Journal of Engineering Science and Technology Review 16 (1) (2023) 75 - 84

Research Article

JOURNAL OF
Engineering Science and Technology Review

www.jestr.org

An Efficient Real Time Decision Making System for Autonomous Vehicle Using Timber Chased Wolf Optimization Based Ensemble Classifier

Swati Jaiswal[1] and Chandra Mohan B[2,*]

[1]School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu, India
[2]Associate Professor, School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu, India

Received 14 December 2022; Accepted 12 February 2023

Abstract

An autonomous vehicle is anticipated to increase comfort, safety, energy efficiency, emissions reduction, and mobility. The development of autonomous vehicles depends on decision-making algorithms that can handle complex and dynamic urban intersections. Hence in this research, a TCWO based ensemble classifier-based instantaneous decision-making model involved in driverless vehicles is devised. The ensemble classifier is designed through the combination of the Timber chased wolf optimization (TCWO) for detecting traffic sign along with decision process is performed. The bidirectional long short term (BiLSTM) and convolutional neural network (CNN) is combined to create the hybrid ensemble classifier, which is more effective. The TCWO is developed by hybridizing the characteristics of GWO and COA that helps to optimizing the classifiers and boots the classification performance. The TCWO based GAN helps for finding lane in the data that effectively reduces the problems of misclassification by generating synthetic data and training the data to differentiate the original and the generated data. The TCWO-based ensemble classifier attained the values of 98.88%, 98.36%, 98.88% while detecting the traffic sign, and 2.41%, 2.41%, 7.39% while predicting the lane using TCWO-based GAN, which is significantly higher than the competent technique.

Keywords: Generative adversarial network, bidirectional long short term memory, convolutional neural network, Timber Cased Wolf Optimization, autonomous vehicles

1. Introduction

An autonomous vehicle is becoming more and more popular as computer and communication technology advance so quickly. Numerous automobile companies is developed more advanced systems for autonomous driving [1]. More than 90% of recorded crashes are caused by driver error, which is the main factor in traffic accidents. An autonomous vehicle (AVs) remains as emerging and feasible solution to avoid crashes resulted by driver mistake. Enhancing driving safety and driver acceptance is a key goal of AV development [14][15][7]. Several automated cars, like Google Car, endorse car to guide their navigation and enable more fluid control [16]. AVs are equipped with reducing technology that enables them to sense their immediate environment and independently navigate using the information gathered. This is primarily made possible by many sensor types like cameras, Light detection and ranging (LiDAR), Inertial Measurement Units (IMU), and Radio detection and ranging (RADAR) [10][11][17], which have vision or non-vision capabilities. AVs must accelerate or decelerate, surrounding maneuver, and deduce stationary and moving obstacles based on these inputs [30][2]. Most essential elements for secured and reliable independent driving is accurate identification of surrounding with the help of radar, LiDAR, camera, LiDAR, and other sensors [29].

An autonomous vehicle is an extensive export model that combines technology for mobility control, path planning, environmental awareness, and decision-making [18]. The ability to develop highly intelligent and trustworthy decision systems has progressively become the focal point of research in driverless vehicles. The decision–making system acts as the central nerve of driverless vehicles and is important for the safe and effective operation of vehicles. 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. The motion control system then takes these driving behaviors into account to attain effective autonomous driving operation [19][20] [13]. The fundamental element of vehicle security and driving efficiency is the driver's behavior decision-making and planning in response to diverse traffic environments and emergency situations. However, making precise, effective, and secure decisions and plans in complicated surroundings remains difficulty for autonomous cars. [1]. The autonomous car makes decisions and designs the local trajectory based on the particular environmental and road situation, traffic laws, and other factors. The machine learning and rule-based method are the two basic approaches to behavioral planning and decision-making. The rule-based behavior decision-making method categorizes autonomous vehicle behavior and creates a library of behavior rules based on driving regulations, knowledge, experience, traffic regulations, etc. [21], [22] [1].

The two main categories of decision-making techniques are traditional techniques and learning-based techniques. Typically, autonomous vehicles work with other traffic participants to navigate complicated, dynamic environments.

*E-mail address: dr.abc@outlook.com

doi:10.25103/jestr.161.10

Due to their poor robustness, traditional methods is not always effective in such driving environments, so learning-based methods is used to improve autonomous vehicle decision-making [23] in addition, learning-based approaches have grown immensely in popularity and significance in the autonomous vehicle field [24] [13]. Numerous institutions and researchers, including Google [25], Carnegie Mellon University [26], Berkeley [27], and Baidu [28], have looked at the issues of strong deliberated decision-making for autonomous vehicles in a dynamic and complex environment. Machine learning-based decision-making techniques have attracted a lot of interest as a result of the advancement of artificial intelligence. This approach uses environmental samples to learn on its own, and after establishing behavior rules utilizing self-learning data obtained from various learning techniques or network structures. The decision output is based on environmental data. Deep learning (DNN), recurrent neural network (RNN), reinforcement learning (RL), and other techniques are the core components of machine learning. [31] [32] [1].

The main concentration of the research is to devise an instantaneous decision-making system in driverless vehicles that depends on an ensemble classifier. The data is accumulated from the Road video dataset. The pre-processing is executed in Road vehicle video data to reduce the noises in the data and the Region of Interest (RoI) is extricated from the video sequence. The preprocessed Video is directed to the ensemble classifier to recognize traffic sign and instruct to make decision. Furthermore, preprocessed video is directed to Modified Lane-GAN, which is optimized for LANE Prediction because Generative Adversarial Network (GAN) has shown good image enhancement and image restoration capabilities. The hyperparameter of the ensemble classifier is optimized where the parameter tuning and cascading are employed optimally through the TCWO algorithm. The main research contribution includes:

- ***Timber chased wolf optimization:*** The timber-chased wolf optimization is proposed through the hybrid characters, such as the hunting and communicating characteristics of the wolfs and coyotes. The reason behind choosing these characters relies in their improved convergence phenomenon towards the global optimal convergence.
- ***Timber chased wolf optimization based GAN:*** The optimized Lane-GAN model highlights the Lane from the road video dataset to support the accurate maneuver detection for which the timber chased wolf trains the GAN model.
- ***Timber chased wolf optimization based Ensemble classifier:*** The maneuver detection is performed through the ensemble deep model with CNN and BiLSTM classifiers using the lane and sign information of the real roads.

Manuscript-organization: Section 2 lists the existing studies along with their techniques, benefits, and difficulties. Section 3 provides a description of the autonomous vehicle decision-making system and its operational methods. Section 4 provides details on the suggested timber chasing wolf optimization, its operational methods, and mathematical model. In section 5, the classifier results are described in depth, and section 6 concluded by highlighting the research's accomplishments.

