European Science Methodical Journal
ISSN (E): 2938-3641
Volume 3, Issue 5, May- 2025

# ARTIFICIAL INTELLIGENCE TECHNIQUES FOR INTELLIGENT CAR AUTONOMOUS DECISION MAKING ON HIGHWAYS

Muthnna Nihad AL-Tameemi
Salah Al-Din Governorate / Iraq
muthana.altmeme.82@gmail.com

**Abstract**:

Decision-making needs to be improved because it is difficult to make decisions for an Autonomous Car (AC) that will prevent deadly traffic accidents, provide comfort and safety, and reduce traffic. Artificial Intelligence (AI) has used a variety of methods and approaches to address these problems, such as Machine Learning (ML) algorithms in conjunction with Deep Learning (DL) techniques. Because it allows for real-time decision-making, object detection, and automation of driving systems, artificial intelligence has emerged as a key component in the development of autonomous cars. This paper creates a policy for autonomous cars decision-making that uses artificial intelligence to handle overtaking tendencies on highways. First, a highway driving environment must be established in which the ego automobile seeks to safely and efficiently navigate through the other cars. The significance of artificial intelligence in driverless cars is examined in this study. The artificial gathers and analyzes data from all of the car's sensors. The car's driving mechanism uses the retrieved data as input. Therefore, artificial intelligence can make choices more quickly in real time by using a perception algorithm. In order to address the overtaking behaviors on highways, we developed a Deep Reinforcement Learning (DRL)-powered autonomous car decision-making system in this study. This is a novel version of the well-known Support Vector Machine (SVM) technique. These cars are controlled using a hierarchical control structure, meaning that the lower level is concerned with monitoring the car's speed and acceleration while the upper level controls driving decisions. The thorough computational processes of the SVM-DRL algorithms are examined and contrasted. To assess the efficacy of the suggested roadway decision-making policy, a number of estimation simulation experiments are carried out. The suggested framework's benefits in terms of control performance and convergence rate are highlighted. The findings of the simulation indicate that highway driving tasks can be completed safely and effectively by the DRL-based overtaking policy. Additionally, we put the learnt decision policy to the test on an actual in normal highway traffic; an autonomous car will execute overtaking decisions and control.

**Keywords**: Artificial Intelligence (AI), Deep Reinforcement Learning (DRL), SVM, Machine Learning (ML), Autonomous Car, Deep Learning (DL).

## Introduction

The car may do many driving tasks without a human driver thanks to Autonomous Driving (AD). Autonomous or automated cars have emerged as a global research hotspot, driven by the immense potential of Artificial Intelligence (AI)[1]. Automobile manufacturers such as Audi , Tesla, Ford, Mercedes-Benz ,Waymo , General Motors, Toyota, and others are producing great strides in creating their own autonomous cars. Researchers in the automobile industry are working to develop the necessary technology to create fully automated cars in the interim. With the advancement of technology and social and economic development, the number of cars on the road is growing rapidly[2].

Autonomous cars consist of four key modules: perception, control, planning, and decision-making. Based on the operations of numerous sensors, including radar, lidar, the Global Positioning System (GPS), and others, perception shows that autonomous cars are aware of the driving conditions. The decision-making controller controls the cars' lane-changing, lane-keep, braking, acceleration, and other driving actions. The planning feature aids automated cars in determining the most efficient routes between two points. In order to complete driving techniques and follow the planned course, finally, an onboard powertrain components would get instructions from the control module to perform precisely. There are six levels in the AD, ranging from L0 to L5, based on the intelligent degrees of the aforementioned modules[3].

Autonomous cars rely heavily on decision-making strategies, which are thought of as the human brain. Manual guidelines either by imitating supervised learning methods or by drawing on human driving experiences are frequently used to construct this policy, determined the motion purpose of the nearby autos using the continuous hidden Markov chain [4]. The policy for multi-criteria decision-making that is being provided aids city automobiles in making practical decisions under various circumstances. The associated model combines the candidate decision generating module with cooperative car-following models. Additionally, the idea of a human-like driving mechanism was brought up. By taking into account the demand for human drivers, it could modify the driving decisions[5].

Artificial Intelligence (AI) technologies like deep learning, computer vision, and machine learning enable these advancements, which enable automobiles to learn from their environment, identify impediments, and make wise driving judgments. The automotive sensor sector now offers new opportunities to enter the business because to advancements in machine learning. A popular machine learning technique with good generalization capabilities is the Support Vector Machine (SVM)[6]. It can map variables into feature spaces that have more dimensions or are infinite using nonlinear methods for either classification (Support Vector Machine (SVM) classification) or regression (Support Vector Machine Regression (SVR)). However, SVR uses the same approach as SVM in the classification problem and is able to predict the value of an endless number of possible outputs. Furthermore, SVR is configured with a tolerance margin to approach the most accurate categorization outcomes. SVM is more flexible in addressing the multi-classification problem than SVM, despite its greater complexity[7]. In this paper, the output threshold range is established for each driving decision, and the SVM algorithm is utilized to forecast the multi-driving decision. The main applications of SVM in driving decision research include driving risk assessment. Currently, the majority of research uses SVM to address problems by directly defining the kernel functions, but occasionally it may be discovered that the kernel function does not correspond to the situation at hand. Thus, to optimize the SVM model, a novel kernel function is proposed to let the objective problem automatically select the ideal kernel function. Because they can identify and categorize objects by examining distinct spectral fingerprints, Support Vector Machines (SVMs) are very useful in this situation[8]. Even in noisy or congested situations, SVMs enhance target recognition and classification by projecting data into higher-dimensional areas. They have proven effective in both academic and industrial settings, with applications ranging from object recognition to handwritten digit recognition. This section examines recent developments in machine learning's application to driverless cars[9].

