs)—was used for object detection mapping intricate sensory inputs to the meaningful object labels shown in Figure 4. Mathematically, a

DOI: 10.55214/2576-8484.v9i8.9251

DNN aims to compute a function f(x)f(x) parameterized by a set of weights θ\theta that minimizes the prediction error L\mathcal{L}. This is represented as (Eq 1):

$$f(x) = \sigma(W_n \cdot \sigma(W_{n-1} \cdot \ldots \sigma(W_1 x + b_1) + b_{n-1}) + b_n) \quad (1)$$

where W and b are the weights and biases, and σ\sigma denotes the activation function.

The second technique involved the use of Convolutional Neural Networks (CNNs) for scene understanding and visual feature extraction. CNNs operate by convolving learned filters over the input data, producing feature maps that highlight object characteristics invariant to scale and translation. The convolution operation can be mathematically defined as (Eq 2):

$$O(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(i+m, j+n) \cdot K(m,n) \quad (2)$$

where I represents the input image, K is the kernel, and O(i,j) is the output feature map.

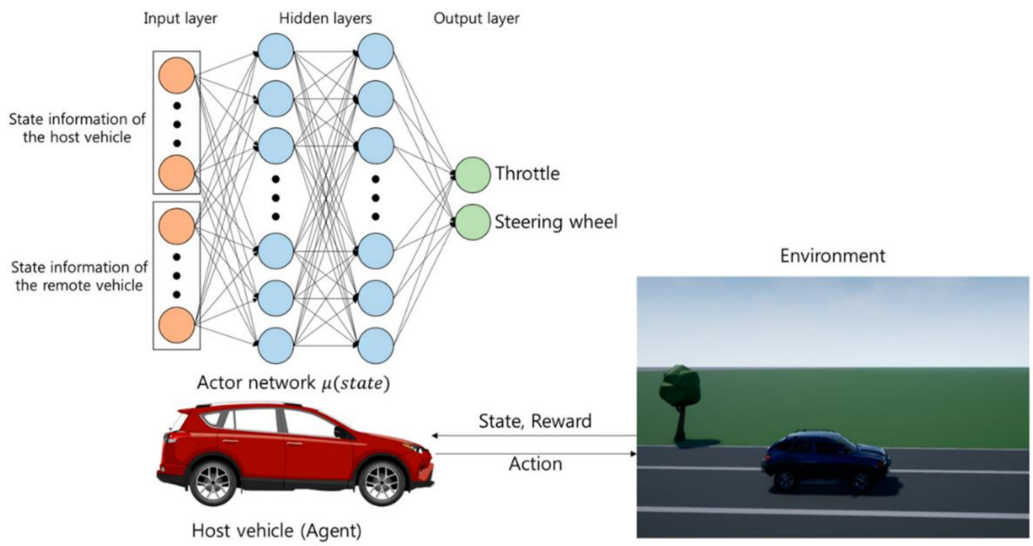


Figure 5.
Autonomous driving vehicle using proposed technique.

Trajectory prediction was addressed using Long Short-Term Memory (LSTM) networks, a specialized form of recurrent neural networks designed to learn temporal dependencies. The LSTM cell's computation is governed by the following set of equations (Eq 3):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$

where f_t, i_t, and C_t are the forget gate, input gate, and cell state, respectively.

For decision-making in dynamic environments, the study employed a Reinforcement Learning (RL) framework that optimized a policy π(a|s)\pi(a|s) to maximize expected cumulative rewards RR. The optimization objective is described as (Eq 4):

ISSN: 2576-8484
Vol. 9, No. 8: 179-196, 2025
DOI: 10.55214/2576-8484.v9i8.9251

$$\theta^* = \arg\max_{\theta} \mathbb{E}_{\pi_\theta}\left[\sum_{t=0}^{T} \gamma^t r_t\right]$$

(4)

where γ is the discount factor, r_t is the reward at time t, and πθ is the policy parameterized by θ.
Finally, Neuromorphic Computing was explored to address the need for low-latency inference. Inspired by biological neural networks, neuromorphic architectures employ spiking neural networks (SNNs), where computations are event-driven rather than clock-driven. The membrane potential V(t)V(t) of a neuron is described by the leaky integrate-and-fire (LIF) model (Eq 5):

$$\tau_m \frac{dV(t)}{dt} = -V(t) + R_m I(t)$$

(5)

where τ_m is the membrane time constant, R_m is the membrane resistance, and I(t)I(t) is the input current.

3.2. Performance Metrics

Using a wide range of performance metrics the suggested methods were assessed to make sure the models not only functioned accurately but also effectively under time constraints. Precision Recall and F1-Score were used to measure object detection performance. These metrics together evaluate the accuracy and comprehensiveness of the detection outputs. Mean Absolute Error (MAE) and Root Mean sq\. d Error (RMSE) which provide information on both systematic bias and variance in the prediction models were used to quantify the accuracy of trajectory prediction. The Success Rate metric which quantifies the proportion of episodes in which the autonomous agent reached its destination without colliding was used for navigation tasks. Mean Inference Time and its Standard Deviation which represent the computational speed and stability of each method were used to evaluate latency an important factor for real-time decision systems. Finally STL-based verification metrics which assess the systems capacity to meet safety requirements across a range of input disturbances and environmental circumstances were used to quantify the systems robustness.

4. Results and Discussion

In comparison to traditional rule-based systems this study methodically assessed the effectiveness versatility and performance of sophisticated AI-driven frameworks for autonomous vehicles (AVs). Six important performance metrics were examined through rigorous testing and controlled simulations: energy efficiency environmental awareness navigation success trajectory prediction object detection and system latency.