2. Related works

An autonomous vehicle decision-making and planning system based on motivation and risk assessment was developed by Yisong Wang *et al.* [1]. This method examined the driving environment at the moment to determine whether there is a motivation to change the driving state or not. This technique increased the computational efficiency of the decision-making process and also ensured safety, but achieved low level computational efficiency. An end-to-end car-following framework for autonomous vehicles was developed by Mehdi Masmoudi *et al.* [2] using automated object detection and navigation decision modules. This approach enhanced the prediction accuracy and captured information about both low-level and high-level objects; but the processing time of the key frames is reliably high. A new security-by-design approach was designed by Mohamed Abdel-Basset *et al.* [3] to estimate the uncertainty of autonomous vehicles and measure cyber risks. As a result, it helped decision-makers to handle the risks of the physical design and their attack surfaces. Although this technology made life safer for walkers and passengers, but it cannot be adjusted for high weather because of the high expense of operating. Kaya Kuru *et al.* [4] initiated fully autonomous unmanned aerial vehicles and the framework worked based on agent-based decentralized control architecture that keeps track of and manages swarms of resource-constraints in real-time with the purpose of maximizing their urban usage. It can operated in hazardous and disaster-prone environments and attain high transit speeds, but the battery capacities are limited. Xianzhe Xu *et al*. [5] developed a model applicable for RSUs by integrating both recentness of the effectual sub-maps that are collected locally from vehicles and the cub-map retrieval cost. The sub-maps retrieval cost are not accumulated at RSUs but need for high-level driving authority. This approach gave an accurate representation of the road ahead and information about the surroundings. An effective fuzzy compromised solution model was created by Muhammet Deveci *et al.* [6] based on the logarithmic method and Power Heronian function that addressed the problem of advantage priority in real-time traffic management techniques. This approach produced better results in locations with heavy mainline traffic, but it has a lower importance rating on the fuzzy linguistic scale. A transfer reinforcement learning framework was developed by Hong Shu *et al.* [7] that enhanced the control performance and learning effectiveness of automated vehicle decision-making issues. Although this approach increased learning effectiveness and performance, the rate of convergence was low. Using the Vehicular Edge Computing (VEC) cloud concept, Andrea Tesei *et al.* [8] a novel secure architecture that enables the deployment of mission-critical, instantaneous driving applications at the network's edge. With this approach, a smaller window of susceptibility and the least amount of influence on the decision-making process are guaranteed. The method's disadvantage was an increase in computing time.

Khaled S. Refaat *et al.* [43] 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. This method promoted large number of agents and attained a reduced loss but the depending upon their planning capability the performance of the system gets varies, which initiates instability. A deep reinforcement learning-enabled decision-making framework was developed by Guofa Li *et al.* [42] that enabled autonomous vehicle to navigate junctions automatically, safely, and effectively. This technique demonstrated that autonomous parking could be successfully implemented with high robustness but higher computational cost acts as a disadvantage.

2.1 Challenges
The various challenges are illustrated in the below section:

- The primary cause of uncertainty in motion prediction in real-world traffic scenarios is the anticipated future behavior of the surrounding cars. The interactions between the vehicles themselves also present significant challenges for the prediction [1].
- Accurately detecting the other participant trajectory and simultaneously weighing efficiency and safety into vehicles interaction are major challenges in the operation of autonomous vehicles robustly [12].
- The guaranteed performance and validation of the autonomous driving pipeline is the challenging task experienced in the existing model due to the complex decision-making methods and the complex planning [9].
- The probabilistic illustration of the traffic scenarios and participants need online validation of the general maneuvers, which remains as the challenging task due to high complexity [18].
- The conventional model requires to evaluate the large space to enable faster computing, which ensures the users with service and real-time booking. Thus, exploring the decision space is the challenging task in decision making [20].

3. Methodology for assisting Decision making system for autonomous vehicle using timber cased wolf optimization based ensemble classifier and GAN network

The main aim of the research is to assist the instantaneous controlling system by the detection and prediction of lane and traffic sign in autonomous vehicles using a TCWO based ensemble and GAN classifier. The enabled TCWO based ensemble classifier makes the decision and the GAN network assists in the prediction of lane. Initially, the data from the real world dataset [33] is gathered and then the preprocessing of the collected data is performed. The preprocessing step acts as a preliminary stage, which makes the data more suitable for the detection of lane and for making decisions. Here, in the preprocessing stage the videos are converted into key frames for reducing the dimensionality and the key frames are processed for obtaining the necessary information. Along with that the region of interest (ROI) is also extracted and the extracted region is fed forwarded to both ensemble and GAN classifier. Both the classifiers are effectively optimized using the TCWO algorithm, which effectively boosted the convergence by the integration of the hunting and the communicative behavior. Hence the traffic sign and the lane is predicted with more accuracy and the decisions are made efficiently. The schematic representation of the methodology is shown in figure 1.

3.1 Input
The data is gathered from the Road vehicle video dataset [33] as a preliminary step and is
given by Eq.1,

$$R = \sum_{m=0}^{g} R_g \tag{1}$$

where, R denotes the dataset consists of videos, R_g represents the number of videos present in the road vehicle dataset which is in the range $[1, g]$.

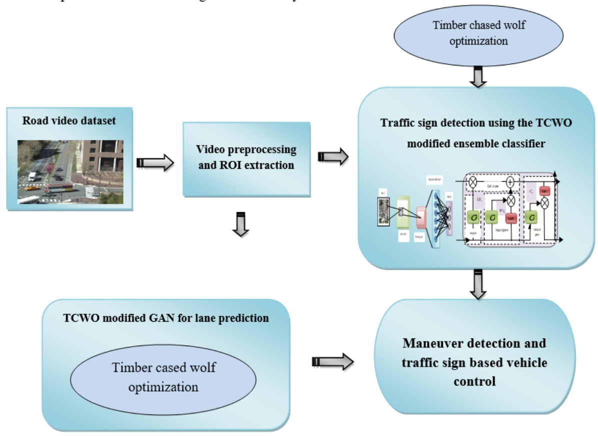


Fig. 1. Block diagram of the decision making autonomous vehicle.

3.2 Video preprocessing and audio extraction
The collected data is preprocessed, where the data is converted into key frames and then the noise in the data is removed in order to improve the quality of the image. After enhancing the image the undesired areas from the image are excluded and the content in the image is retrieved as RoI and is used for further processing.

3.3 Traffic sign prediction using TCWO modified ensemble classifier
The TCWO modified ensemble classifier is used for the detection of the of the traffic sign to enhance the decision making of the autonomous vehicles. The modified ensemble classifier is developed by the hybridization of the CNN and BiLSTM classifier, where the necessary features needed for the detection of traffic sign is determined using the CNN and the BiLSTM classifier better predicts the traffic sign by analyzing the information in both forward and backward directions. The suggested TCWO algorithm enabled in the modified ensemble classifier tunes the best hyper parameters for the classifier, such as the biases and interconnection weights that provides the optimized solution and the output obtained from the classifier is mathematically modeled by the below equation as follows,

$$C = d_1 C_1 + d_2 C_2 \tag{2}$$

where, C_1 and C_2 denotes the output from the CNN AND BiLSTM classifier and the hyper parameters of the classifiers are represented by d_1 and d_2.

