An advanced deep learning model for maneuver prediction in real-time systems using alarming-based hunting optimization

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ABSTRACT

The increasing trend of autonomous driving vehicles in smart cities emphasizes the need for safe travel. However, the presence of obstacles, potholes, and complex road environments, such as poor illumination and occlusion, can cause blurred road images that may impact the accuracy of maneuver prediction in visual perception systems. To address these challenges, a novel ensemble model, named ABHO-based deep CNN-BiLSTM has been proposed for traffic sign detection. This model combines a hybrid convolutional neural network (CNN) and bidirectional long short-term memory (BiLSTM) with the alarming-based hunting optimization (ABHO) algorithm to improve maneuver prediction accuracy. Additionally, a modified hough-enabled lane generative adversarial network (ABHO based HoughGAN) has been proposed, which is designed to be robust to blurred images. The ABHO algorithm, inspired by the defending and social characteristics of starling birds and Canis latrans, allows the model to efficiently search for the optimal solution from the available solutions in the search space. The proposed ensemble model has shown significantly improved accuracy, sensitivity, and specificity in maneuver prediction compared to previously utilized methods, with minimal error during lane detection. Overall, the proposed ensemble model addresses the challenges faced by autonomous driving vehicles in complex and obstructed road environments, offering a promising solution for enhancing safety and reliability in smart cities.

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1. Introduction

In recent years, autonomous driving has emerged as one of the most desirable research areas in the artificial intelligence (AI) community. Vehicles can now operate automatically to carry out routine driving activities effectively and safely [1]. The four functional modules that make up autonomous vehicles' core components are environment sensing, decision-making, motion planning, and motion control [2]. The decision-making and motion planning modules, which link environment sensing with motion control, constitute the autonomous vehicle's "brain" and are considered to be of the utmost importance [3], [4]. The lane-changing choice is an important component of the research in this area, and the driving decision-making system is the key technology for maintaining the driving safety of AVs [5]–[7]. Making decisions in unpredictable and dynamic traffic settings is one of the difficulties in achieving full automation of driving [8]. Making decisions involves coming up with a series of motion behaviors to carry out certain tasks, like merging into a crowded lane, navigating an unguarded crossroads, and overtaking with ease on a highway [1], [9]. The robot motion planning algorithm frequently serves as an inspiration for conventional motion planning techniques, such as artificial potential fields (APF).

A heuristic-based hybrid APF-based motion planning technique was presented in [10]. Combining the proposed methods with optimization algorithms significantly enhanced their performance [11]. An autonomous vehicle's decision-making layer must take into account interactive and synergetic input from other cars to produce human-like driving behaviors. The intentions and responses of nearby cars may be modeled and predicted using probabilistic approaches and partially observable Markov decision processes (POMDP) [1]. Despite significant advancements, there are few reports of autonomous vehicles (AVs) making decisions that take into account other vehicles' social interactions. Capturing the features during vehicle interactions is crucial for improving the decision-making of AVs [4].The emergence of connected and autonomous vehicles (CAVs) that can sense their environment, make decisions, exercise autonomous control, and exchange data with other vehicles and infrastructure is the result of the quick development of communication technology and autonomous driving technology [12]–[14]. The authors in [15] construct a decision-making system by merging Markov Decision Process (MDP) and RL since RL can offer numerous advantages in tackling complex uncertain sequential decision issues. Deep neural networks (DNN) are used to create a human-like decision-making system that can adjust to actual driving circumstances [4], [16].

Traditional control methods, such as constant spacing (CS) policy, constant time headway (CTH) policy, and sliding mode control (SMC) [17]–[19], have a poor ability to adapt to the environment and are unable to make precise and efficient decisions based on a variety of complex driving situations, particularly in situations where CAVs and conventional driver-controlled vehicles coexist [14]. The search engine, probabilistic sampling, prospective field, approximation curve, and mathematical optimization approaches are the five primary groups among the many algorithms that have been researched for path planning [3]. The most popular and useful path planning algorithm is the one called graph search. In terms of avoiding collisions, the graph search method performs well. The thickness of the grid, however, frequently affects its ideal course. A typical sampling approach that effectively searches the best path while taking non-holonomic restrictions into account is known as rapidly exploring random trees (RRT) [20]. However, RRT needs to continue to strengthen its security and the fineness of its intended course [4]. One drawback of these techniques is that some gesture parameters, which are frequently employed in path planning, are non-linear and non-convex, which might lead to the NP-hard (non-deterministic polynomial-time hard) issue [11], [21].

In this research, traffic sign detection and maneuver prediction-based vehicle control are used to control autonomous driving cars. Social behaviors, such as driving patterns and targets of the vehicles in the immediate surrounding area, are taken into account. The hybridized algorithm is utilized for both traffic sign detection and maneuver prediction, which is motivated by advanced algorithms for AV control and decision-making. The modified Hough-enabled Lane GAN model is used to accurately segment the surrounding driving area in the input image for maneuver prediction, while the ensembled CNN-BiLSTM classifier is then applied to predict the traffic sign and make accurate decisions for autonomous driving. In addition, Alarming-based hunting optimization, the alarming-based hunting optimization (ABHO) algorithm is well implemented in the modified Hough-enabled Lane GAN and the ensembled CNN-BiLSTM classifier for lane detection and traffic sign prediction. The shared weights in the lane detection technique and the tunable parameters in the traffic sign prediction technique are controlled by the ABHO algorithm.

The research utilizes several techniques for autonomous driving, including a modified Hough-enabled Lane GAN model for maneuver prediction, an ensemble CNN-BiLSTM classifier for traffic sign detection, and the ABHO algorithm for controlling shared weights in the lane detection technique and tunable parameters in the traffic sign prediction technique. The paper is organized into sections on existing works, safe driving in an intelligent environment method, results, and a conclusion.

2. Related works and Challenges

The implementation of autonomous vehicles (AVs) is expected to have a considerable positive impact on traffic safety by reducing the number of accidents by up to 94%. However, AV accidents can still occur due to various unforeseen environmental obstacles, such as human-driven vehicles, bicycles, animals, and passengers. Even fully autonomous cars cannot guarantee being completely crash-free under these circumstances. As a result, ethical concerns arise when dealing with such challenges, particularly when human lives are at stake. This section provides an overview of traditional approaches to decision-making-based autonomous vehicles, including path selection and braking, as well as their benefits and challenges.