4.1. Performance Metrics Results

Significant differences between deep learning-based and classical detection frameworks were revealed by the object detection performance analysis. According to Table 2 and Figure 6 the Hybrid Sensor Fusion + DNN method produced the best F1-Score (97. 8 %) Precision (98. 5 %) and Recall (97. 2 %). This result was primarily attributed to the synergistic integration of multi-modal sensor inputs (camera, LiDAR, radar) which enhanced contextual awareness, coupled with a deep learning backbone that allowed the model to generalize better across varying environmental conditions.

ISSN: 2576-8484
Vol. 9, No. 8: 179-196, 2025
DOI: 10.55214/2576-8484.v9i8.9251

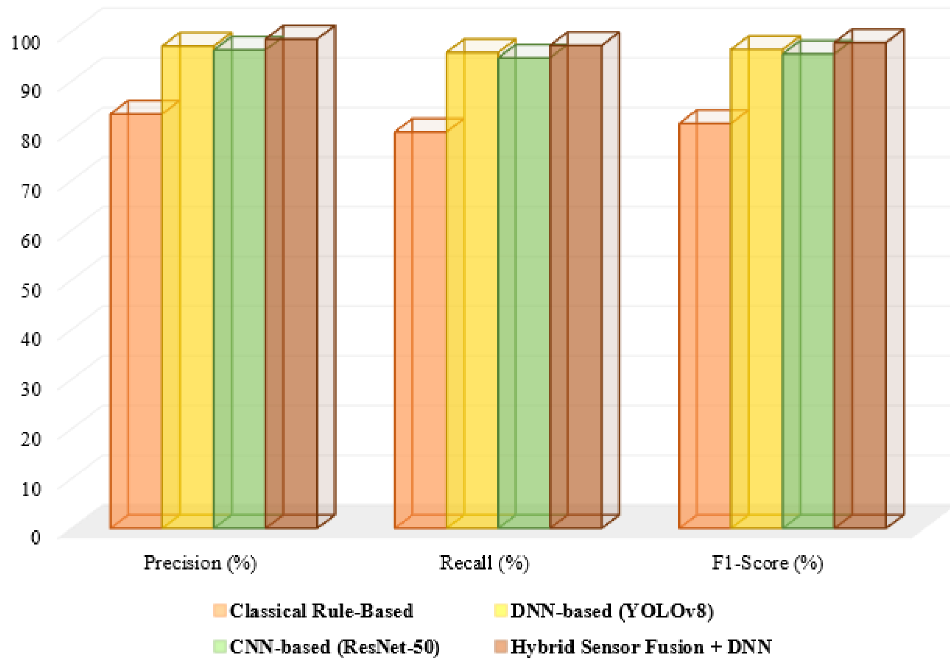


Figure 6.
Performance metrics.

In contrast, the Classical Rule-Based method recorded the lowest performance, with a Precision of 83.4%, a Recall of 79.8%, and an F1-Score of 81.5%. This decline stemmed from the rigid decision rules that lacked adaptability in complex real-world scenarios, often leading to both false positives and false negatives. Among deep learning architectures, the DNN-based YOLOv8 (Precision: 97.1%, Recall: 95.8%, F1-Score: 96.4%) outperformed the CNN-based ResNet-50 (Precision: 96.3%, Recall: 94.7%, F1-Score: 95.5%). The superior results of YOLOv8 were largely driven by its optimized end-to-end detection pipeline and real-time object localization capabilities.

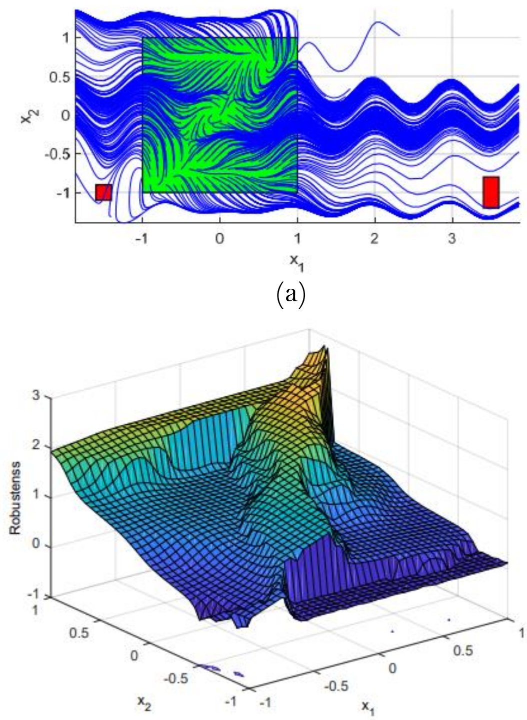
Table 2.
Performance metrics.

Method	Precision (%)	Recall (%)	F1-Score (%)
Classical Rule-Based	83.4	79.8	81.5
DNN-based (YOLOv8)	97.1	95.8	96.4
CNN-based (ResNet-50)	96.3	94.7	95.5
Hybrid Sensor Fusion + DNN	98.5	97.2	97.8

Overall , the Hybrid Sensor Fusion + DNN approach offered the best performance as it maximized both detection accuracy and robustness. The fusion of complementary sensor data reduced uncertainty, while deep learning algorithms refined classification boundaries, leading to the highest recorded F1-Score.