Recently, support vector machines have gained attention as a potentially helpful tool in the hunt for stronger decision-making processes. A complex machine learning technique that performs exceptionally well in classification tasks is the Support Vector Machine (SVM). It accomplishes this by finding the optimal hyperplane that has the largest margin between data points of different classes. SVM has several advantages in the context of autonomous cars, making it a perfect choice for enhancing highway safety and efficiency[10].

Techniques for Deep Reinforcement Learning (DRL) are regarded as an effective means of addressing lengthy sequential decision-making difficulties. Many initiatives have been made in recent years to investigate topics related to DRL-based autonomous driving. Constructed a hierarchical framework to use the Reinforcement Learning (RL) technique to understand the policy for making decisions. The advantage of this study is not dependent on the labeled driving data from the past. DRL techniques were used in address the path-following and collision avoidance issues for automated car[11]s. In these two studies, the relevant control performance outperforms the traditional RL approaches. Additionally, took into account both path planning and the amount of fuel used by autonomous cars. It has been demonstrated that the associated algorithm, DRL, can successfully complete these two-driving tasks. Han et al. used the DRL method, which considers the information of neighboring automobiles as network feedback knowledge, to determine whether to change lanes or maintain lanes for networked autonomous cars . The resulting policy can improve driving comfort and traffic flow[12].

In this study, a policy permitting autonomous cars to overtake on highways is built using the suggested approach. First, an ego car seeks to navigate a certain driving scenario effectively and safely in the highway-based driving environment under study. The ego's and the surrounding automobiles' longitudinal and lateral motions are then controlled through a framework of hierarchical control. In addition, the suggested algorithms are developed and useful to determine the decision-making process for the roads approach. A performance of the suggested control system is finally examined through the execution of several simulation tests. According to simulation data, an overtaking policy could safely and effectively complete highway driving tasks.

The following describes how this article is organized: Sections 2 and 3 explain related works, the highway driving environment, and the ego and neighboring automobiles' control modules. Section 4 provides definitions for the SVM and DRL algorithms. The pertinent outcomes of a number of simulation tests are displayed in Section 5. Lastly, Section 6 conducts the conclusion.

## 1. Related works

The foundation of contemporary autonomous driving systems is Artificial Intelligence (AI), with a variety of technologies like machine learning, deep learning, and computer vision allowing cars to sense and engage with their surroundings. In order to enable autonomous systems to make judgments in real time, machine learning algorithms are mostly employed to teach them to identify patterns in enormous volumes of data. Object identification and classification tasks—which are essential for recognizing pedestrians, other cars, and road signs—have advanced thanks in large part to deep learning, a branch of machine learning.

The most popular type of AC testing is called "Shadow Driving," in which a driver is prepared to stop an accident before it happens or take over if the AC decides to disengage. This approach is demonstrated to require a minimum of 275 million miles to ensure that ACs will be at least as safe as humans. If there were to be any updates to the AC being tested, some, if not all, of those miles would also need to be redone. Test tracks are also frequently used for real-world testing because they enable businesses to test particular, occasionally extreme scenarios[13].

The study emphasized the importance of applying AI-based techniques to enhance lane change maneuvers performed by driverless cars. Their model mimicked real-world traffic conditions and scenarios by using Convolutional Neural Networks and Long Short-Term Memory networks (LSTMs) to make sequential judgments depending on input. According to simulation studies, the agent might pick up the best lane change rules, which would enable it to make better decisions and be more adaptable as traffic conditions change[14].

The development of a hybrid decision-making model that blends machine learning and rule-based reasoning was a major advancement. To assess if changing lanes was safe given the speed and distance to oncoming traffic, they employed fuzzy logic and support vector machines. The hybrid approach demonstrated improved lane change decision accuracy in a variety of traffic scenarios, underscoring the potential synergy between rule-based systems and artificial intelligence. The program was trained and its outcomes verified by the researchers using a big dataset of actual driving scenarios[15].

Convolutional Neural Networks are capable of efficiently extracting local and global characteristics derived from data, including text and images. The developed a CNN prediction model that had an absence trigger rate of 0.037% and an average To predict where a car turning left will be at an intersection when making a turn accurateness of 84.96%, allowing them to accurately predict the intentions of bicycles and pedestrians. In order to forecast the position of a left-turning car at an intersection during a turn created a Conv-LSTM model that uses CNNs to extract behavioral data at various periods[16].

According to[17] , while the deployment of autonomous Cars (ACs) offers many benefits, like increased safety and a smaller environmental effect, there are also serious hazards associated with security and privacy flaws. By utilizing their individual advantages to strengthen antivirus software against malevolent attacks, blockchain and artificial intelligence integration provide a viable way to allay these worries. According to the report's thorough examination of security threats, current research, and potential avenues for future study, even if prior research examines this junction, more study is necessary to completely understand the potential of this amalgamation in preserving ACs.

## 2. The Control Module and Driving Environment

This section introduces the highway driving situation under study. A three-lane freeway setting is created without sacrificing generality. Additionally, a controller for motion that is hierarchical is explained for controlling the ego's and the surrounding automobiles' longitudinal and lateral movements. The upper-level models include reduce total braking caused by lane changes and the intelligent driver model [17]. A car's velocity and acceleration are managed by the bottom level.

### 3.1 Highway Driving Scenario

In autonomous driving, decision-making refers to choosing a series of rational driving actions to accomplish certain driving tasks. These actions include lane-changing, lane-keeping, braking, and accelerating on highways. Avoiding crashes, running quickly, and staying in the desired lane are the primary goals. Overtaking is a common driving action that involves accelerating and passing other cars[18].