In this section, the autonomous vehicle-based decision-making process using various strategies is revealed. An effective fuzzy CoCoSo approach was created by [22] built on the logarithmic method and Power Heronian function to address the problem of additional benefit selection in vehicular management techniques. Three primary stages make up the suggested MCDM paradigm. The MCDM's inputs, such as criteria, options, and experts, are chosen in the first step. The logarithmic technique is used to determine the optimal parameters in the second step. The final stage ranks the options according to the Power Heronian function. The suggested fuzzy LM PH'CoCoSo methodology's efficacy is undeniable. However, the technical intricacy of the fuzzy WPHA and fuzzy WGPHA functions for evaluating the computational technique can be a constraint. The decision-making and mobility control for traffic movements of an autonomous vehicle (AV) taking into account the human behaviors of other traffic users were addressed in this [4] unique integrated approach. When making decisions and predicting the condition of a course of an autonomous vehicle, the Stackelberg Game theory and Model Predictive Control (MPC) are both employed. The ability of the agile solution to handle various social contacts with other vehicle drivers demonstrates its viability and efficacy. Only the velocity and acceleration behaviors are taken into account for obstacle vehicles because the lane-change behaviors of these vehicles are not part of the high-speed driving situation. An automated, safe, and effective decision-making paradigm for AVs was put forth by [23] for driving at junctions. To find the best navigation rule in terms of security and protection, the deep Q-network method was used. The suggested approach might aid in developing the decision-making component of AVs to improve travel convenience and traffic flow. This study's shortcomings include the fact that the bigger standard deviations meant that driving comfort was reduced. In an environment of rapid change, [14] presented an autonomous braking decision-making technique that chooses the best course of action using deep reinforcement learning (DRL). To increase safe driving, the automobile can proactively adopt the best braking behavior in an urgent situation once the strategy has been trained correctly. To execute high-level control techniques to coordinate CAVs in typical circumstances, multi-agent reinforcement learning is necessary.

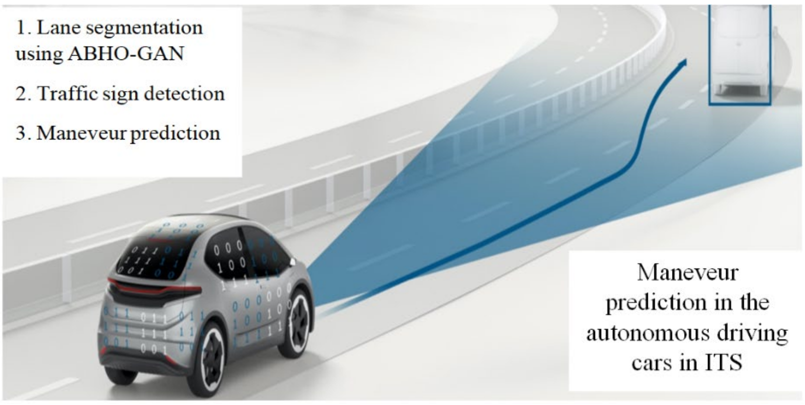
A unique LC decision (LCD) model is presented by [7] that enables autonomous cars to acquire judgments that are similar to those made by humans. This approach integrates the XGBoost algorithm with a deep autoencoder (DAE) network. The presented method is currently only relevant to the traditional LC decision-making mechanism in straight lanes or curved lanes on motorways due to the complication and instability of regular traffic. A predictive control paradigm for moral judgments in driverless vehicles is presented forth by [24] using the principles of rational ethics. The author proposes the use of powerful AI tools and reasonable procedures to develop ethical guidelines for autonomous vehicles. One such approach is the Lexicographic Optimization-based Model Predictive Controller (LO-MPC), which prioritizes barriers and restrictions to ensure the flexible application of ethical principles. To address lane change decision-making [11], the author proposes a risk-aware driving decision strategy using deep reinforcement learning's Risk Awareness Prioritized Replay Deep Q-Network (RA-PRDQN). This approach aims to identify a sequence of actions that minimize risk and prevent accidents with the host car in congested environments with both static and dynamic obstacles. The sample selection probability function can be improved by considering vehicle location sets and incorporating stopping behavior for speed regulation using deep reinforcement learning. Another decision-making [1] system prioritizes the safe and effective operation of autonomous vehicles. The author presents a simulation of passing driving situations and defines standard methods such as the intelligent driver model and minimization of overall braking caused by merging traffic. For highway overtaking, the author proposes using the Dyna-H algorithm, which combines a modified Q-learning algorithm with a heuristic planning approach. Overall, these approaches aim to develop safe and ethical decision-making systems for autonomous vehicles. To develop online decision-making techniques for autonomous vehicles, deep learning and enhanced RL algorithms must also be combined. The proposed model achieved high accuracy in detecting traffic signs and predicting lanes compared to the existing techniques [25]. The research aims to enhance the decision-making capabilities of autonomous vehicles to ensure safety, energy efficiency, and mobility. The author [23] efficiently ranked the agents relying upon their importance in making decisions, using the CNN network that effectively learned the features and obtained the domain knowledge. The decision–making system acts as the central nerve of driverless vehicles and is important for the safe and effective operation of vehicles [26]. While considering the surrounding environment, the other car motion and the evaluation of self-esteemed vehicles, decision-making is indicated to develop reasonable and safe driving characteristics at the human level [27].

The challenges considered during the development of effective decision-making of autonomous vehicles are as follows:

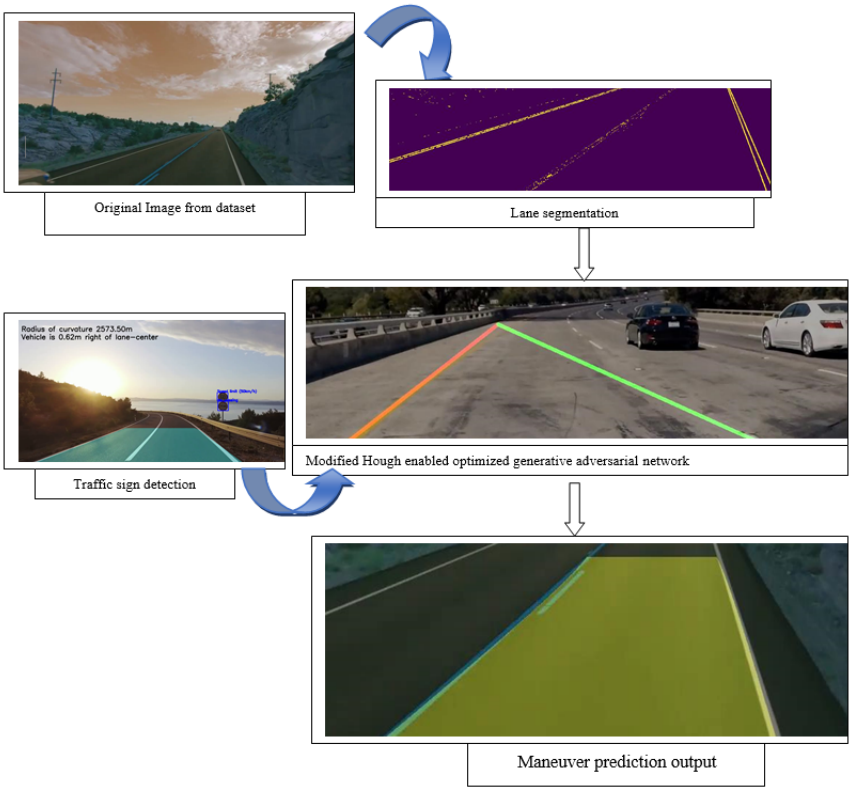
- In the decision-making process for motion planning, Stackelberg game theoretic optimization and Model Predictive Control (MPC)-based optimization are used to determine the optimal course of action, which is then executed within predefined limits. However, if these limits are too narrow, the motion planner may struggle to find viable alternatives. On the other hand, setting the boundaries too broadly can significantly increase the computational complexity of position control [4].
- Therefore, it is crucial to strike a balance between setting limits that are too narrow or too broad. This will ensure that the motion planner can find feasible solutions within a reasonable timeframe. Achieving the optimal direction of flow within the expected timeframe is a complex task that requires careful consideration and balancing of various factors [4].
- However, using a fuzzy control system on a vehicle has the drawback of requiring a level of understanding to define fuzzy rules and similarity measures. The choice of the membership function is where a fuzzy logic-based control technique becomes challenging. Bandwidth is significantly impacted by the settings for the membership function and fuzzy word set [14].
- The fact that various motion requirements employed in motion planning are frequently non-linear and non-convex poses a drawback of the risk awareness prioritized replay deep Q-network technique [11]. This may result in the NP-hard (non-deterministic polynomial-time hard) problem.
- One major drawback of probabilistic-based techniques is that they solely use specialized information to provide rule-based action, failing to make the right decisions in disruptive environments and ignoring the learning aspects of the human drivers in navigation [11].
- The diminishing gradient experienced during training presents the biggest difficulty in using simple RNNs. The number of instances the gradient signal is ultimately multiplied can be as great as the time steps taken. When dealing with sequence data, a standard Recurrent Neural Network (RNN) may not be suitable for capturing long-term dependencies. This is because, in a deep or extended sequence analysis, the gradient of the network's output may struggle to impact the weights of the preceding layers. As a result, it becomes challenging for the network to record long-term dependencies in the sequence data. The network's weights won't be properly updated under gradient vanishing, leading to very low weight values [28].

3. Method

In this section decision-making system for the autonomous driving cars using deep models are discussed. The autonomous vehicles require a strong decision controller to support the safe-driving experience in the smart cities for which the road video dataset is acquired. To the video frames, traffic sign detection and maneveur prediction is done using modified CNN-BiLSTM classifier and ABHO-Hough GAN model. The algorithm, ABHO is designed for training the classifier parameters to support the prediction with accuracy. The ABHO algorithm is developed by integrating the hunting characteristics of Canis latrans with the leadership hierarchy and alarming nature of starling birds. On the other hand, the pre-processed video data is fed forward to the ABHO-Hough GAN model, which is tuned by ABHO that has shown good image enhancement and image restoration capabilities. ABHO-Hough GAN model has the tendency to update the performance based on the optimization algorithm and effective maneuver detection. Fig.1 (a) and Fig.1 (b) shows the illustration of the intelligent transportation using maneveur prediction.



(a) Real-time Driving scenario in autonomous driving system



(b) Illustration of decision-making in autonomous vehicle

Fig. 1. The illustration of the intelligent transportation using maneveur prediction

3.1. Road vehicle video database

The road vehicle video database [4] is utilized in this research for traffic sign detection and maneveur prediction as the initial step, which is expressed as

$$D = \sum_{i=0}^{d} D_d \tag{1}$$

where, the utilized road vehicle database is denoted as D, and the total available videos in the database is denoted as D_d, which is in the range of 0 to d. Each video from the database is supposed to hold Ff number of video frames and for ensuring the accurate support system, the frame-wise processing is enabled.

3.2. Traffic sign detection using Optimized CNN-BiLSTM classifier

The video frames are acquired from the road video, for which the traffic sign detection is done through the designed ABHO-Ensembled model. Fig. 2 shows ABHO-Ensembled model with three layers of CNN, a layer of convolution, leaky RelU, and MaxPooling, which makes-up the ensemble model's initial channel. The deep CNN holds the filter size as 264 with the kernel size of of dimension. Initially, the frame is processed using the CNN structure of the first channel to extract spatial characteristics, but the depth of time features extracted from the raw high-dimensional data is insufficient. To finish the extraction of the data time-series features and extract the long-term dependencies between the data features, the BiLSTM structure of dimension is employed. While the model is being trained, the BiLSTM structure can prevent gradient disappearance and gradient explosion. After reshaping the output from CNN, the BiLSTM utilizes the dropout size, which is then fed to the dense layer for an efficient detection of the traffic sign in each frame.

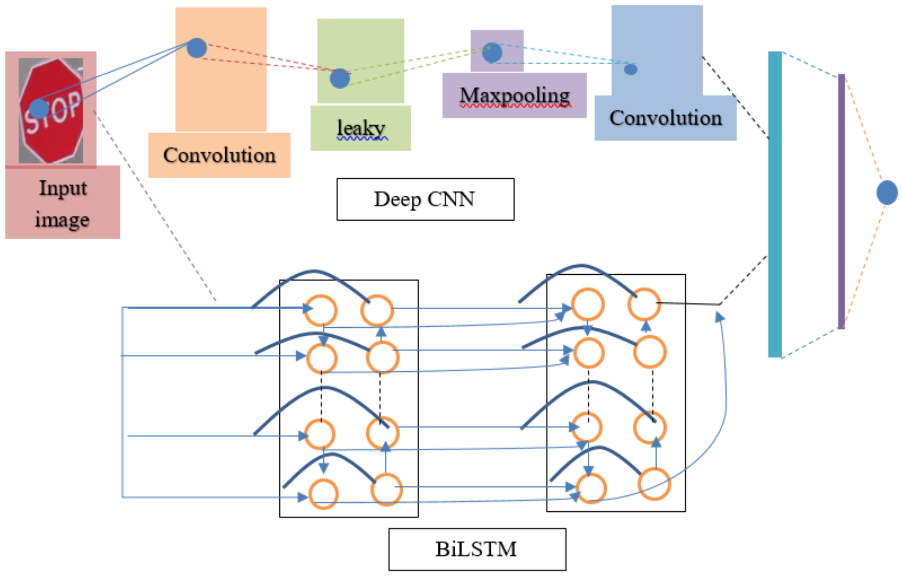


Fig. 2. ABHO-Ensembled model for traffic sign detection

3.2.1. Algorithm for tuning the Ensemble model

The traffic sign detection is the basic need for ensuring the safe driving using the autonomous cars and the accurate detection depends on the ensembled fusion parameters, which is decided optimally using ABHO. ABHO is proposed by employing the exceptional behavior of the Canis latrans [29] and the starling bird [30] for the observation of traffic signs in the road video. The ability of the Canis latrans relies in the effective balance between the exploitation and exploration stages. The social grading system of the guiding beta and a lack of emphasis on following dominant norms are what distinguish the Coyote's algorithmic behavior. The ABHO approach places more emphasis on social interactions and opinion-sharing during the hunting process. Certain common issues, such as the excessive processing time and inadequate searching potential in the Canis latrans performance, are resolved through the characteristics, such as scary as well as the defending characters of the starling bird. The combined behavior enhances the resilience and power of the suggested ABH optimization, leading to a good performance. The starling bird is highly intelligent and has a good memory when compared to many other small birds. The technique is to be used to solve global optimization issues due to its simplicity, scalability, and high performance. The performance of the starling bird is evaluated to the optimization problems that belong to popular engineering applications.