3.3.1 Architecture of CNN classifier
CNN classifier reduces the dimensionality of the images without losing any information and it includes three layers such as pooling layer, convolutional layer, and fully connected layer. The convolutional layer produces the feature maps as the output, by the convolution process using number of kernels. In order to create the feature maps, each convolutional layers input is combined with the previous layer output according to the filter size and strides. Max Pooling is used to extract the minimum value from the Feature map and finally, the output is obtained from the fully connected layer, which is the network detection output. The

fully connected layers output is mathematically represented as,

$$C_1 = Fn[Hh_p^u] \quad (3)$$

where, $p$corresponds to the convolutional layer, $Hh_p^u$is the convolutional output and is given by Eq.4,

$$Hh_p^u = Dd_p + \sum\sum Vv_u^p * Re_u^p \quad (4)$$

where, Vv_u^pillustrates the weights of p^{th}convolutional layer and $u$illustrates the feature map. Re_u^p is the u^{th}feature map from the p^{th}convolutional layer and $Dd_p$is the bias respect to the p^{th}layer. Thus, $T \in [Dd_p, Vv_u^p]$are determined by TCWO algorithm. The CNN classifier framework is exhibited in Fig. 2.

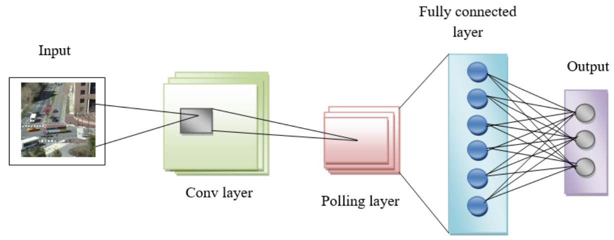


Fig. 2. Architecture of CNN.

3.3.2 Architecture of Bi-LSTM classifier

BiLSTM classifier increases the amount of information available to the network. Two LSTM models with opposing directions compensate BiLSTM. BiLSTM offers a number of benefits while learning massive amounts of time series data. The forward LSTM and the backward LSTM compensate the bi-LSTM. The single unit of LSTM is explained below and the framework is illustrated in fig. 3.

Fig. 3. Single unit of LSTM.

Single unit of LSTM:An efficientclassifier with respect to deep neural networks is the LSTM classifier, which captures the non-linear interaction within the characteristics and preserves input data feature. The LSTM classifier successfully determines the unsuitable and irrelevant data relationship, which helps to improve classifier accuracy. The classifier has deep layers, a large amount of memory, and needs intensive computing, which aids in a detailed feature evaluations. The LSTM classifier performance is improved further by using the feedback layers to carry the data history. The input gate is given by Eq.5,

$$Wx_r = \sigma(Vv^w * W_r + Vv^N * Nn_{r-1} + Vv^O \bullet F_{r-1} + Dd_w) (5)$$

where, W_r stands for the input vector, Vv^p stands for the weight within the input layer and the input gate. The gate activation function is informed byσ,Vv^O for the weight between the input layer and the cell output, and Vv^N for the weight within the the input layer and the memory output. Dd_w stands for the input layer bias, and Nn_{r-1} and F_{r-1} represent the previous output of the cell and memory unit, respectively. $\bullet$ stands for element-wise multiplication, and $*$ stands for the convolutional operator. The Forget gate output is calculated as Eq.6,

$$Qj_r = \sigma(Vv_{Qj}^w * W_r + Vv_{Qj}^{Nn} * Nn_{r-1} + Vv_{Qj}^O \bullet F_{r-1} + Dd_w^{Qj}) \quad (6)$$

where, Vv_{Qj}^willustrates the weight within input and forget gate, Vv_{Qj}^Orepresents the weight within output gate and cell, and Vv_{Qj}^{Nn} denotes the weight within output gate and the previous layers memory unit. Dd_w^{Qj}denotes the forget gate bias. The weight activation function within memory unit, input layer and cell state, models the output from the temporary cell state. Based on the weight within the memory and output layers, the output layer output is represented by Eq.7 as C_2. The LSTM classifier framework is illustrated in Fig.4.

$$C_2 = \eta(Vv_N^{mm} Nn_r + Dd^{mm}) \quad (7)$$

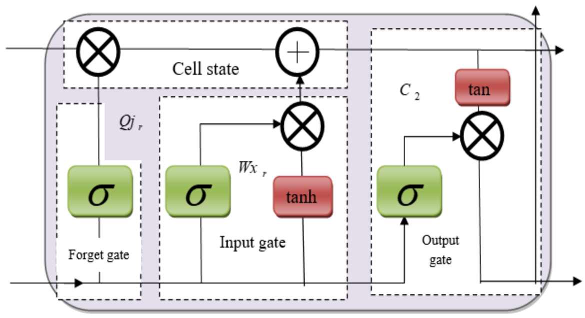


Fig. 4. LSTM-framework.

3.4 Modified Generative Adversarial network for lane Prediction

The GAN network is used for the enhancement of the image for better prediction of the lane. GANs are composed of two main neural networks such as generator and discriminator, which fight for the ability to recognize, replicate, and interpret differences between the normal region and the lane. The GAN network has high restoration capabilities of the image using the generator and discriminator. When the quality of the image is low it initiates difficulties in the recognition of lane, hence to deal with the blurred or low quality image the GAN network is utilized. The GAN has the capability to generate synthetic data samples by providing noise to the generator. The discriminator effectively differentiates the normal and the lane region, and the optimal solution in the GAN is determined using the TCWO optimization, which reduces the overfitting issues and reduces the cost function. The architecture of GAN is depicted in figure 5.

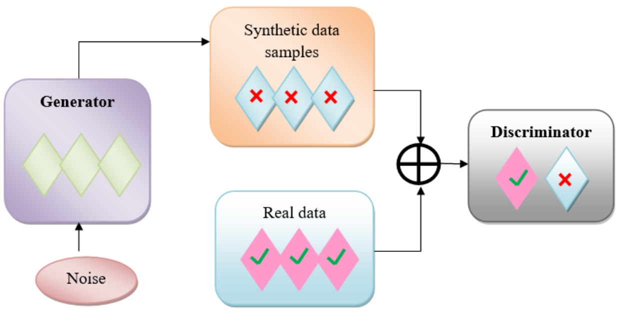


Fig. 5. Architecture of GAN network.

4. Timber cased wolf optimization

Timber cased wolf optimization (TCWO) is devised by the standard integration of GWO [34] and COA [35] that effectively hybridize the hunting and communication characteristics of the timber and chaser wolf, which helps to enhance the optimization process.