Fig. 1 depicts the driving scenario for the research, and decision-making problem for autonomous cars on the highway is covered in this work. Other green automobiles are referred to as surrounding cars, whereas the orange car is the ego car. The driving environment has three lanes, and the decision-making policy that is produced in this study can be readily applied to other scenarios. The ego car would start out at a random speed in the middle lane.

The ego car's goal is to run as fast as it can without colliding with any nearby cars. This objective is therefore understood to be efficiency and safety. The neighboring cars' starting positions and speeds are created at random. It suggests that there are unknowns regarding the actual driving situation. Additionally, the ego car can pass other cars from the right or left and likes to stay in lane 1 (L=1) in order to mimic the actual situations.

All of the nearby cars were in front of the ego car when this driving responsibility first began. A quantity of close automobiles in each lane shows that there are cars in the vicinity. The ego car would be interrupted by either hitting other cars or running out of time. In this work, the process of running from the beginning to the end is referred to as an episode.

The following parameters are established for the driving situation without compromising generality: The ego car's width and length are such that its top speed is 40 m/s and its starting speed is set at m/s. 20 Hz is the simulation frequency, and each episode lasts 100 seconds. IDM

European Science Methodical Journal
ISSN (E): 2938-3641
Volume 3, Issue 5, May- 2025

and MOBIL control the surrounding cars' behaviors by randomly selecting their initial velocity from m/s[19].

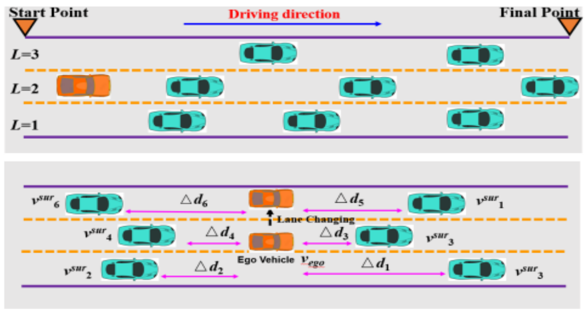


Figure 1: Driving on a highway in a situation where decision-making is difficult[20]

### 3.2 Car Behavior Controller

Fig.2 illustrates how a hierarchical control system masters the motions of every car in roadway situations. The upper-level employs Intelligent Driver Model (IDM) and MOBIL to regulate the automobile's behaviors, while the lower-level aims to let the ego car follow a target lane and track a predetermined target speed. The reference model suggests that it controls the ego vehicle, and the DRL is used in this work to control the ego automobile. It also acts as a standard for assessing the DRL-based decision-making process[21].

Intelligent Driver Model (IDM) is a popular microscopic model at the top level for achieving car-following and collision-free. IDM often determines the longitudinal behavior in automated automobiles' adaptive cruise controllers. Generally speaking, IDM is calculated as the longitudinal acceleration.

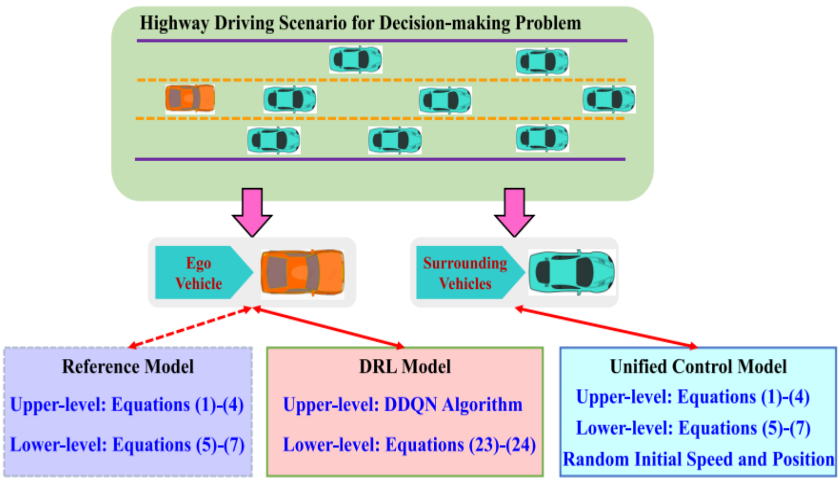


Figure 2: The ego car and its surrounding cars are controlled hierarchically[22].

### 3.3 Car Motion Controller

The longitudinal and lateral movements of the autos are regulated at the lower level. In the former, a proportional controller controls the acceleration as follows:

$$\alpha = K_p(\nu_{\mathrm{tar}} - \nu) \qquad (1)$$

Where the proportional gain is denoted by $K_{\mathrm{p}}$.

To manage the car's location and lateral direction, the controller employs a simple proportional-derivative operation. The location shows how the car's lateral speed $\nu_{\mathrm{lat}}$ is calculated.

$$\nu_{\mathrm{lat}} = -K_{\mathrm{p,lat}}\Delta_{lat} \qquad (2)$$

Where $\Delta_{lat}$ is the car's lateral position with respect to the lane's center line and $K_{p,lati}$ is the position gain. The heading control and the yaw rate commandφ are then connected as follows:

$$\varphi^{\cdot} = K_p,\varphi(\varphi_{tar} - \varphi) \qquad (3)$$

where $K_{p,lat}$ is the heading gain and $\varphi_{tar}$ is the goal heading angle to follow the desired lane.

Therefore, bi-level control architecture in Fig. 2 the responsible for the motions of the surrounding autos. It is presumed that the ego car is aware of these cars' position, speed, and acceleration. This restriction encourages the ego car to use trial-and-error to learn how to drive in the given situation. To achieve this educational process and determine the policy for making decisions about roads, the DRL approach is presented and established in the next section.

## 4 Methodology

The current study uses (SVM-DRL) approaches to help with highway environment decision-making, as seen in Fig.3.