1) Inspiration

The Coyote algorithm, which is based on the Canis lupus genus, inspired by the Canis latrans species, and serves as both an ecological and swarm intelligence criterion, is the basis for the population-based approach that is suggested. Even though the Canis latrans is used as the pack leader, the social hierarchy and dominant standards of these species are disregarded by its unique mathematical structure configuration. Furthermore, unlike grey wolf hunting, Canis latrans hunting emphasizes the social structure and experiences that share as a whole rather than only hunting prey. By considering the social organization of the Canis latrans and their environmental adaption, the suggested method offers a unique mathematical model in comparison to metaheuristics. It also provides novel techniques to balance the exploration and exploitation phases of the optimization process. The Canis latrans's behavior has been linked to both internal (such as gender, social standing, and pack membership) and extrinsic (like snowfall height, snowpack severity, climate, and corpse weight) factors. As a result, the alarming-based hunting mechanism was proposed based on the social settings of the Canis latrans and starling birds.

2) Mathematical modeling of alarming-based hunting optimization

The three top most significant phases in the ABHO algorithm is the initialization, fitness evaluation of the population, and establishing ranking depending on the measured fitness.

- Initialization: According to the social environment, the Canis latrans's worldwide population in addition to the starling bird population is randomly generated, which is expressed as,

$$P = \{P_1, P_2, P_3, \dots P_i, \dots P_x \tag{2}$$

where, x be the total population in an attained cluster, the solutions are denoted as P and equation (3) provides the following random values that are generated individually for the a^{th} Canis latrans in the u^{th} pack at the dimension of k .

$$G_{a,k}^{u,r} = c_k + e_k(y_k - C_k) \tag{3}$$

where the k^{th} resolution parameter is utilized to represent the upper and lower bounds as c_k *and* y_k in the social context G ,respectively.

- Population ranking: The fitness values are measured for the attained solutions individually for the effective ranking, which assists to proceed with the following hunting process.
- Establish ranking groups: As the consequence of establishing the feasible random solutions, the Canis latrans's deviation resultant to the social conditions is determined by the following equation,

$$fitnes = F(P) \tag{4}$$

The Canis latrans are dispersed randomly across the population, therefore they may decide to separate from the group and become alone instead of joining them. The maximum capacity of Canis latrans that may be separated from the group over the total population.

- Choose producer position: Unlike followers, producers can look for food in a wider variety of locations, and the producers are expected to have substantial energy stores and give followers access to foraging places or directions. It is in charge of locating locations with abundant food supplies. The evaluation of an individual's fitness values determines their degree of energy reserves. The starling bird starts chirping as alarm messages as soon as they spot the predator. The producers must guide all followers to the safe location if the alert value exceeds the safety level. Each iteration updates the producer's location as follows:

$$P^{t+1} = \begin{cases} P^t * exp^{\left(\frac{-i}{\beta, max^t}\right)} & if \begin{matrix} r_2 < T \\ r_2 \geq T \end{matrix} \\ P^t + U.W & \end{cases} \tag{5}$$

Depending on the social characteristics of the Canis latrans, the position of the starling bird is updated as,

$$P^{t+1} = \begin{cases} \frac{1}{2}\left[w_1 y_1 + w_2 y_2 + P^t \left(1 + exp^{\left(\frac{-i}{\beta, max^t}\right)}\right)\right] r_2 < T \\ P^t + U.W + rand \times P_{pers}^{best} \end{cases} \tag{6}$$

where the weights of Canis latrans group are denoted as w_1 and w_2, the personal best population is represented as P_{pers}^{best}. The random variable is represented as r_2 and U with the threshold of T at the iteration of t.

- Choose follower position: The regulations must be upheld by the followers, who should also act as producers by acting like the starling bird with the highest energy. Many hungry followers are more prone to fly to different locations in search of food to increase their energy. Followers look for food by following the producer who can offer the best food. While waiting for food, some followers may be constantly watching the producers and struggling for it to increase their predation rate. Some followers keep a closer eye on the producers, as was already mentioned. They quickly leave their present designation to struggle for food as soon as they learn that the producer has acquired nice food. If they succeed, they can instantly receive the producer's food; if not, the regulations are still followed. The following is a description of the follower's role updating formula.

$$P^{t+1} = \begin{cases} \text{U}. \exp(P_{worst} - P^t) + U_{max}. (P^{best} - P^t) \\ P_{pers}^{t+1} + \left|P^t - P_{pers}^{t+1}\right|. B^+ . W + V^{t+1} \end{cases} \tag{7}$$

where the matrix is represented as B and W, in which the velocity of a producer in approaching the food and staying away from enemies is denoted as V.

- Choose remaining followers: The starling bird in the center of the group randomly walks to be close to others, whereas the starling bird at the group's edge swiftly goes into the safe region to gain a better position when aware of the danger. It is possible to express the mathematical model as follows:

$$P^{t+1} = \begin{cases} P_{pers}\left|P^t - P_{pers}\right| + \beta\left|P_{glo} - P^t\right| \\ \frac{1}{2}\left[2P^t + k\left(\frac{P^t - P_{worst}}{(fitness - P_{worst}) + \varepsilon}\right)\right] + w_1 y_1 + w_2 y_2 \end{cases} if\ fitness > F_{glo} \tag{8}$$

where the worst as well as the global fitness is denoted as F_{worst} and F_{glo}. The Canis latrans share other groups' perspectives and methods for moving from one location to another, yet they lack these traits when hunting and adapting to new social conditions. Therefore, the integration of the defending characters of the starling bird prevents the Canis latrans from falling into the local optimum, and there needs to be a solution back so that the algorithm can avoid reaching the local optimum. Incorporating an integrating operation to increase the algorithm's ability to avoid the local optimum is the most popular remedy for this problem. In this work, the optimization is improved by integrating the social characteristics of Canis latrans with the starling bird. By incorporating the defending behavior while renovating the social state during opinion sharing, the ABHO optimization has greater flexibility, quick resolution, and incredibly consistent findings. Thus, to improve the effectiveness of the ABHO optimization and fine-tune the classifier's hyperparameters for improved vehicle control.