4.1 Motivation

The timber wolf (grey wolf) belongs to the canidae family and this wolf is the top predator of the food chain.Almost every wolfresides in groups, which consists of 5–12 members in each group. Each wolf has a unique role in the population and they have a fairly rigid social order, as illustrated in Fig.6.α is the leader of the timber wolves present in the first layer and is responsible for making decisions regarding habitat and hunting. The second layer consists of subordinate timber wolf, known asβ, which supports $\alpha$for leadership management or other wolf pack operations. The third layer consists of δwolves and is responsible for taking charge of boundaries of the territory, alerting the wolf pack in case of any danger, and caring for the sick and injured timber wolves. The lowest ranking timber wolf in the population known asωpresent in the fourth layer and these wolf acts as the subordinate to all other dominating timber wolves. Although, it may appear that the ωwolves are not significant members of the wolf pack, they are crucial in maintaining the population's internal balance. The wolf pack's leadership structure is important for successful hunting. First, the timber wolves search and follow the prey. Next, αtimber wolf directs the other wolves to encompass the prey on all sides, and finally,αtimber wolf orders the βandδwolves to hunt the prey. If the prey manages to escape, the other wolves that are fed from behind will keep attacking it until timber wolves manage to capture it.

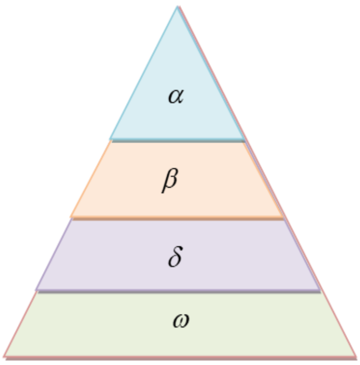


Fig. 6. Hierarchy of grey wolves.

4.2 Mathematical representation for the TCWO

In the section the behaviors of timber wolf such as social structure, surrounding behavior and hunting stages are mathematically described as follows:

i) Social structure

The TCWO algorithm simulates the wolf leadership hierarchy and predatory aspects using the timber wolf characteristics of hunting, search, encirclement, and other activities in the predation process. Assuming, Nrepresents the wolves' number and $d$denotes the search area and the wolf's position $i^{th}$is represented as$Z_i = \left(Z_{i_1}, Z_{i_2}, Z_{i_3}, \ldots\ldots Z_{i_d}\right)$. The fittest solution of wolf is regarded as the alpha (α) wolf. The subsequent best solutions are referred to as delta (δ) and beta (β) wolves, respectively. The other candidate solutions is assumed as omega (ω) wolves. According to this algorithm, the best prey's location is determined by alpha wolf.

ii) Surrounding behavior

During the hunt, grey wolves surround their prey, and this behavior can be mathematically described as Eq. (8),(9),

$$E = \left|G \times Y_q(i) - Y(i)\right| \tag{8}$$

$$Y(i+1) = Y_q(i) - B \times E \tag{9}$$

where, set i is the current iteration, set $Y_q(i)$ illustrates the position vector of prey, $Y(i)$ illustrates the wolf's position vector, and Gdenotes control coefficient, which is formulated by Eq.10,

$$G = 2s_1 \tag{10}$$

where, S_1 is a set of random numbers between [0, 1] and a convergence factor B is estimated as Eq.(11), (12),

$$B = 2bs_2 - b \tag{11}$$

$$b = 2\left(1 - \frac{i}{I_{max}}()\right) \tag{12}$$

where, the set S_2 is the random variable within range [0, 1]. The set b is the control coefficient, which directly reduces from 2 to 0 over the course of iterations, that is, b_{max}= 2, b_{min} = 0.

iii) Hunting stage

When the alpha timber wolf determines the prey, the wolf starts surrounding the prey and is continued by the other wolves. Hence the αwolf is responsible for determining the prey and it also instructs the other wolves to capture the prey. The position of α,β and δ in the grey wolves is used to determine the prey's location because they are the one that present closer to the prey. The mathematical notation of the encircling behavior wolves based on their hierarchy is represented as Eq. (13),(14),(15),

$$E_\alpha = |G_1 \times Y_q(i) - Y(i) \tag{13}$$

$$E_\beta = |G_2 \times Y_q(i) - Y(i)| \tag{14}$$

$$E_\delta = |G_3 \times Y_q(i) - Y(i)| \tag{15}$$

The grey wolves position isα, β and$\delta$are given by Eq. (16),(17),(18),

$$Y_1 = Y_\alpha - B_1 \times E_\alpha \tag{16}$$

$$Y_2 = Y_\beta - B_2 \times E_\beta \tag{17}$$

$$Y_3 = Y_\beta - B_3 \times E_\beta \tag{18}$$

After targeting the prey, the final updated position vectors for the three categories, α, β, and $\delta$is given by Eq. (19),

$$Y(i+1) = \frac{Y_1 + Y_2 + Y_3}{3} \tag{19}$$

iv) Attacking the prey

The timber wolves start attacking the prey, when the target prey completely stops moving and in order to show this behavior an attribute b is used for the determining the target prey random movement. $b$is defined in the interval $[-2b, b]$, which is considered to be decreasing for various iterations. Timber wolves attack when$B < 1$, and they wait for the ideal opportunity to do so when$B > 1$.

v) Search prey

The timber wolves hunt for prey while keeping track of their location in relation to wolvesα, β, and δ. The timber wolves divide into several groups to look for prey and then join together to attack the prey. But the joining behavior of the wolves is not defined and if their communication behavior gets enhanced, then the timber wolves could hunt efficiently within a stipulated time and the probability of the escaping of the prey also gets decreased. Hence for the efficient hunting, the interactive behavior of the cased wolf is incorporated to the position of the timber wolves and is mathematically represented as Eq. (20), (21), (22),

$$\theta_{best} = 0.5(Y(i+1)) + 0.5\left(n - com_k^{o,c}\right) \tag{20}$$

$$\theta_{best} = 0.5\left[\left(\frac{Y_1+Y_2+Y_3}{3}\right) + \left(f\left(n - com_k^{o,c}\right)\right)\right] \tag{21}$$

$$\theta_{best} = 0.5\left[\left(\frac{Y_1+Y_2+Y_3}{3}\right) + \left(f\left(com_k^{o,c} + t_1 \bullet \lambda_1 + t_2 \bullet \lambda_2\right)\right)\right] \tag{22}$$

where, $n - com_k^{o,c}$is represented as a communication behavior of the k^{th}cased wolf of the o^{th}pack in the c^{th} instance of time, λ_2 and $\lambda_1$denotes the pack and alpha influence. t_2 and $t_1$represents the pack and alpha influence weights. Initially it represented as random numbers ranges from $[0,1]$ with uniform probability. If the characteristic$G < 1$, the wolves search in different locations. If the$G > 1$, the wolves join together and choose their target based on weight. The Pseudocode for the TCWO is interpreted in table 1.