### 4.1 Data Collection

The Federal Highway Administration (FHWA) gathered the NGSIM dataset; it is commonly recognized as one of the most comprehensive and precise field datasets for the study and advancement of traffic micro-simulation. It uses trajectory data from digital cameras taken at tenths of second intervals to provide precise vehicle locations along 0.5- to 1.0-kilometer road segments. The I-80 in the San Francisco Bay Area and the US 101 in Los Angeles are two notable instances of actual road data in this dataset. These datasets, which include wide-area detector data, vehicle trajectory data, and other auxiliary data, are very helpful for studying driver behavior[21].

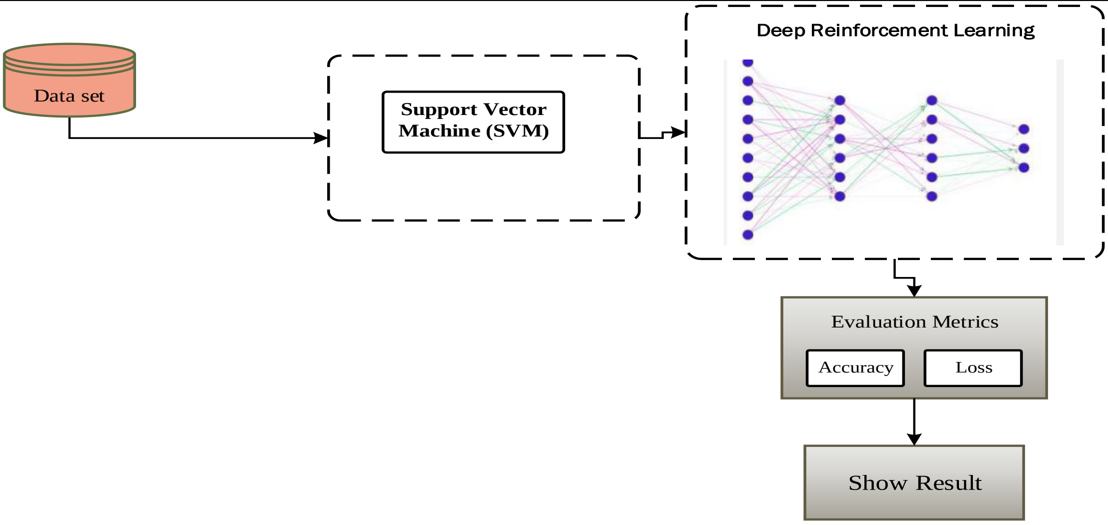


Figure 3: proposed method

### 4.2 Support Vector Machine

Support vector machines are a type of machine learning that is based on statistical learning theory, which was. Among its qualities are exceptional model generalization performance and a strong learning capacity for small data. Time series prediction, function approximation, and classification have all benefited from the effective use of SVM, which has made significant strides in theoretical study and algorithm implementation in recent years. SVM was initially applied to linear discrete data to address the binary classification problem[23]. The fundamental idea is to determine the best hyperplane that meets the criteria for data classification and to maximize the difference between two sample points while preserving the precision of the categorization, as seen in Figure 4.

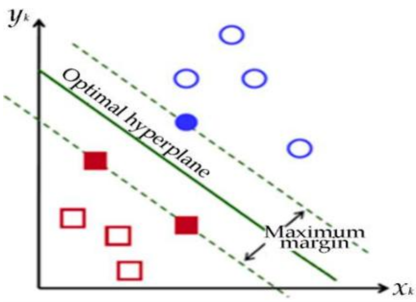


Figure 4: optimum hyperplane concept[24].

If linear classification is used, let's say the training sample is $SV=\{(x1,y1),(x2,y2),\ldots,(xm,ym)\}$SV={(x1,y1),(x2,y2),…,(xm,ym)}, $x\in Rd$x∈Rd, $yk\in\{-1,1\}$yk∈{−1,1}, the input variable is $x_k$, $yk$ represents the severity of collision injuries, and the quantity of training samples is represented by $m$, and the d-dimensional real number space is represented by $k$=1,2,…,m.

According to SVM linear classification, a hyperplane $\boldsymbol{\omega} \bullet x+b=0$, where $b$ is the bias and $\boldsymbol{\omega}$ is an adjustable weight vector, can accurately classify all samples.

$$(\boldsymbol{\omega}\cdot x_k+b)\geq 1,=1,2,\ldots,m \qquad (4)$$

Determine the classification interval by calculating:

$$_{\{xk|yk=1\}}\boldsymbol{\omega}\cdot xk+b/\ \|\boldsymbol{\omega}\|\ -max_{\{xk|yk=-1\}}\boldsymbol{\omega}\cdot xk+b/\|\boldsymbol{\omega}\|= 2/\|\boldsymbol{\omega}\| \qquad (5)$$

Maximizing the classification interval, or minimizing the $\|\boldsymbol{\omega}\|$, is necessary for the optimal hyperplane. Consequently, a minimum function that complies with the following restriction can be used to represent the optimal hyperplane problem:

$$(\boldsymbol{\omega})=1/2\|\boldsymbol{\omega}\|^2=1/2(\boldsymbol{\omega}\cdot\boldsymbol{\omega}) \qquad (6)$$

Three kinds of frequently utilized kernel functions are as follows:

(1) A polynomial kernel function

(2) Function of the radial basis kernel

(3) The sigmoid kernel function

This research develops a three-classification collision injury severity prediction model (non-fatal, non-incapacitating, and without injury). It is necessary to extend the SVM model in order to construct multiple SVM classifiers, as the basic SVM model mentioned above only takes into account the binary classification problem[25]. Fig. 5 illustrates how the three crash injury severity categories are categorized in the training into three binary combos: Non-incapacitating and non-fatal, non-incapacitating and non-incapacitating, and non-incapacitating and non-fatal. Three SVM training models for the binary class are produced following training. Each sample in the test is classified using these three SVM training models, and then when training is completed, three binary-class SVM training models are generated. A sample category is determined by using three models for SVM training to categorize each taster during testing is chosen based on The classification result category with the most results [23].