Fig. 3 shows the Proposed ABHO pseudocode, This system adjusts the positions of the starling bird and reduces energy waste in a random movement to reach ideal solutions with the fewest iterations.

Total population x
Output: Best population
Initialization
    Initialize population
        $P = \{P_1, P_2, P_3, \dots P_i, \dots P_x$
    Population ranking
        Based on fitness
    Establish ranking groups
        $While^{(t<t_{max})}$
            {
            $Call^{C_1=F(P)_{producer1(x)}}$
            $For^{\forall i, i=\{1,\dots,x\}}$, # producer 1
                {
                Update position based on equation (6)
                }
            End for
            $Call^{C_2=F(P)_{follower2(x)}}$
            $For^{\forall(x+1\geq i\leq m)}$, # Follower 2
                {
                Update position based on equation (7)
                }
            End for
            $Cal^{C_3=F(P)_{remaining\ followers\ (x)}}$
            $For^{\forall(m+1\geq i\leq m)}$, # Remaining followers
                {
                Update position based on equation (8)
                }
Rank population
    Update the ranked groups
        $Return\ P_{best}$
            $t = t + 1$
End while

Fig. 3. Proposed ABHO pseudocode

Once the traffic sign in the traversing road is detected, the lane segmentation is processed using ABHO-Hough GAN model for maneveur prediction. Thus, both the lane segmentation as well as the maneveur prediction is performed in order to control the autonomous vehicle.

3.3. Modified Hough enabled optimized generative adversarial network for lane segmentation and maneveur prediction

Once the traffic sign detection is accomplished, the lane segmentation and maneveur prediction is guided using the ABHO-Hough GAN model, which comprises of a generator as well as the discriminator. In this research, a ABHO-Hough GAN model is developed for the background subtraction of driving scenes, where the lanes are determined by a discriminator using shared weights and evaluated by a generator depending on the input road vehicle data. The ABHO-Hough GAN model is a remarkable tool for identifying shapes and curves in the road vehicle video images. To determine the particular location or gain geometrical details of the vehicle, it is used to detect loops, ellipses, and lines. The Hough transform is a great tool for recognizing lane lines for the self-driving automobiles in the target area, and the actual benefit of this model is that it predicts lanes that are precise and narrow rather than the broad, flexible boundaries that CNN's typically introduce. The hough Lane transform recognizes lanes in multiple continuous frames as opposed to only the current frame, which is dissimilar from the aforementioned deep-learning-based methods that only detect lanes and are considered a time-based issue. The proposed technique can provide robust performance in lane detection under difficult circumstances with more detailed information. Using the sign detection and lane segmentation outputs, the maneveur detection is proceded using the optimized GAN. In Fig. 4, Hough Lane enabled optimized GAN model is presented, where the lane segmentation is done using the optimized GAN model, and the hough lane transform supports the maneveur prediction, where the ABHO algorithm guides the segmentation model to acquire the accurate prediction. The detailed sketch on the ABHO algorithm is presented in section 3.2.1.

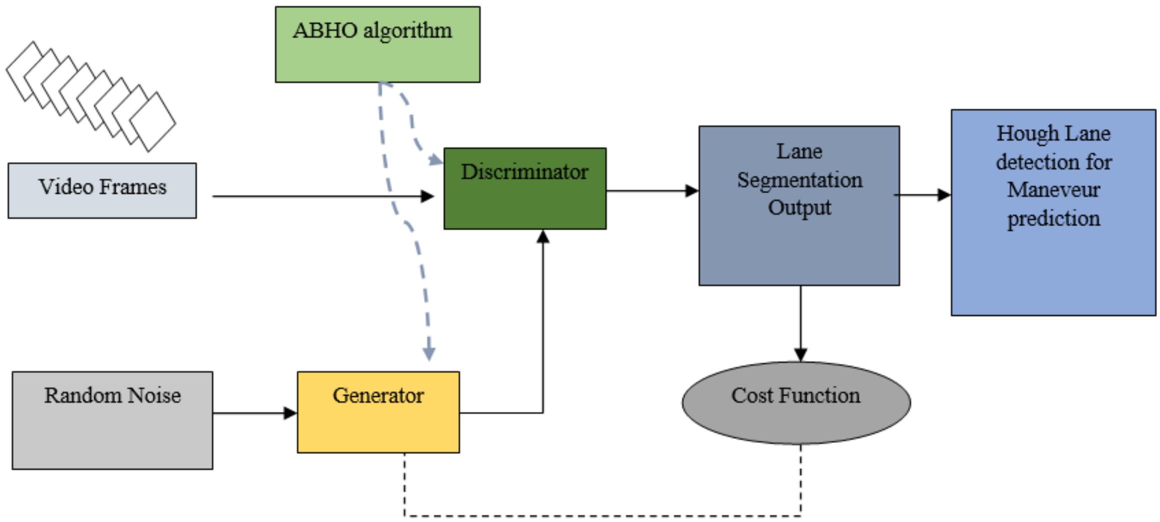


Fig. 4. ABHO-Hough GAN model for Maneuver prediction

4. Results and Discussion

In this section, the reliability of the ABHO-Hough GAN for the maneuver prediction and ABHO-tuned CNN-BiLSTM for traffic sign detection is revealed depending on the performance using the various epoch. The comparative analysis is implemented to show the better efficiency of the proposed model in the research area of an autonomous vehicle. The implementation of both lane prediction and traffic sign detection is done in python on windows 10 OS with 8 GB RAM and the road vehicle video dataset is used for estimation.

The road dataset was enumerated through the aerial images over 1171. Every aerial image is disguised over 2.25 square kilometers with 1500 dimensions from 1500 pixels. The data was divided into three sets in terms of unpremeditated. The following sets are an 1108-image training set, a 14-image validation set, and a 49-image test set. The dataset contains a large amount of urban, suburban as well as rural districts which is present in 2600 square kilometer. To obtain knowledge of real-time decision-making, the test data was helped by enclosing more than 110 square kilometers unaided. The experimental validation of the approach is visualized in Fig. 5.