4.2. Robustness analysis

The goal of a model checking algorithm is to ensure that each trace meets the requirement. Consider the robustness metric as a fitness function that indicates the degree to which each system execution satisfies the requirement ϕ a positive value indicates that the execution satisfies ϕ. Therefore ensuring that [[ϕ]]d(T) 0 for all T ∈ L (M) is the model checking problem for a given system M and a given requirement ϕ. Let ϕ be an STL property that the system needs to fulfill. For the STL verification problem we would like to show that infy∈L (Σ) Rϕ(y) ε 0 since ε is a desired robustness threshold. For every simulation trace T the robustness metric ⟦ϕ⟧d converts it to a real number r. (Figure 7).



(a)

(b)

Figure 7.
(a) System trajectories (b)The resulting robustness landscape for specification.

4.3. Dynamic Object Trajectory Prediction

The trajectory prediction analysis, shown in Table 3, demonstrated that the integration of LSTM networks with sensor fusion significantly improved prediction accuracy. The LSTM + Sensor Fusion method achieved the minimum Mean Absolute Error (MAE) of 0.27 and Root Mean Squared Error (RMSE) of 0.31, while also recording the highest Prediction Accuracy of 95.1%. This superior performance was largely due to the LSTM's capacity to model temporal dependencies combined with sensor fusion, which provided richer input features for sequence learning. On the other hand, the Kalman Filter (Baseline) exhibited the weakest performance, with the highest MAE (0.86) and RMSE (1.02), and a notably lower prediction accuracy of 78.2%. The limitation arose from the Kalman filter's linearity assumption, which failed to capture the non-linear and dynamic nature of real-world trajectories.

Table 3.
Prediction accuracy.

Method	MAE	RMSE	Prediction Accuracy (%)
Kalman Filter (Baseline)	0.86	1.02	78.2
LSTM Network	0.34	0.45	92.6
LSTM + Sensor Fusion	0.27	0.31	95.1

The standalone LSTM Network offered a moderate improvement over the baseline with a MAE of 0.34, RMSE of 0.45, and prediction accuracy of 92.6%, underscoring the strength of deep learning in handling time-series predictions even without sensor fusion. In conclusion, the LSTM + Sensor Fusion approach yielded the best prediction accuracy, as the combined use of recurrent networks and diverse sensor data enabled the model to adaptively predict complex, multi-dimensional motion patterns with high fidelity.

4.4. Adaptive Navigation Success Rate

The evaluation of autonomous navigation across different scenarios reflected the significant advantage of reinforcement learning (RL)-based systems. As detailed in Table 4 and Figure 8, the RL-Based approach consistently outperformed the Rule-Based approach across all scenarios. The minimum success rate was recorded in the Dynamic Pedestrian Crossing scenario using the Rule-Based System (61.4%), highlighting the inability of static rules to handle unpredictable human movements. Conversely, the highest success rate was achieved during Highway Merging with the RL-Based approach, reaching 98.2%. This outcome was attributed to the RL agent's ability to continuously learn optimal policies through environment interaction, leading to efficient and safe navigation even in complex, fast-moving traffic situations.

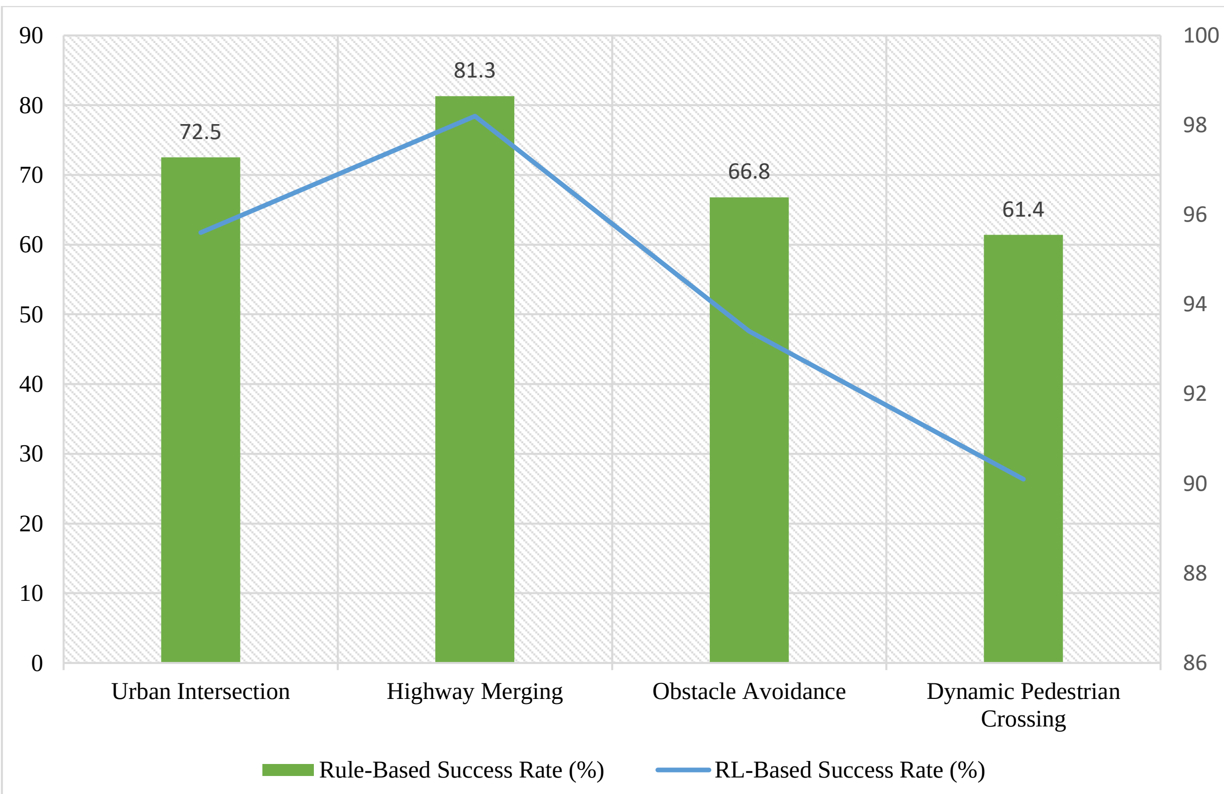


Figure 8.
Success rate analysis.