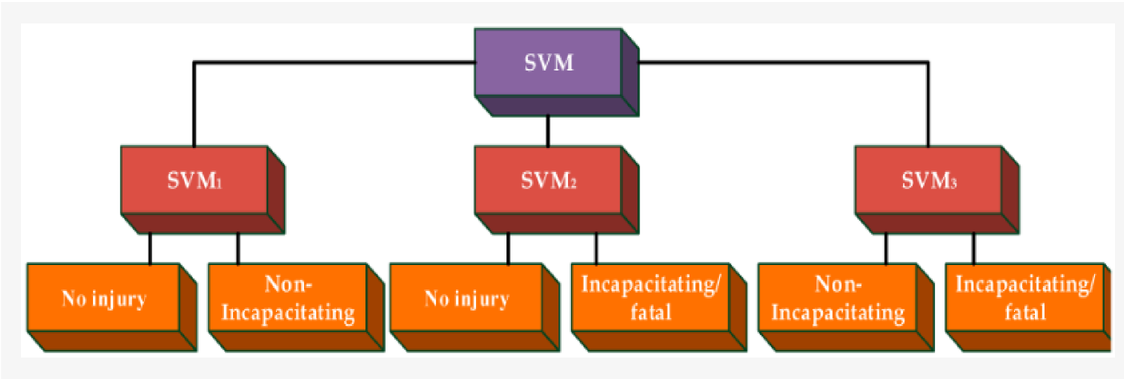


Figure 5: Building SVM with several classifiers[26].

To give autonomous cars a similar foundation in emergency scenarios, crash damage severity prediction models that correlate to various options (braking, turning, and braking + turning) must be developed. This is because autonomous cars try to forecast the severity of collisions in order to make emergency judgments with the fewest possible injuries.

### 4.3 Deep Reinforcement Learning Methodology

The DRL algorithms are introduced in this section. First, the relationship between the agent and the environment in DRL is described. Machine learning is one area of artificial intelligence disturbed with using data to improve the efficiency of computer algorithms. The three primary subcategories of machine learning are reinforcement learning (RL), supervised learning, and unsupervised learning. In reinforcement learning, an autonomous agent seeks to maximize a predefined reward function in order to learn how to carry out tasks within an environment. When the agent interacts with its surroundings and does the right thing, it is rewarded. Conversely, the agent is punished with harmful incentives or penalties if the action they choose is unpleasant[27].

The goal of unsupervised learning, however, is to uncover hidden patterns in unlabeled data. Although it may be beneficial to find such structures, this method is unable to maximize rewards, which is one of Reinforcement Learning's (RL) main objectives.

The Reinforcement Learning is used to solve situations where there are a lot of different actions and states in the environment. Artificial Neural Networks (ANN) and other function approximates can be used to address the difficulties presented by huge state and action spaces. Deep reinforcement learning is the term used to describe the application of a neural network in Reinforcement Learning (RL) as a function approximator.

RL problems are usually structured using Markov Decision Processes (MDPs), which include a reward function (R), a transition function (T) between states, a collection of acts and states, the tuple (S, A, T, R) is frequently used. $T(s_t, a_t, s_{t+1})$ is the probability of changing to a new state s + 1 from statuses at time stage t following action a. This probability varies from 0 to 1. $R(s_t, a_t, s_{t+1})$ and $r_t$ are immediate rewards from this transition, respectively. An illustration of the basic elements of the autonomous car RL model is shown in Fig. 6.

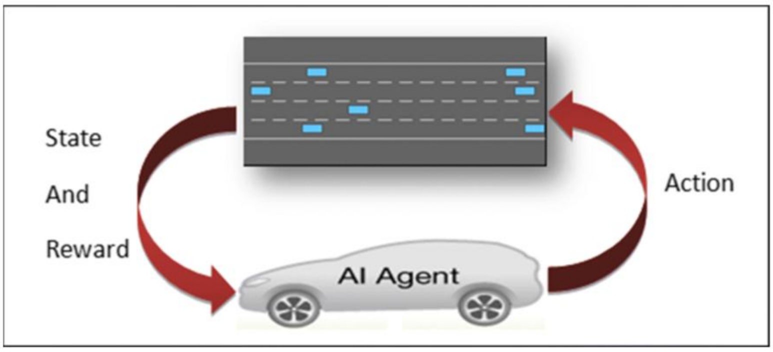


Figure 6: DRL model for self-driving cars[28]

Following time step t, the expected discounted return Rt is defined as follows:

$$R_t = \sum_t^{\infty} \gamma^t . r_t \qquad (7)$$

Where γ is a discount factor that falls between 0 and 1. The range of the discount factor γ is 0 to 1. The value of T may be unlimited (∞) or finite, contingent on the particular issue. A policy π (a|s) is the attribution of action probabilities to states. The expected return from state (s) under policy π is represented by the value function vπ (s), which is expressed as follows:

$$(st)=[_{Rt}|S_{t,\pi}] \quad (8)$$

The following is the exploit–value Q (s, a) function:

$$(s_t,a_t)=[R_t|S_t,a_{t,\pi}] \quad (9)$$

This includes the Bellman equation in an iterative fashion:

$$(s_t,a_t)=[r_t+\gamma\ maxQ^{\pi}(s_{t+1},a_{t+1})] \quad (10)$$

However, not all reinforcement learning issues may be represented as Markov decision processes (MDPs). It is possible that the states may not be completely or else immediately discernible from the environment. In these circumstances, difficulties may stay expressed using Partially Observable Markov decision processes (POMDPs). Treating these challenges as MDPs is one way to deal with them, which entails using prior knowledge and combining it with current observations[25]. For example, four successive images in Atari Games can be used to make observations[29] . Reinforcement learning's primary goal is to identify a strategy that optimizes predicted returns. Its two main components are learning a policy through a policy network and learning a Q function through a critic network. The Q learning part of the method seeks to minimize Equation (5) in order to roughly represent the ideal Q function Q∗(s, a), as shown by Equation (4). With tuples (s, a, r, s', a') made up of parameters φ and aggregated experiences d and a critic network Q(s, a), the Mean Squared Bellman Error (MSBE) can be stated as follows:

$$(\emptyset,\theta)=[(Q_{\emptyset}(s,a)-(r+\gamma\ (1-d)maxQ_{\emptyset}(\acute{s},\acute{a})))]^{2} \quad (11)$$

To choose actions that maximize Q*(s, a), Learning the deterministic policy uϕ (s) is the goal of the policy network. Gradient ascent can be used to accomplish this. Nonetheless, the DDPG method makes use of target networks and a replay buffer to preserve stability throughout the learning process. These target networks are made up of a policy target network and a target critic network. The constraints ϕ lag behind the originals, even if the architecture of both networks is identical[30].

## 5. Results and Discussion

This section compares and assesses the suggested highway decision-making policy strategy with another approach in order to determine its efficacy; once the simulation results show that the optimal option policy, we look at collected rewards to show how the suggested algorithms can learn. High-level decision-making using AI-based techniques is comparatively successful. However, some upcoming research and development challenges that are currently anecdotal remain significant opportunities for the future and merit cautious consideration. We suggest that the following topics be discussed openly: Adaptability, or the capacity to make pertinent decisions and actions in unsuitable settings; (ii) ethics (human and legal aspects of the decision); (iv) context, or the relaxation of rules; (v) the multimodal transport service; and (iii) adequate perception and control stages (data quality, reliability, and robustness) are all necessary for making relevant decisions.

The two layers' algorithms are first taught offline before being implemented in real-time settings. Based on the computation performance studies, our suggested method has the potential to implement motion planning and real-time decision-making. The training data samples are gathered utilizing high-fidelity consistency and dynamics in both levels are guaranteed to bridge the gap between the simulated and actual surroundings. In conclusion, our algorithm can handle motion planning and decision-making issues in real-world settings.

The control function of the SVM-DRL algorithms suggested for an agent's decision-making process is evaluated in a highway traffic setting. The simulation findings demonstrate that the decision policy is ideal after we first compare and validate its efficacy with another evaluation approach. Second, we analyze the accumulated rewards to show that the suggested algorithm can learn.

We used the kernel function in the SVM models with the 25% test samples. Prediction accuracy is calculated as the ratio of the samples' accurate classification number. To establish a baseline for performance assessment, the DRL algorithm was evaluated in the same setting as the suggested RL techniques. Because of their dependability and computational efficiency, rule-based techniques like DRL are frequently used even if they are not flexible enough to handle dynamic and complex driving conditions. DRL is therefore a reliable point of reference. As seen in Table 1, the DRL findings are first contrasted with those of the base SVM approach.

Table 1: A comparison between DRL and SVM

| Methods | Accuracy | | | |
|---|---|---|---|---|
| | Training set | Testing set | True positive | False negative |
| SVM | 90.64% | 88.75% | 88.75% | 88.75% |
| DRL | 97.16% | 96.03% | 96.03% | 96.03% |

The findings show that DRL performs noticeably better than SVM in terms of preventing collisions, lowering the average number of collisions. Additional tests were carried out to assess the performance of DRL variations after the initial comparison between SVM and DRL.

Since the approaches were convergent between 12,000 and 14,000 episodes, 20,000 episodes were initially selected. However, following hyperparameter adjustments, the methods converged around 7,000 episodes. Each approach has a different training time. Base DRL training took 10 hours, Noisy DRL and Double DRL took 11 hours, Duelling DRL took 16 hours, and Average DRL took 19 hours.

Although Average DRL has a greater loss value than the alternative techniques, it has the smoothest curve in the loss graph of methods shown in Fig. 7, and it is the most stable. In contrast, Noisy DRL has more fluctuations than other approaches and the lowest loss value.

This notable enhancement indicates the efficacy of our methodology and implies that it presents a more promising option for practical uses like driving on highways.

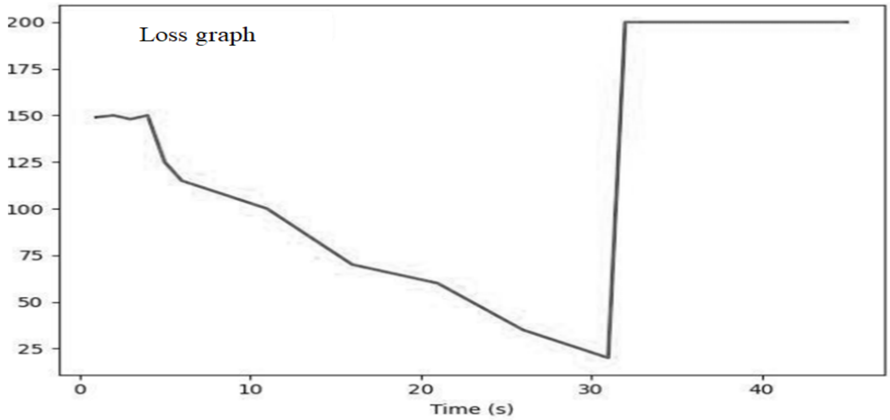


Figure 7: The training loss graph.