The performance metrics used for the traffic sign detection along with the ABHO-tuned CNN-BiLSTM is explained as follows

- ***Accuracy:*** The percentage of samples that the ABHO-based CNN-BiLSTM properly identifies while determining the autonomous vehicle's decision-making system is known as accuracy, and it is given by,

$$acc = \frac{total\ true\ prediction}{Total\ true\ and\ false\ prediction} \tag{9}$$

- **Sensitivity:** The true positive outcome of the result from ABHO-based CNN-BiLSTM when the decision-making occurs on the autonomous vehicle, described the sensitivity in terms of probability and it is given as,

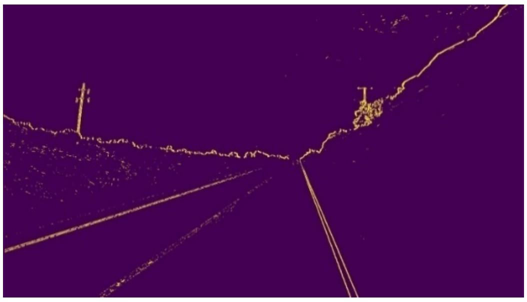
$$sen \frac{Total\ true_{pos}}{Total\ true_{pos}\ and\ False_{neg}} \tag{10}$$

- **Specificity:** The true negative of the result from ABHO-based CNN-BiLSTM when the decision-making occurs on the autonomous vehicle, described the specificity in terms of probability and it is given as,

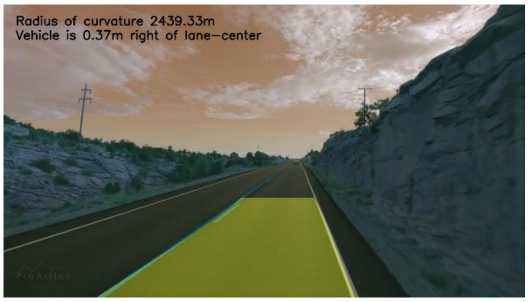
$$sen \frac{Total\ true_{neg}}{Total\ true_{neg}\ and\ False_{pos}} \tag{11}$$

(a) Original Road image acquired from the input dataset

(b) Traffic sign detection



(c) Lane detection



(d) Maneuver prediction

Fig. 5. Autonomous driving system- Experimentation.

The performance metrics used for the lane detection along with the ABHO-Hough GAN is explained as follows.

- **Mean Absolute Error:** The distinction between the magnitudes of the measurement of an individual with the quantity of true value for the ABHO-based Hough GAN, when identifying the lane prediction on an autonomous vehicle is defined as the Mean Absolute Error (MAE) and it is given as,

$$MAE = \frac{1}{v} \sum_{j=1}^{v} |q_j - q| \tag{12}$$

where, the total error is represented as v, and $|q_j - q|$ denotes an absolute error.

- **Mean Square Error:** The error quantity in the statistical model as well as the difference between the experimental and predicted rate from the ABHO-based Hough GAN in the decision-making function processed for lane prediction on the autonomous vehicle which is estimated in terms of Mean Square error (MSE) and it is given as,

$$MSE = \frac{1}{r} \sum_{j=i}^{r} (g_j - g_j)^2 \tag{12}$$

where, the available data is denoted as r, g_j describes prediction, and g_j represents the observed value.

- **Root mean squared error:** ABHO-based Hough GAN in an autonomous vehicle is used to determine land prediction in terms of using the mean square value of error in the root which was described as root mean squared error (RMSE) and it is given as,

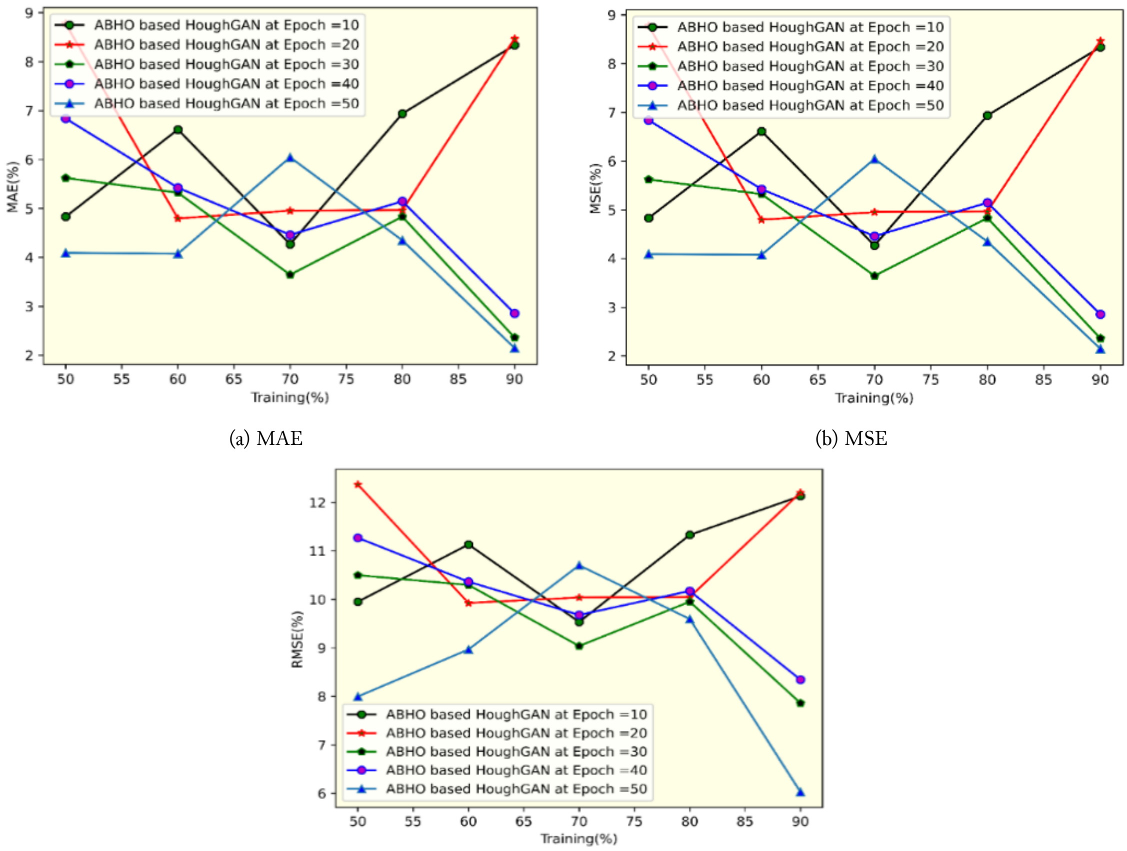
$$RMSE = \sqrt{\frac{1}{Z}\sum_{j=1}^{Z}(Q_Z - R_j)^2} \tag{13}$$

where, the observed sample is denoted as R_j, a predicted sample is represented as Q_Z with Z observations.

The performance depending on maneuver prediction and traffic sign detection using ABHO-based Hough GAN as well as the ABHO-based deep CNN-BiLSTM are described in the following section.

4.1. Manuveur prediction and traffic sign detection analysis

The error-based values such as MAE, MSE, and RMSE for ABHO-based Hough GAN for the lane prediction are represented in Fig. 6 (a) represents both the percentage of MAE as well as the training percentage based on the epoch value.