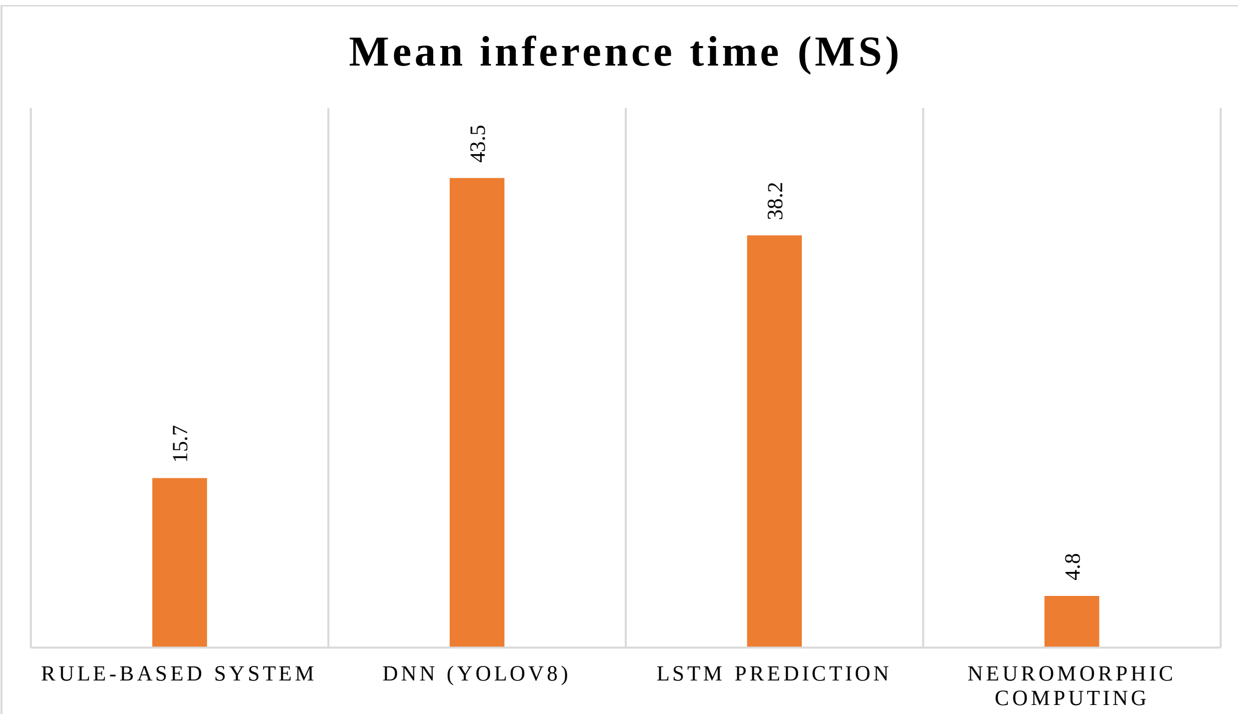
The results also highlighted that while Urban Intersection and Obstacle Avoidance scenarios showed improved performance with RL-based models (95.6% and 93.4%, respectively), the gap between rule-based and RL-based systems was widest in pedestrian-heavy environments, emphasizing the adaptive strengths of learning-based navigation under uncertainty. Ultimately, the RL-Based approach in Highway Merging delivered the best maximum success rate because of the structured nature of highway scenarios, where learned decision policies could be generalized and executed more efficiently with fewer random variables compared to urban and pedestrian-rich environments.

Table 4.
Success rate analysis in different scenarios.