Table 1. Pseudocode for the timber chassed wolf optimization

S.No	Pseudocode for the timber chased wolf optimization
1.	Initialization
2.	Initialize: α,β,δ,ω.
3.	Social structure
4.	Find best solution
5.	Surrounding behavior
6.	Define:E,$Y(i+1)$
7.	Hunting stage
8.	Evaluate Fitness: E_α, E_β, E_δ
9.	Position update: Y_1, Y_2 ,Y_3
10.	Update final position: $Y(i+1)$
11.	Attacking stage
12.	{
13.	if($B < 1$)
14.	Attack
15.	Else
16.	Wait
	}
17.	Searching
	{
18.	if($G < 1$)
19.	Diverge
20.	Else
21.	Unite
	}
22.	Determine optimal solution
22.	$\theta_{best} = 0.5\left[\left(\frac{Y_1+Y_2+Y_3}{3}\right) + \left(f\left(com_k^{o,c} + t_1 \bullet \lambda_1 + t_2 \bullet \lambda_2\right)\right)\right]$
23.	End
24.	End

5. Result

The results are discussed for the TCWO based ensemble classifier and GAN is enumerated in the below section.

5.1 Experimental setup

The experiment is performed using the python in the windows 10 OS with 8 GB RAM and the research is evaluated using the road video dataset.

5.2 Dataset description

There are 1171 aerial images illustrating the state of roads in the Roads Dataset. Each image has a dimension of 1500 by 1500 pixels and covers 2.25 square kilometers. We divided the data into three sets at random: a 1108-image training set, a 14-image validation set, and a 49-
image test set. The dataset covers more than 2600 square kilometers and includes a wide range of urban, suburban, and rural districts. The test set alone covers over 110 square kilometers and that helped researches to attain knowledge about the real-time decision-making systems in autonomous vehicles.

5.3 Parameter metrics

The metrics for the evaluation of TCWO tuned ensemble classifier is sensitivity, accuracy, and specificity and is described as follows:

- **Accuracy:** Accuracy is described as the fraction of samples that are correctly identified by the TCWO based ensemble classifier in determining the decision making system in autonomous vehicle and is given by Eq. 23,

$$W_{acc} = \frac{W_{TP}+W_{TN}}{W_{TP}+W_{FP}+W_{TN}+W_{FN}} \tag{23}$$

- **Sensitivity:** Sensitivity is characterized as probability that a test result is true positive outcome by the TCWO based ensemble classifier in determining the decision making system in autonomous vehicle and is given by Eq. 24,

$$\boldsymbol{W_{Sen}} = \frac{\boldsymbol{W_{TP}}}{\boldsymbol{W_{TP}+W_{FN}}} \tag{24}$$

- **Specificity:** Specificity is characterized as probability that a result is true negative by the TCWO based ensemble classifier in determining the decision making system in autonomous vehicle and is given by Eq. 25,

$$\boldsymbol{W_{Sen}} = \frac{\boldsymbol{W_{TN}}}{\boldsymbol{W_{TN}+W_{FP}}} \tag{25}$$

- **Mean Absolute Error:**Mean Absolute Error (MAE) is defined as the magnitude of the difference between the individual measurement and the true value quantity of the TCWO based modified GAN in determining the lane prediction in autonomous vehicle and is given by Eq. 26,

$$T_{MAE} = \frac{1}{x}\sum_{i=1}^{x} |y_i - y| \tag{26}$$

where, number of error is denoted as x, and absolute error is represented as $|y_i - y|$.

- **Mean Square Error:** Mean squared error (MSE) estimates the quantity of error in statistical models and also evaluates the average squared difference between the predicted and observed values of the TCWO based modified GAN in determining the lane prediction in autonomous vehicle and is given by Eq. 27,

$$S_{MSE} = \frac{1}{w}\sum_{i=1}^{w}\left(z_i - \hat{z}_i\right)^2 \quad (27)$$

here, number of data points is denoted as w, predicted value is denoted as $z_i$and observed value is denoted as $\hat{z}_i$.

- **Root mean squared error:** Root mean squared error (RMSE) is described as the root of the mean square of all of the error, for determining the lane prediction using TCWO based modified GAN in autonomous vehicle and is given by Eq. 28,

$$J_{RMSE} = \sqrt{\frac{1}{j}\sum_{i=1}^{j}(A_i - M_i)^2} \quad (28)$$

where, observations is denoted as M_i, predicted values of the variable is denoted as A_i and j represents the number of observations.

5.4 Evaluation based on traffic prediction

The performance and the comparative evaluation of TCWO based ensemble classifier is performed and classifier performance with different epochs is elaborated in detail in the below section.

- ***Comparative methods:*** The TCWO-based ensemble classifier is evaluated with Support Vector Machine (SVM) classifier [M-1][36], RNN [M-2] [37], Deep CNN [M-3][38], Deep CNN classifier with Sparrow Search Optimization (SSO) [M-4][39], Deep CNN classifier with Grey Wolf Optimization (GWO) [M-5][34], Deep CNN classifier with Fire Hawk Optimization (FHO) [M-6][40], Deep CNN-Bidirectional Long Short Term Memory (BiLSTM) [M-7][41], Deep CNN-BiLSTM with Coyote Optimization Algorithm (COA) [M-8][35], Deep CNN-BiLSTM with Grey Wolf Optimization (GWO) [M-9][34], TCWO based ensemble classifier.

5.4.1 Performance evaluation based on training percentage

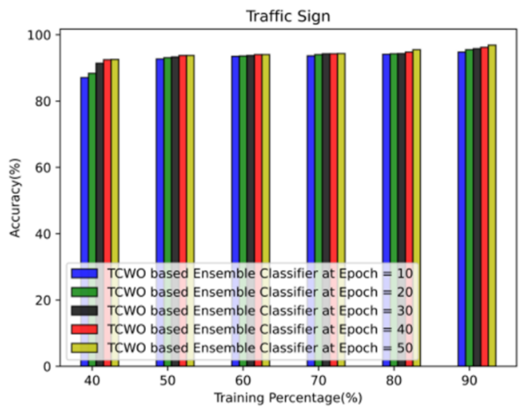
The performance evaluation for the TCWO based ensemble for different epochs 10, 20, 30, 40, 50 is depicted in fig.7. At first, the accuracy of the methods is measured and the values of 94.79 %, 95.49 %, 95.83 %, 96.24 %, 96.88 % is attained by the TCWO based GAN as represented in fig.7 a) at 90% training. Similarly, the sensitivity of the TCWO based GAN classifier is measured, which obtained the values of 95.16%, 93.75 %, 95.45 %, 96.36 %, 97.50 %, 97.56 % for the training percentage 90 shown in fig.7 b). The specificity of the TCWO based GAN classifier is 96.30 %, 96.77 %, 97.33 %, 98.00 %, 98.08 % for the training percentage 90 shown in fig.7c).