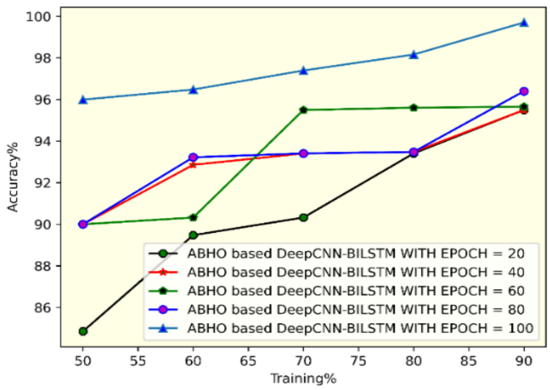
(a) MAE (b) MSE

(c) RMSE

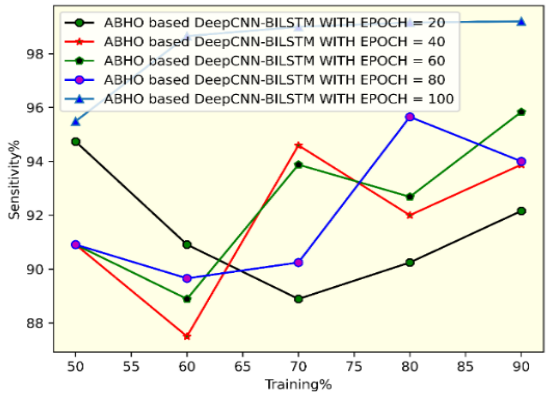
Fig. 6. Manuveur prediction analysis

When the number of training data is 90 for the epoch value 20, and then the attained value of MAE for the ABHO-based Hough GAN is 8.469. Fig. 6 (b) represents both the percentage of MSE as well as the training percentage, based on the epoch value. When the number of training data is 50 for the epoch value 20, then the attained value of MSE for the ABHO-based Hough GAN is 8.776. Fig. 6 (c) represents both the percentage of RMSE as well as the training percentage, based on the epoch value. When the number of training data is 90 for the epoch value 20, then the attained value of RMSE for the ABHO-based Hough GAN is 12.203.

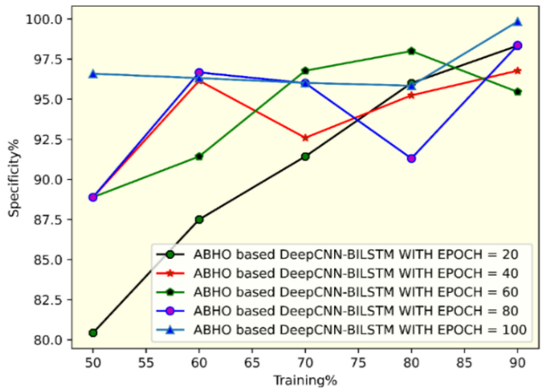
The performance measures-based values such as accuracy, sensitivity, and specificity for ABHO-based deep CNN-BiLSTM for traffic sign detection are represented below in Fig. 7 (a) represents both percentage of accuracy as well as the training percentage based on the epoch value. When the number of training data is 50for the epoch value is 20, then the attained value of accuracy for the ABHO-based deep CNN-BiLSTM is 84.848.



(a) Accuracy



(b) Sensitivity



(c) Specificity

Fig. 7. Traffic sign detection analysis

Fig. 7 (b) represents both percentages of sensitivity as well as the training percentage based on the epoch value. When the number of training data is 60for the epoch value is 40, then the attained value of sensitivity for the ABHO-based deep CNN-BiLSTM is 87.500. Fig. 7 (c) represents both percentage of specificity as well as the training percentage based on the epoch value. When the number of training data is 50 for the epoch value is 20, then the attained value of specificity for the ABHO-based deep CNN-BiLSTM is 80.429.

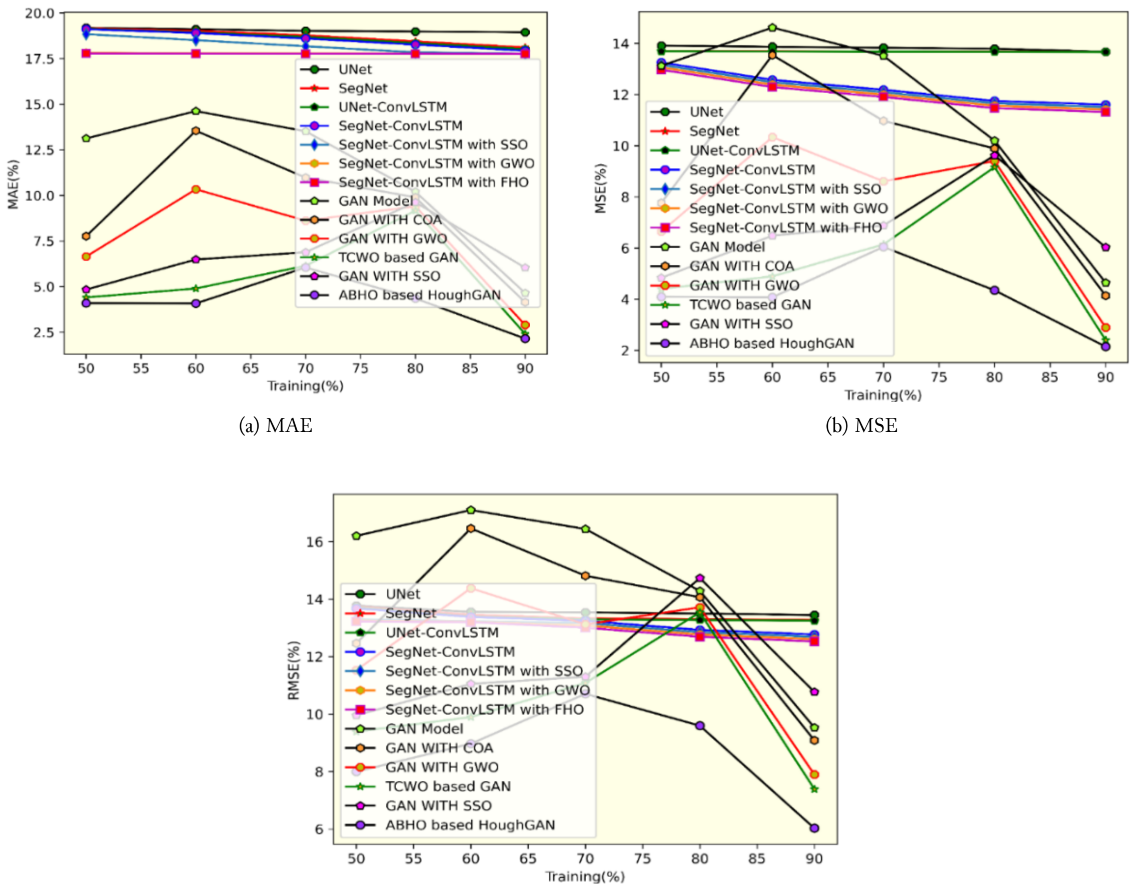
The methods considered for comparing the reliability of lane detection are [25], [31]–[33], SegNet-ConvLSTM with SSO, SegNet-ConvLSTM with GWO, SegNet-ConvLSTM with FHO, GAN Model, GAN with COA, GAN with GWO, TCWO based GAN, GAN with SSO. The methods considered for comparing the reliability of traffic sign prediction are [34]–[40], TCWO-based ensemble deep CNN-BiLSTM, and deep CNN-BiLSTM with SSA, respectively.