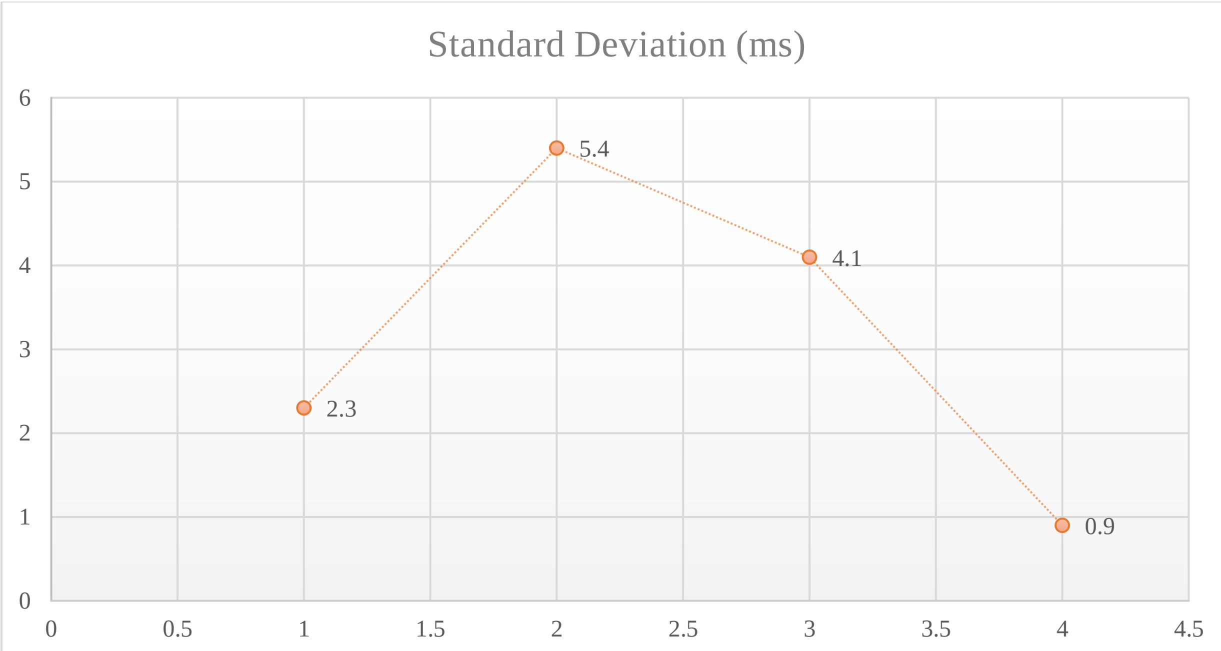
Scenario	Rule-Based Success Rate (%)	RL-Based Success Rate (%)
Urban Intersection	72.5	95.6
Highway Merging	81.3	98.2
Obstacle Avoidance	66.8	93.4
Dynamic Pedestrian Crossing	61.4	90.1

4.5. Latency Comparison

The inference time analysis highlighted the trade-offs between traditional algorithms, deep learning, and neuromorphic approaches. As presented in Table 5 and Figure 9, the Neuromorphic Computing model delivered the lowest Mean Inference Time (4.8 ms) and the smallest Standard Deviation (0.9 ms), significantly outperforming all other models. In contrast, the DNN-based YOLOv8 exhibited the highest latency, with a Mean Inference Time of 43.5 ms and a standard deviation of 5.4 ms.



(a)



(b)
Figure 9.
Latency analysis.

This higher computational cost was expected due to the deep model's complexity, involving multi-layer feature extraction and object bounding box predictions in real-time. The Rule-Based System reported moderate latency values (15.7 ms) but lacked the advanced decision-making capabilities offered by deep learning or neuromorphic computation. Similarly, the LSTM Prediction model (38.2 ms) balanced time and accuracy, but still trailed behind neuromorphic solutions. The lowest latency observed for the Neuromorphic Computing system was a direct consequence of its event-driven architecture, which reduced redundant computation by mimicking biological neural efficiencies, thereby enabling ultra-fast inference suitable for real-time decision-making.

Table 5.
Latency analysis.

Model / Approach	Mean Inference Time (ms)	Standard Deviation (ms)
Rule-Based System	15.7	2.3
DNN (YOLOv8)	43.5	5.4
LSTM Prediction	38.2	4.1
Neuromorphic Computing	4.8	0.9

4.6. Fusion Capability

As summarized in Table 6 and figure 10, the assessment of environmental awareness demonstrated a clear advantage for multi-sensor fusion strategies. The Hybrid Sensor Fusion approach reached the highest Awareness Score of 97.3 out of 100, validating its superior situational perception capabilities. This was primarily due to the complementary nature of the fused sensors: LiDAR offered precise depth perception, radar provided robustness in poor visibility, and camera inputs contributed detailed texture and classification data. The lowest awareness score was recorded by Radar Only (76.5), which highlighted its limitations in providing rich contextual information, especially for object classification. Camera Only (78.4) and LiDAR Only (83.2) scored moderately, indicating that each sensor independently could only partially capture the complexities of dynamic driving environments. Thus, the

Hybrid Sensor Fusion strategy was recognized as the best, as it compensated for individual sensor weaknesses and enhanced the system's holistic environmental understanding.