5.4.2 Comparative analysis with reference to training percentage

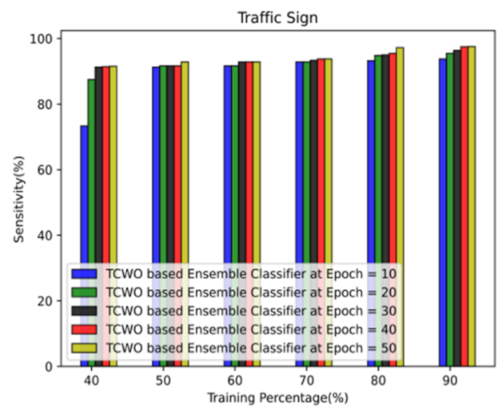
The comparative analysis using metrics sensitivity, specificity and accuracy is estimated and is depicted in fig.8. The accuracy estimation is illustrated in fig.8 a) and the TCWO based ensemble classifier obtained the enhancement of 5.35 over deep CNN at 90% training. Likewise the TCWO based ensemble attained the enhancement of 6.16 over deep CNN and the analysis is depicted in fig.8 b). At last the improvement in terms of specificity is measured and the TCWO based GAN achieved the improvement of 3.68 over deep CNN at 90% depicted in fig.8 c). The evaluation illustrates that the TCWO-based classifier exhibits better performance than the previous existing methods.

5.6 Evaluation based on lane prediction

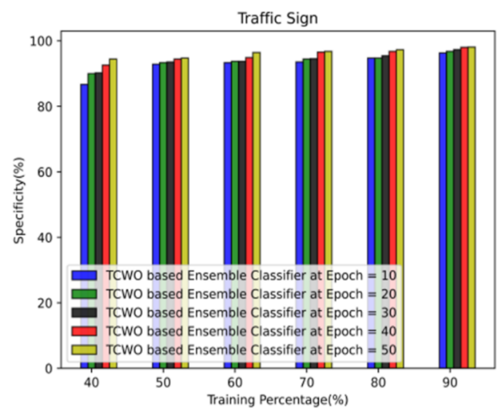
The performance and comparative evaluation of the TCWO based GAN is performed and the classifier performance with different epochs, which detailed in the subsequent section.



(a)



(b)

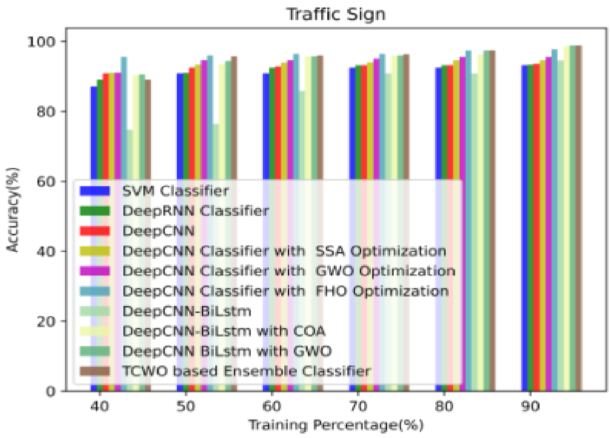


(c)

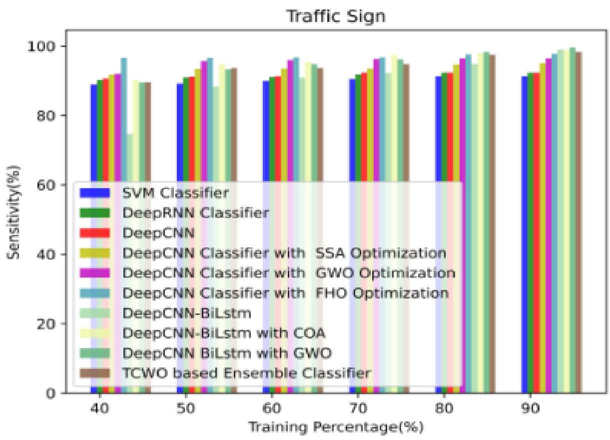
Fig. 7. Performance analysis of the TCWO-based GAN training percentage on account of a) accuracy b) sensitivity c) sensitivity

5.6.1 Performance evaluation on lane prediction

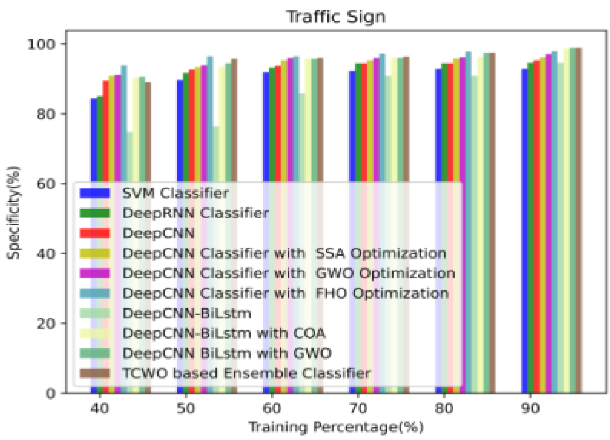
The performance analysis for the TCWO based GAN for the varying epochs and training percentage is exhibited in fig.9.Initially, the MAE of the methods is measured and obtain value of 1.21, 1.09, 0.76, 0.76, 0.46 by the TCWO based GAN demonstrated in fig.9 a) at 80% training. The MSE of the TCWO based GAN is observed, which attain the values of 1.21, 1.09, 0.76, 0.76, 0.46 at 80% training illustrated in fig.9 b). At last the RMSE of the TCWO based GAN is observed and the values of 1.34, 1.28, 1.07, 1.07, 0.83 at 80% of training is illustrated in fig.9 c).



(a)

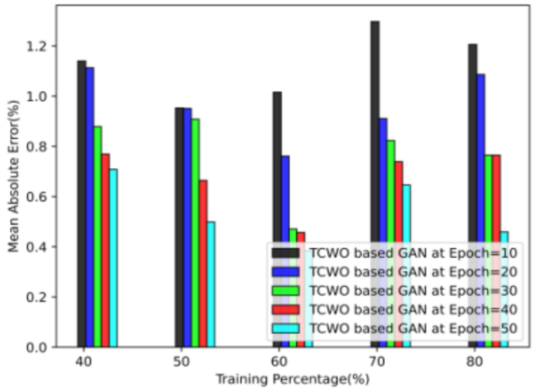


(b)

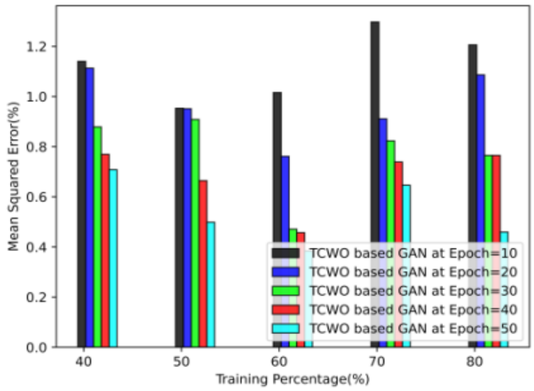


(c)

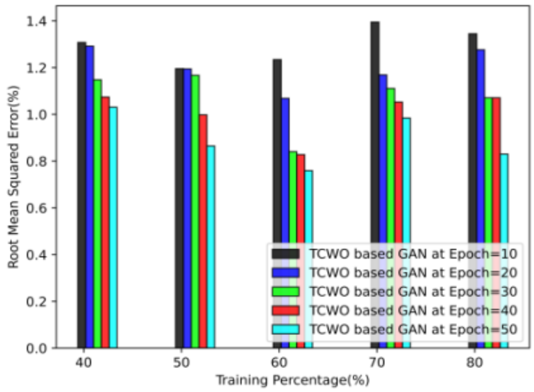
Fig. 8. Comparative analysis of the TCWO-based GAN concerning. (a) accuracy (b) sensitivity, (c) sensitivity.