Fig. 8 displays a comparison of the DRL and SVM algorithms' respective performances. Note that we set the mempool size or the maximum number of transactions in the mempool, to 10 in order to decrease the state space and allow the DRL algorithm to function in our compute environment. The DRL method is shown to converge to the reward.

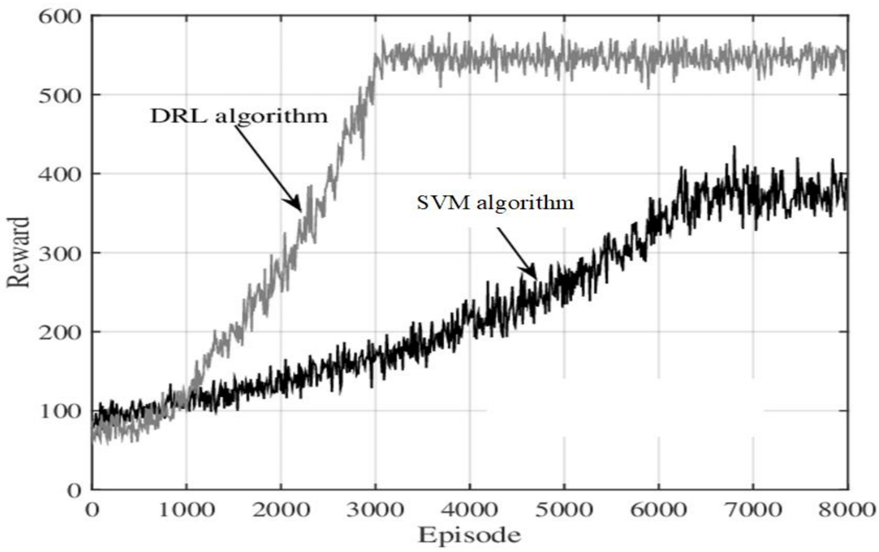


Figure 8: Comparison of DRL and SVM performance

## 6. Conclusion

Artificial intelligence techniques are marketed as very effective and promising options in the realm of autonomous car development. Autonomous cars have established themselves as key players in the broad implementation of smart city infrastructures. The degree of human confidence and dependability that people place in a car is largely determined by its capacity to communicate decision-making procedures and assist passengers in understanding why the car behaved in a particular way. The two most important elements in lowering passengers' stress and anxiety levels are visual explanations and the guarantee of security. This initiative attempts to bring together the domains of explainable AI and autonomous car systems' decision-making processes to offer lucid insights into the part explain ability plays in boosting human confidence in AI solutions. In this study, the AL approaches are used to discuss the roadway decision-making problem. The SVM and DRL algorithms are applied in the intended driving scenarios to provide a safe and effective control framework. The optimality, convergence rate, and adaptability are shown based on a number of simulation tests. Furthermore, the testing findings are examined, and the provided method's potential for use in practical settings is demonstrated. In the future, Hardware-In-Loop (HIL) studies will be used to apply roadway decision-making online. It is also possible to predict the associated overtaking strategy using the real-world highway database that has been obtained.

## Reference

1. A. Hossin, S. Yin, R. Dan, and L. Chen, “Integrating artificial intelligence in unmanned vehicles: navigating uncertainties, risks, and the path forward for the fourth industrial revolution,” Humanit. Soc. Sci. Commun., pp. 1–15, 2025, doi: 10.1057/s41599-025-04554-z.
2. Y. Liao, J. Zhang, S. Wang, S. Li, and J. Han, “Study on Crash Injury Severity Prediction of Autonomous Vehicles for Different Emergency Decisions Based on Support Vector Machine Model,” MDPI, 2018, doi: 10.3390/electronics7120381.
3. R. Zhao, Z. Chen, Y. Fan, and Y. Li, “Towards Robust Decision-Making for Autonomous Highway Driving Based on Safe Reinforcement Learning,” MDPI, pp. 1–26, 2024.
4. H. Abdulbaqi, A. M. S. Taha, A. R. Mohammed, H. Z. Q. Kanaan, and Kadhim, “Detection and localization of wrist fractures in x-ray imagery using deep learning teaching Keyword s,” Rev. Comput. Eng. Res., vol. 11, no. 3, pp. 85–98, 2024, doi: 10.18488/76.v11i3.3850.
5. A. Rizehvandi, S. Azadi, and A. Eichberger, “Decision-Making Policy for Autonomous Vehicles on Highways Using Deep Reinforcement Learning ( DRL ) Method,” MDPI, pp. 564–577, 2024.
6. G. Bathla et al., “Autonomous Vehicles and Intelligent Automation : Applications , Challenges , and Opportunities,” Hindawi Mob. Inf. Syst., vol. 2022, 2022.
7. S. T. Ahmed and S. M. Kadhem, “Applying the MCMSI for Online Educational Systems Using the Two-Factor Authentication,” Int. J. Interact. Mob. Technol., vol. 15, no. 13, pp. 162–171, 2021, doi: 10.3991/ijim.v15i13.23227.