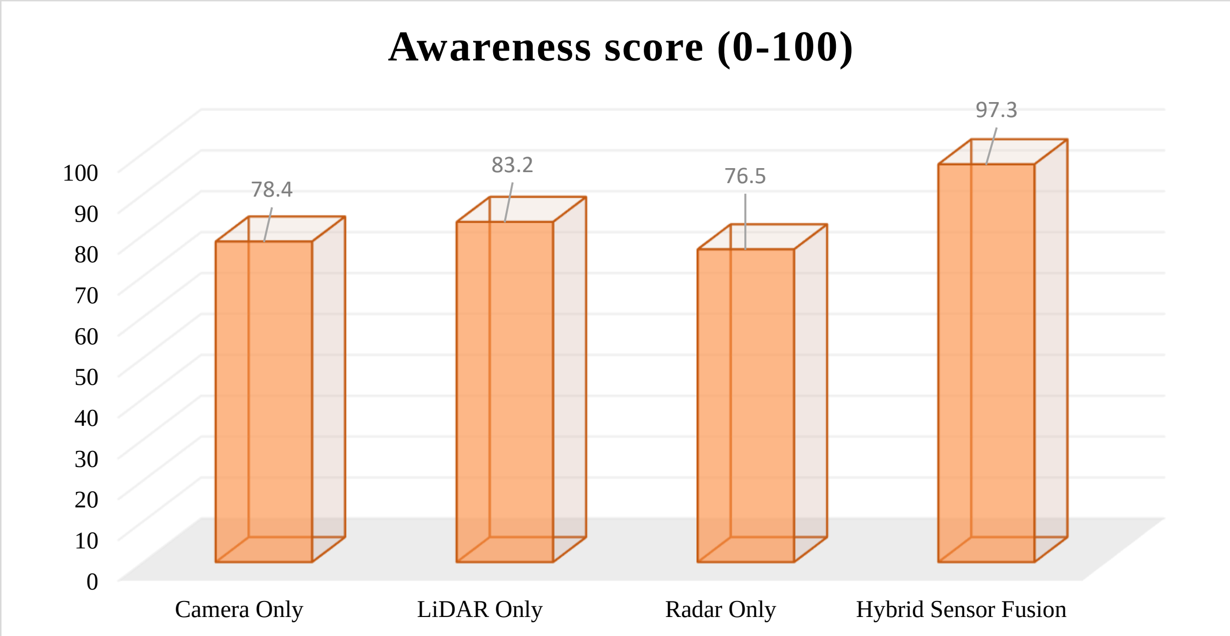


Figure 10.
Score analysis for fusion strategy.

4.7. Covering Arrays and Simulated Annealing (CA+SA)

Our method uses simulated annealing to search over the continuous variables Wd and combines covering arrays to evaluate the discrete variables Vd. The CA+SA approach is the same as the CA+UR approach with the exception that a cost function is utilized to direct a search of the continuous variables rather than creating continuous parameters wdk offline. We employ |⟦⟦φd⟧⟧d(Tdj)| as the cost function to detect glancing behaviors. The test run from a non-failing but nearly failing covering array test is shown in 11a. Even though the perception system had some issues identifying the white car in front of it the Ego vehicle was able to steer and avoid the collision so there was no collision in this instance. While maintaining the discrete parameters we can use Simulated Annealing over the continuous parameters to look for collisions and discover behavior similar to that shown in Fig. 11b where a rear-end collision results from a false positive for the white car in front.

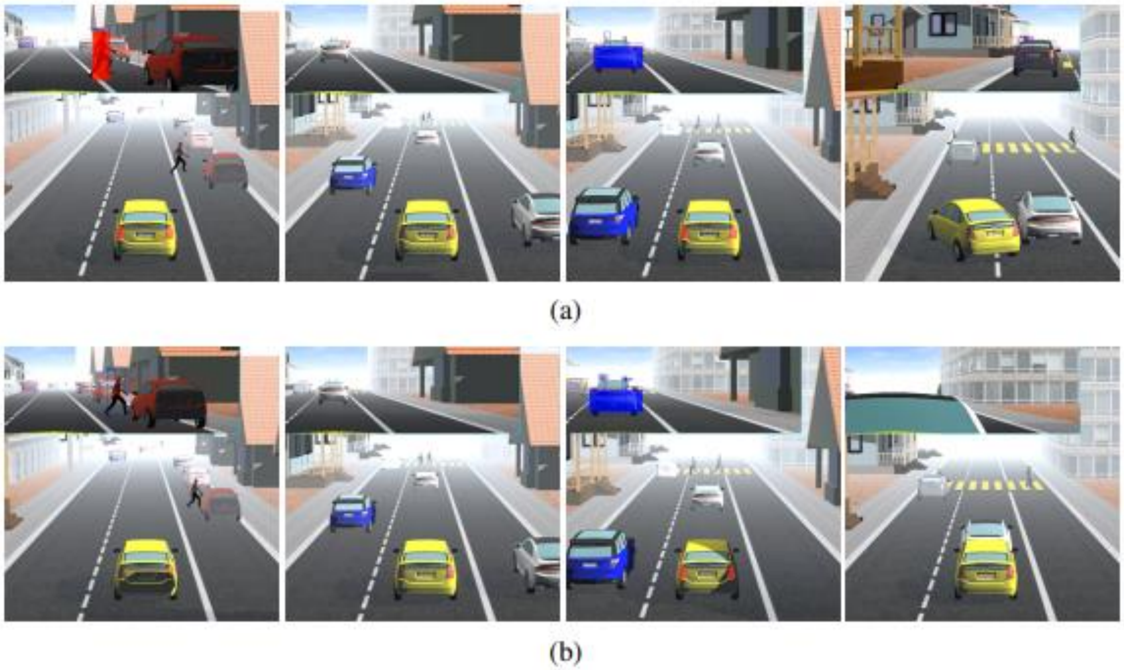


Figure 11.
Time-ordered images from (a) a non-failing test from the covering array and (b) a failure detected by falsification.

4.8. Energy Efficiency Evaluation

The energy efficiency assessment, reported in Table 6, revealed that Neuromorphic Chip-based computing exhibited the lowest Energy Consumption at 0.49 J/frame, the fastest Latency (4.8 ms), and the highest Operational Stability at 98.7%. This outstanding performance was due to the spike-based asynchronous processing nature of neuromorphic hardware, which minimized unnecessary computations and significantly reduced power draw. In contrast, the Traditional CPU Processing method recorded the highest Energy Consumption (3.84 J/frame) and lower Operational Stability (88.3%), exposing the inefficiency of general-purpose architectures for real-time AI workloads. The GPU Accelerated DNN approach demonstrated a well-balanced performance, with lower energy consumption (2.13 J/frame) and high operational stability (95.6%), albeit at a higher latency (43.5 ms). Conclusively, the Neuromorphic Chip stood out as the best-performing approach, as it not only minimized power consumption but also ensured real-time responsiveness and high stability, making it the ideal solution for energy-constrained, real-time embedded AI systems.