Accurate and reliable traffic sign recognition is crucial for self-driving vehicles to make informed decisions and avoid accidents. With better prediction accuracy, automated driving systems can respond more quickly and appropriately to traffic signs, such as speed limit signs, stop signs, and yield signs, leading to improved safety for passengers and other road users. Additionally, accurate traffic sign recognition can help optimize vehicle speed and reduce energy consumption, leading to improved efficiency and reduced emissions. Overall, the practical implications of improved traffic sign prediction accuracy are numerous and essential for the successful implementation of automated driving systems in real-world environments.

4.2. Comparison of maneuver prediction models

For evaluating the errors MAE, MSE, and RMSE, the proposed ABHO-based Hough GAN is compared with the other existing methods represented in Fig. 8 (a) represents the MAE for both the proposed as well as the existing depending on the percentage of trained data. When the number of training data is 90 %, the error rate of the proposed method is 2.149. Then the attained improved variation of MAE for the ABHO-based Hough GAN is 64.39 % when compared with the existing GAN with SSO model.

Fig. 8 (b) represents the MSE for both the proposed as well as the existing depending on the percentage of trained data. When the number of training data is 80 %, the error rate of the proposed method is 4.348. Then the attained improved variation of MSE for the ABHO-based Hough GAN is 54.82 % when compared with the existing GAN with SSO model. Fig. 8 (c) represents the RMSE for both the proposed as well as the existing depending on the percentage of trained data. When the number of training data is 90 %, the error rate of the proposed method isb6.027. Then the attained improved variation of RMSE for the ABHO-based Hough GAN is 44.03 % when compared with the existing GAN with SSO model.



(a) MAE

(b) MSE

(c) RMSE

Fig. 8. Comparative analysis for maneuver prediction models

For evaluating the performance measures accuracy, sensitivity, and specificity, the proposed ABHO-based deep CNN-BiLSTM is compared with the other existing methods. The accuracy for both the proposed as well as the existing depending on the percentage of trained data. When the number of training data is 90 %, the accuracy rate of the proposed method is 99.703 %. Then the attained improved variation of accuracy for the ABHO-based deep CNN-BiLSTM is 2.20 % when compared with the exiting deep CNN-BiLSTM with the SSA model.

When the number of training data is 90 %, the sensitivity rate of the proposed method is 99.200 %. Then the attained improved variation of sensitivity for the ABHO-based deep CNN-BiLSTM is 1.47 % when compared with the exiting deep CNN-BiLSTM with the SSA model. When the number of training data is 90 %, the specificity rate of the proposed method is 99.839 %. Then the attained improved variation of specificity for the ABHO-based deep CNN-BiLSTM is 4.11 % when compared with the exiting deep CNN-BiLSTM with the SSA model.

The performance of the ABHO-based maneuver prediction and traffic sign detection approaches is presented in Table 1 and Table 2. The proposed model outperforms other methods in terms of accuracy, sensitivity, and specificity for both traffic sign detection and maneuver prediction, which is crucial for effective decision-making and control of autonomous vehicles. The proposed maneuver prediction model also exhibits lower mean absolute error, mean square error, and root mean square error compared to existing models.

Table 1. Comparison for maneuver prediction

Methods	Manaveur prediction 90 % Training		
	MAE	*MSE*	*RMSE*
UNet	18.940	13.670	13.445
SegNet	18.111	13.667	13.278
UNet-ConvLSTM	18.022	13.664	13.247
SegNet-ConvLSTM	17.932	11.605	12.768
SegNet-ConvLSTM with SSO	17.770	11.510	12.687
SegNet-ConvLSTM with GWO	17.767	11.414	12.607
SegNet-ConvLSTM with FHO	17.765	11.319	12.526
GAN Model	4.646	4.646	9.529
GAN with COA	4.142	4.142	9.083
GAN with GWO	2.895	2.895	7.895
TCWO based GAN	2.406	2.406	7.387
GAN with SSO	6.034	6.034	10.768
ABHO based HoughGAN	**2.149**	**2.149**	**6.027**

Table 2. Comparison for traffic sign detection

Methods	Traffic Sign Detection 90 % Training		
	Accuracy (%)	*Sensitivity (%)*	*Specificity (%)*
SVM	93.182	91.304	92.857
DeepRNN	93.333	92.308	94.595
DeepCNN	93.590	92.308	95.238
DeepCNN with SSA	94.643	95.122	96.154
DeepCNN with GWO	95.522	96.429	97.059
DeepCNN with FHO	97.778	97.727	97.917
DeepCNN-BiLSTM	94.593	98.970	94.593
DeepCNN-BiLSTM with COA	98.667	98.875	98.667
DeepCNN-BiLSTM with GWO	98.875	99.619	98.875
TCWO based Ensample with DeepCNN-BiLSTM	98.875	98.364	98.875
DeepCNN-BiLSTM with SSA	97.505	97.737	95.740
ABHO based deep CNN-BiLSTM	**99.703**	**99.200**	**99.839**

5. Conclusion

This research proposes an efficient and precise autonomous decision-making technique for AVs to promptly exit hazardous situations. The approach involves developing traffic sign detection and maneuver prediction models using ABHO-based deep CNN-BiLSTM and ABHO-based HoughGAN techniques. The modified Hough-enabled lane GAN is responsible for accurately segmenting the driving area from the input image based on shared weights to facilitate decision-making. The ensemble CNN-BiLSTM classifier is used to anticipate traffic signs and assist the driver in making informed decisions.

The ABHO-based model improves traffic sign prediction accuracy by 2.20%, 1.42%, and 4.11. The use of the modified Hough-enabled lane GAN technique and ensemble CNN-BiLSTM classifier for lane detection and traffic sign prediction respectively, both effectively implemented by the ABHO algorithm, can provide a strong foundation for the development of a comprehensive autonomous decision-making approach. The ABHO algorithm can also contribute to improving the accuracy and efficiency of the models by regulating shared weights and tunable parameters more precisely.The performance improvement achieved in the traffic sign prediction model in this research can potentially be further enhanced in future work. Additionally, future research can explore the interactions of coexisting AVs and employ multi-agent learning algorithms to implement wide control algorithms to manage CAVs in typical circumstances. Other potential avenues for future work may include exploring the robustness and scalability of the proposed approach, as well as addressing ethical and legal issues related to the use of AVs. Moreover, there is the challenge of integrating the autonomous decision-making approach with existing transportation infrastructure and regulatory frameworks. New regulations and policies will need to be developed to ensure the safe and effective deployment of autonomous vehicles on public roads. The integration of autonomous vehicles into existing transportation infrastructure will also require significant upgrades to road infrastructure and communication systems.

Declarations

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