(a)



(b)



(c)

Fig. 9. Performance analysis of the TCWO based GAN concerning to (a) MAE (b) MSE (c) Root MSE

5.7.1 Comparative analysis on lane prediction

The comparative analysis is using metrics like MSE, MAE, and RMSE is measured and is given in fig.10. The MAE values is measured and it is shown in fig.10 a) and the TCWO based GAN shows the improvement of 16.89% over GWO, at 90% training. Likewise, for 90% of training the TCWO based-GAN achieves 16.89%improvement of over GWO while estimating the MSEand it is represented in fig.10 b). Finally performance enhancement in terms of RMSE is measured and the TCWO based GAN shows improvement of 6.43% over GWO for 90% shown in fig.10 c). The analysis illustrates the TCWO-based GAN method achieved higher performance than the competent methods.

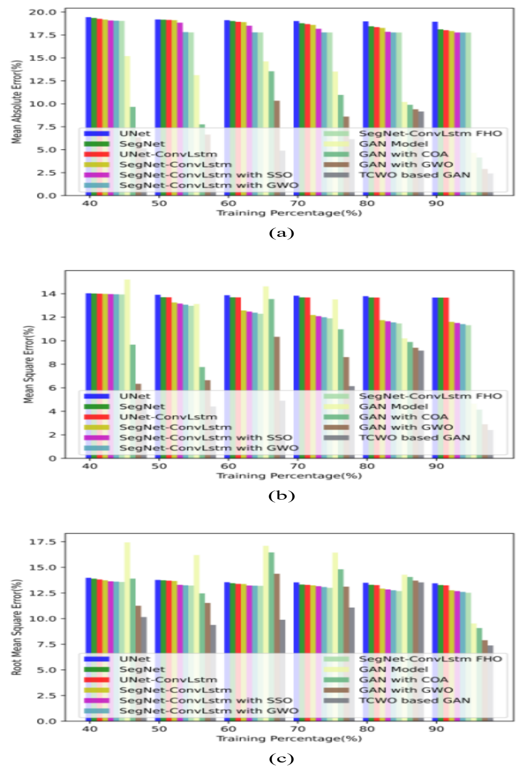


Fig. 10. Comparative evaluation of the TCWO based GAN on concerning to a) MAE b) MSE c) RMSE

Conclusion and future work

An efficient real time decision making system for autonomous vehicle using Timber chased wolf optimization based ensemble classifier is devised. Data from the Road vehicle video is gathers and then preprocessing is performed for improvement in quality, intensity and resolution of the image after RoI extraction. Then the modified ensemble classifier detects the traffic sign and instructs the user to take Decision. Similarly, modified GAN is used for lane prediction. Finally the classification is made using the timber cased wolf optimization. This research relies on the metrics values estimation and the parameters of specificity, accuracy, and sensitivity is attained the of 98.88%, 98.36%, 98.88% for traffic sign detection using TCWO-based ensemble classifier and the parameters of MAE, MSE, RMSE is attained the values of 2.41%, 2.41%, 7.39% for lane prediction using TCWO based modified GAN. The proposed decision making model achieves high metric values than the conventional methods, which shows the efficiency of the model. Theuses of autonomous vehicles for practical applications such as keep roadways safer,reducing accidents, and helps in industries. Future efforts will be made to establish the online application of autonomous vehicle decision-making policies.

References

1. Wang, Y., Wang, C., Zhao, W. and Xu, C., "Decision-Making and Planning Method for Autonomous Vehicles Based on Motivation and Risk Assessment". *IEEE Transactions on Vehicular Technology*, 70(1), 2021, pp. 107-120.
2. Masmoudi, M., Friji, H., Ghazzai, H., and Massoud, Y., "A Reinforcement Learning Framework for Video Frame-Based Autonomous Car-Following". *IEEE Open Journal of Intelligent Transportation Systems*, 2, 2021, pp. 111-127.
3. Abdel-Basset, M., Gamal, A., Moustafa, N., Abdel-Monem, A. and El-Saber, N., "A Security-by-Design Decision-Making Model for Risk Management in Autonomous Vehicles". *IEEE Access*, 9, 2021, pp. 107657-107679.
4. Kuru, K., "Planning the Future of Smart Cities with Swarms of Fully Autonomous Unmanned Aerial Vehicles Using a Novel Framework". *IEEE Access*, 9, 2021, pp. 6571-6595.
5. Xu, X., Gao, S., Tao, M., "Distributed Online Caching for High-Definition Maps in Autonomous Driving Systems". *IEEE Wireless Communications Letters*, 10(7), 2021, pp. 1390-1394.
6. Deveci, Muhammet, Dragan, Pamucar, and Ilgin Gokasar, "Fuzzy Power Heronian function based CoCoSo method for the advantage prioritization of autonomous vehicles in real-time traffic management". *Sustainable Cities and Society*, 69, 2021, pp. 102846.
7. Shu, H., Liu, T., Mu, X., and Cao, D., "Driving Tasks Transfer Using Deep Reinforcement Learning for Decision-Making of Autonomous Vehicles in Unsignalized Intersection". *IEEE Transactions on Vehicular Technology*, 71(1), 2022, pp. 41-52.
8. Tesei, A., Luise, M., Pagano, P. and Ferreira, J., "Secure Multi-access Edge Computing Assisted Maneuver Control for Autonomous Vehicles". *IEEE 93rd Vehicular Technology Conference (VTC2021-Spring)*, Helsinki, Finland, 2021, pp. 1-6.
9. Muhammad, K., Ullah, A., Lloret, J., Ser, J. D. and de Albuquerque, V. H. C., "Deep Learning for Safe Autonomous Driving: Current Challenges and Future Directions". *IEEE Transactions on Intelligent Transportation Systems*, 22(7), 2021, pp. 4316-4336.
10. Balaji, T. S., and S. Srinivasan, "Comparative study of different controllers in an autonomous vehicle system". *Materials Today: Proceedings*, 2021.
11. Halla-aho, Lauri, Nigussie, Ethiopia, and Jouni Isoaho, "Conceptual design of a trust model for perceptual sensor data of autonomous vehicles". *Procedia Computer Science*, 184, 2021, pp. 156-163.
12. Wang, Zi-jia, Chen, Xue-mei, Wang, Pin, Meng-xi, Li, and Zhang, Pin, "A decision-making model for autonomous vehicles at urban intersections based on conflict resolution". *Journal of advanced transportation*, 2021, pp.1-12.
13. Liu, Q., Li, X., Yuan, S. and Li, Z., "Decision-Making Technology for Autonomous Vehicles: Learning-Based Methods, Applications and Future Outlook". *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*, Indianapolis, IN, USA, 2021, pp. 30-37.
14. Guofa, Li, Yang, Yifan, Zhang, Tingru, Xingda, Qu, Dongpu, Cao, Cheng, Bo, and Keqiang, Li, "Risk assessment based collision avoidance decision-making for autonomous vehicles in multi-scenarios". *Transportation research part C: emerging technologies*, 122, 2021, no.102820.
15. Feng, X., Hu, J., Huo, Y. and Zhang, Y., “Autonomous Lane Change Decision Making Using Different Deep Reinforcement Learning Methods”. *19th COTA International Conference of Transportation Professionals, Nanjing, China,* 2019, pp. 5563-5575.
16. Lefevre, S., Carvalho, A. and Borrelli, F., "Autonomous car following: A learning-based approach". *IEEE Intelligent Vehicles Symposium (IV)*, Seoul, Korea (South), 2015, pp. 920-926.
17. Kassas, Z. Z. M., Maaref, M., Morales, J. J., Khalife, J. J., and Shamei, K., "Robust Vehicular Localization and Map Matching in Urban Environments Through IMU, GNSS, and Cellular Signals". *IEEE Intelligent Transportation Systems Magazine*, vol. 12, no. 3, pp. 36-52.
18. Bishop, R., "A survey of intelligent vehicle applications worldwide". *Proceedings of the IEEE Intelligent Vehicles Symposium, IEEE*, 2000, pp. 25-30.
19. Z. Li, C. Lu, Y. Yi and J. Gong, "A Hierarchical Framework for Interactive Behaviour Prediction of Heterogeneous Traffic Participants Based on Graph Neural Network". *IEEE Transactions on Intelligent Transportation Systems*, 23(7), 2022, pp. 9102-9114.
20. Li, Z., Gong, J., Lu C. and Yi, Y., "Interactive Behavior Prediction for Heterogeneous Traffic Participants in the Urban Road: A