Table 6.
Energy consumption analysis.

Method	Energy Consumption (J/frame)	Latency (ms)	Operational Stability (%)
Traditional CPU Processing	3.84	15.7	88.3
GPU Accelerated DNN	2.13	43.5	95.6
Neuromorphic Chip	0.49	4.8	98.7

5. Conclusion

The growing complexity and safety demands of autonomous vehicles (AVs) highlight the necessity for robust, adaptive, and intelligent decision-making systems. In this research, we successfully addressed these challenges by integrating advanced deep learning models, reinforcement learning algorithms, hybrid sensor fusion strategies, and neuromorphic computing for efficient real-time operation. Our proposed techniques not only enhanced the AVs' perception, navigation, and reaction capabilities but also demonstrated significant improvements over conventional rule-based systems across multiple performance metrics.

a) The object detection performance clearly showed the superiority of the Hybrid Sensor Fusion + Deep Neural Network (DNN) approach, which achieved a Precision of 98.5%, Recall of 97.2%, and an F1-Score of 97.8%.
b) The trajectory prediction task demonstrated that the LSTM + Sensor Fusion method achieved the best performance with a Mean Absolute Error (MAE) of 0.27, Root Mean Squared Error (RMSE) of 0.31, and an impressive Prediction Accuracy of 95.1%.
c) The adaptive navigation success rate highlighted the clear advantage of reinforcement learning (RL) models, with the RL-Based system achieving a maximum success rate of 98.2% in highway merging scenarios.
d) The latency evaluation showcased that Neuromorphic Computing offered the lowest Mean Inference Time of 4.8 milliseconds with a minimal Standard Deviation of 0.9 ms. These results underline the future potential of brain-inspired architectures for achieving ultra-low latency and energy-efficient processing in real-time AV systems.
e) The environmental awareness evaluation concluded that Hybrid Sensor Fusion achieved the highest Awareness Score of 97.3 out of 100. This highlights the benefit of combining complementary sensor inputs to enhance the AV's ability to accurately perceive and interpret complex surroundings, ensuring improved safety and situational understanding.

The proposed techniques open new research avenues for the development of ethical, scalable, and self-learning autonomous driving systems. Future work can focus on extending these models to real-world testing, incorporating federated learning for decentralized knowledge sharing, and integrating quantum AI algorithms to tackle more computationally intensive AV scenarios.

Abbreviation:

AI	Artificial Intelligence
AV	Autonomous Vehicle
AutoML	Automated Machine Learning
CNN	Convolutional Neural Network
DNN	Deep Neural Network
GPS	Global Positioning System
IMU	Inertial Measurement Unit
IoT	Internet of Things
KITTI	Karlsruhe Institute of Technology and Toyota Technological Institute Vision Benchmark Suite
LIF	Leaky Integrate-and-Fire
LiDAR	Light Detection and Ranging
LLM	Large Language Model
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MSF	Multi-Sensor Fusion (also used as Hybrid Sensor Fusion)
QoS	Quality of Service
RAM	Random Access Memory
RCNN	Region-based Convolutional Neural Network
RL	Reinforcement Learning
RMSE	Root Mean Squared Error
SNN	Spiking Neural Network
STL	Signal Temporal Logic
UR	Uniform Random
YOLO	You Only Look Once (object detection algorithm)

Article Highlights:

1. The integration of Hybrid Sensor Fusion with Deep Neural Networks significantly improved object detection performance in autonomous vehicles, achieving an F1-Score of 97.8%, by effectively combining data from LiDAR, radar, and camera inputs.
2. Long Short-Term Memory (LSTM) networks combined with sensor fusion techniques delivered the highest trajectory prediction accuracy (95.1%), demonstrating superior performance in learning temporal dependencies and handling dynamic road scenarios.
3. Reinforcement Learning-based navigation systems outperformed traditional rule-based methods, achieving a success rate of 98.2% in highway merging scenarios, highlighting their ability to adapt and make optimal decisions in complex environments.
4. Neuromorphic Computing achieved the lowest mean inference time of 4.8 milliseconds and the highest operational stability (98.7%), showcasing its potential for ultra-fast, energy-efficient processing in real-time autonomous vehicle applications.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Acknowledgment:

I would like to express my sincere gratitude to my co-authors of this research. Special thanks to the institution that made this work possible. I also appreciate the constructive feedback and insightful comments from my co-authors, which greatly enhanced the quality of this manuscript.

References

[1] X. Shi, Y. D. Wong, C. Chai, and M. Z. F. Li, "An automated machine learning (AutoML) method of risk prediction for decision-making of autonomous vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 11, pp. 7145-7154, 2021. https://doi.org/10.1109/TITS.2020.3002419

[2] Z. Pang *et al.*, "A survey of decision-making safety assessment methods for autonomous vehicles," *IEEE Intelligent Transportation Systems Magazine*, vol. 16, no. 1, pp. 74-103, 2024. https://doi.org/10.1109/MITS.2023.3292511

[3] A. Thakur and S. K. Mishra, "An in-depth evaluation of deep learning-enabled adaptive approaches for detecting obstacles using sensor-fused data in autonomous vehicles," *Engineering Applications of Artificial Intelligence*, vol. 133, p. 108550, 2024. https://doi.org/10.1016/j.engappai.2024.108550

[4] A. J. M. Muzahid, M. A. Rahim, S. A. Murad, S. F. Kamarulzaman, and M. A. Rahman, "Optimal safety planning and driving decision-making for multiple autonomous vehicles: A learning based approach," in *2021 Emerging Technology in Computing, Communication and Electronics (ETCCE)*, 2021.