8. A. I. Altameemi, S. J. Mohammed, Z. Q. Mohammed, and Q. K. Kadhim, "Enhanced SVM and RNN Classifier for Cyberattacks Detection in Underwater Wireless Sensor Networks," Int. J. Saf. Secur. Eng., vol. 14, no. 5, pp. 1409–1417, 2024.
9. K. Lv, X. Pei, and C. Chen, "A Safe and Efficient Lane Change Decision-Making Strategy of Autonomous Driving Based on Deep Reinforcement Learning," MDPI, 2022.
10. [D. Garikapati, "Autonomous Vehicles : Evolution of Artificial Intelligence and the Current Industry Landscape," MDPI, 2024.
11. C. Medrano-berumen and M. İ. Akbaş, "Validation of decision-making in artificial intelligence- based autonomous vehicles," J. Inf. Telecommun. ISSN, 2021, doi: 10.1080/24751839.2020.1824154.
12. A. Bennajeh, S. Bechikh, L. Ben Said, and S. Aknine, "Bi-level Decision-making Modeling for an Autonomous Driver Agent : Application in the Car-following Driving Behavior Bi-level Decision-making Modeling for an Autonomous Driver Agent : Application in the Car-following Driving," Appl. Artif. Intell., vol. 33, no. 13, pp. 1157–1178, 2019, doi: 10.1080/08839514.2019.1673018.
13. R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee, "Applications of Artificial Intelligence in Transport : An Overview," MDPI, 2019, doi: 10.3390/su11010189.
14. Y. Lu, X. I. N. Xu, S. Member, and X. Zhang, "Hierarchical Reinforcement Learning for Autonomous Decision Making and Motion Planning of Intelligent Vehicles," IEEE Access, vol. 8, 2020, doi: 10.1109/ACCESS.2020.3034225.
15. S. Atakishiyev and G. S. Member, "Explainable Artificial Intelligence for Autonomous Driving : A Comprehensive Overview and Field Guide for Future Research Directions," IEEE Access, vol. 12, no. July, pp. 101603–101625, 2024, doi: 10.1109/ACCESS.2024.3431437.
16. S. N. Hamedon, J. Johari, and F. A. Ruslan, "A Review on Artificial Intelligence for Autonomous Vehicle Behavior Prediction in Mixed Traffic Environment," J. Electr. Electron. Syst. Res., 2023, [Online]. Available: https://doi.org/10.24191/jeesr.v25i1.002.
17. S. B. Pereira, "Human factors , artificial intelligence and autonomous cars : Perspectives for a complex implementation," Sandor B. Pereira y Róber D. Botelho Hum. factors, Artif. Intell. Auton. cars, no. 1, 2021.
18. M. A. Khan, "Intelligent Environment Enabling Autonomous Driving," IEEE Access, vol. 9, pp. 32997–33017, 2021, doi: 10.1109/ACCESS.2021.3059652.
19. V. P. M, P. Mathiyalagan, M. S. Arunkumar, M. Kumar, and M. Devi, "Artificial Intelligence Applications in Autonomous Vehicles Navigating the Future of Transportation Systems," ITM Web Conf., vol. 01002, 2025.
20. S. T. Ahmed and S. M. Kadhem, "Early Alzheimer ' s Disease Detection Using Different Techniques Based on Microarray Data : A Review," iJOE – Vol. 18, No. 04, 2022, no. Mci.
21. O. Rawlley and S. Gupta, "Artificial intelligence-empowered vision-based self driver assistance system for internet of autonomous vehicles," WILEY, no. October, 2023, doi:

10.1002/ett.4683.

22. S. Taha Ahmed and S. Malallah Kadhem, “Using Machine Learning via Deep Learning Algorithms to Diagnose the Lung Disease Based on Chest Imaging: A Survey,” Int. J. Interact. Mob. Technol., vol. 15, no. 16, p. 95, 2021, doi: 10.3991/ijim.v15i16.24191.
23. C. Lu, “Intelligent Intersection Management Systems Considering Autonomous Vehicles : A Systematic Literature Review,” IEEE Access, vol. 7, pp. 91946–91965, 2020, doi: 10.1109/ACCESS.2019.2927412.
24. S. T. Ahmed and S. M. Kadhem, “Optimizing Alzheimer ’ s disease prediction using the nomadic people algorithm,” Int. J. Electr. Comput. Eng., vol. 13, no. 2, pp. 2052–2067, 2023, doi: 10.11591/ijece.v13i2.pp2052-2067.
25. O. F. Alwan, Q. K. Kadhim, R. B. Issa, and S. T. Ahmed, “Artificielle Early Detection and Segmentation of Ovarian Tumor Using Convolutional Neural Network with Ultrasound Imaging,” Rev. d ’ Intell., vol. 37, no. 6, pp. 1503–1509, 2023.
26. B. J. Khadhim, Q. K. Kadhim, W. K. Shams, S. T. Ahmed, and W. A. Wahab Alsiadi, “Diagnose COVID-19 by using hybrid CNN-RNN for chest X-ray,” Indones. J. Electr. Eng. Comput. Sci., vol. 29, no. 2, pp. 852–860, 2023, doi: 10.11591/ijeecs.v29.i2.pp852-860.
27. Q. K. Kadhim, R. Yusof, H. S. Mahdi, and S. R. Selamat, “The Effectiveness of Random Early Detection in Data Center Transmission Control Protocol - based Cloud Computing Networks,” Int. J. Commun. Antenna Propag., vol. 7, no. October, pp. 1–7, 2017, doi: 10.15866/irecap.v7i5.10104.
28. Q. K. Kadhim, R. Yusof, H. S. Mahdi, S. S. Ali Al-Shami, and S. R. Selamat, “A Review Study on Cloud Computing Issues,” in Journal of Physics: Conference Series, 2018, vol. 1018, no. 1, doi: 10.1088/1742-6596/1018/1/012006.
29. B. J. Khadhim, Q. K. Kadhim, W. M. Khudhair, and M. H. Ghaidan, “Virtualization in Mobile Cloud Computing for Augmented Reality Challenges,” Proc. 2021 2nd Inf. Technol. to Enhanc. E-Learning other Appl. Conf. IT-ELA 2021, no. June 2022, pp. 113–118, 2021, doi: 10.1109/IT-ELA52201.2021.9773680.
30. H. A. A. Mohammed, I. Nazeeh, W. C. Alisawi, and Q. K. Kadhim, “Anomaly Detection in Human Disease : A Hybrid Approach Using GWO-SVM for Gene Selection,” Rev. d ’ Intell. Artif., vol. 37, no. 4, pp. 913–919, 2023.