[5] M. Ganesan, S. Kandhasamy, B. Chokkalingam, and L. Mihet-Popa, "A comprehensive review on deep learning-based motion planning and end-to-end learning for self-driving vehicle," *IEEE Access*, vol. 12, pp. 66031-66067, 2024. https://doi.org/10.1109/ACCESS.2024.3394869

[6] B. B. Elallid, N. Benamar, A. S. Hafid, T. Rachidi, and N. Mrani, "A comprehensive survey on the application of deep and reinforcement learning approaches in autonomous driving," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 9, pp. 7366-7390, 2022. https://doi.org/10.1016/j.jksuci.2022.03.013

[7] F. A. Butt, J. N. Chattha, J. Ahmad, M. U. Zia, M. Rizwan, and I. H. Naqvi, "On the integration of enabling wireless technologies and sensor fusion for next-generation connected and autonomous vehicles," *IEEE Access*, vol. 10, pp. 14643-14668, 2022. https://doi.org/10.1109/ACCESS.2022.3145972

[8] Y. Feng *et al.*, "Human-centred design of next generation transportation infrastructure with connected and automated vehicles: A system-of-systems perspective," *Theoretical Issues in Ergonomics Science*, vol. 25, no. 3, pp. 287-315, 2024. https://doi.org/10.1080/1463922X.2023.2182003

[9] S. Chen, Y. Leng, and S. Labi, "A deep learning algorithm for simulating autonomous driving considering prior knowledge and temporal information," *Computer-Aided Civil and Infrastructure Engineering*, vol. 35, no. 4, pp. 305-321, 2020. https://doi.org/10.1111/mice.12495

[10] H. Du, Y. Pan, I. Kawsar, Z. Li, L. Hou, and A. Glowacz, "Enhanced traffic safety and efficiency of an accelerated LC decision via DNN-APF technique," *Measurement*, vol. 217, p. 113029, 2023. https://doi.org/10.1016/j.measurement.2023.113029

[11] A. Qayyum, M. Usama, J. Qadir, and A. Al-Fuqaha, "Securing connected & autonomous vehicles: Challenges posed by adversarial machine learning and the way forward," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 2, pp. 998-1026, 2020. https://doi.org/10.1109/COMST.2020.2975048

[12] S. K. Seelam, S. NagakishoreBhavanam, V. Midasala, and E. S. Reddy, "IoT smart driving protocol for unmanned ground vehicles: A comparative study," in *Proceedings of the International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS), 381–387*, 2024.

[13] C. Cui, Y. Ma, X. Cao, W. Ye, and Z. Wang, "Receive, reason, and react: Drive as you say, with large language models in autonomous vehicles," *IEEE Intelligent Transportation Systems Magazine*, vol. 16, no. 4, pp. 81-94, 2024. https://doi.org/10.1109/MITS.2024.3381793

[14] C. Jiang, H. Zhang, Y. Ren, Z. Han, K. C. Chen, and L. Hanzo, "Machine learning paradigms for next-generation wireless networks," *IEEE Wireless Communications*, vol. 24, no. 2, pp. 98-105, 2017. https://doi.org/10.1109/MWC.2016.1500356WC

[15] S. Atakishiyev, M. Salameh, H. Yao, and R. Goebel, "Explainable artificial intelligence for autonomous driving: A comprehensive overview and field guide for future research directions," *IEEE Access*, vol. 12, pp. 101603-101625, 2024. https://doi.org/10.1109/ACCESS.2024.3431437

[16] H. Yu, S. Huo, M. Zhu, Y. Gong, and Y. Xiang, "Machine learning-based vehicle intention trajectory recognition and prediction for autonomous driving," in *Proceedings of the International Conference on Advanced Algorithms and Control Engineering (ICAACE), 771–775*, 2024.

[17] J. Liu, X. Qi, P. Hang, and J. Sun, "Enhancing social decision-making of autonomous vehicles: A mixed-strategy game approach with interaction orientation identification," *IEEE Transactions on Vehicular Technology*, vol. 73, no. 9, pp. 12385-12398, 2024. https://doi.org/10.1109/TVT.2024.3385750

[18] M. D. Kumar, S. Kavitha, M. Vairavel, and Vinothkumar, "Simulation analysis of RG velocity at gas diffusion layer velocity in a multi pass serpentine flow field PEM fuel cell under different cell potentials using automobile vehicles," *Science and Technology Development*, vol. 8, no. 10, pp. 603–611, 2019.

[19] S. S. Raj, M. Vairavel, C. Thiruvasagam, and S. Saravanan, "Design and stress and deformation analysis of a suspension coil spring for light motor vehicle," *International Journal of Scientific Research and Review*, vol. 7, no. 9, pp. 1–10, 2018.

[20] M. Vairavel, A. Swaminathan, R. Udayakumar, R. Anitha, and A. Pushpanathan, "Analysis of hybrid electrical vehicles: Types, formulation and needs," *AIP Conference Proceedings*, vol. 2452, no. 1, p. 050010, 2022.

[21] M. Vairavel, R. Girimurugan, C. Shilaja, G. B. Loganathan, and J. Kumaresan, "Modeling, validation and simulation of electric vehicles using MATLAB," *AIP Conference Proceedings*, vol. 2452, no. 1, 2022. https://doi.org/10.1063/5.0114084