Graph-Neural-Network-Based Multitask Learning Framework". *IEEE/ASME Transactions on Mechatronics*, 26(3), 2021, pp. 1339-1349.
21. Zhao, L., Ichise, R., Sasaki, Y., Zheng, Liu and Yoshikawa, T., "Fast decision making using ontology-based knowledge base". *IEEE Intelligent Vehicles Symposium (IV)*, Gothenburg, Sweden, 2016, pp. 173-178.
22. Turan, M. C., Hartavi A. E. and Altuğ, E., "Development of a rule based upper level control algorithm for a co-operative vehicle in automated highway system". *IEEE International Conference on Vehicular Electronics and Safety (ICVES 2012)*, Istanbul, Turkey, 2012, pp. 454-459.
23. F. Leon and M. Gavrilescu, "A review of tracking, prediction and decision making methods for autonomous driving". *Mathematics,* 9(6), 2021, pp. 37.
24. Fayyad, J., Jaradat, M., Gruyer, D. and Najjaran, H., "Deep Learning Sensor Fusion for Autonomous Vehicle Perception and Localization: A Review". *Sensors*, 20(15), 2020, pp. 4220.
25. S. Gibbs, Google Sibling Waymo Launches Fully Autonomous Ride-Hailing Service. Retrieved from https://www.theguardian.com/technology/2017/nov/07/google-waymo-announces-fully-autonomous-ride-hailing-service-uber-alphabet, -e Guardian, London, UK, 2017/11/07.
26. Zelinski, S., Koo, T. J. and Sastry, S., "Optimization-based formation reconfiguration planning for autonomous vehicles". 2003 IEEE International Conference on Robotics and Automation (Cat. No.03CH37422), Taipei, Taiwan, 3, 2003, pp. 3758-3763.
27. Urmson, C., Baker, J. C., Salesky Rybski, B. P., Whittaker, W., Ferguson, D. and Darms, M., "Autonomous driving in traffic:boss and the urban challenge". AI Magazine, 30(2), 2009, pp. 17–28.
28. Whittaker, H., Fan, Z., Liu, C. *et al.*, "Baidu apollo em motion planner". *Robotics*, 2018.
29. Wang P. and Chan, C.-Y., "Vehicle collision prediction at intersections based on comparison of minimal distance between vehicles and dynamic thresholds". *IET Intelligent Transport Systems*, 11(10), 2017, pp. 676–684.
30. Hubmann, C., Becker, M., Althoff, D., Lenz, D. and Stiller, C., "Decision making for autonomous driving considering interaction and uncertain prediction of surrounding vehicles". *IEEE Intelligent Vehicles Symposium (IV)*, Los Angeles, CA, USA, 2017, pp. 1671-1678.
31. Zhou, X., Wang, W., Wang, T., Lei, Y. and Zhong, F., "Bayesian Reinforcement Learning for Multi-Robot Decentralized Patrolling in Uncertain Environments". *IEEE Transactions on Vehicular Technology*, 68(12), 2019, pp. 11691-11703.
32. Zyner, A., Worrall, S. and Nebot, E., "A recurrent neural network solution for predicting driver intention at unsignalized intersections". *IEEE Robot. Automat. Let.,* 3(3), 2018, pp. 1759–1764.
33. Road vehicle video dataset is taken from https://www.kaggle.com/datasets/aryashah2k/highway-traffic-videos-dataset
34. Gupta, Shubham, and Kusum, Deep, "A novel random walk grey wolf optimizer". *Swarm and evolutionary computation*, 44, 2019, pp. 101-112.
35. Pierezan, J. and Dos Santos Coelho, L., "Coyote Optimization Algorithm: A New Metaheuristic for Global Optimization Problems". *IEEE Congress on Evolutionary Computation (CEC)*, Rio de Janeiro, Brazil, 2018, pp. 1-8.
36. Tanveer, M., Rajani, T., Rastogi, R., Shao, Y.H. and Ganaie, M. A., "Comprehensive review on twin support vector machines". *Annals of Operations Research*, 2021, pp. 1-46.
37. Veerasamy, V., Abdul Wahab, N. I., Othman, M. L., Padmanaban, S.K., Sekar, K., Ramachandran, R., Hizam, H., Vinayagam, A. and Islam, M. Z., "LSTM recurrent neural network classifier for high impedance fault detection in solar PV integrated power system". *IEEE Access*, 9, 2021, pp. 32672-32687.
38. Hamm, Charlie A., Wang, Clinton J., Savic, Lynn J., Ferrante, M., Schobert, I., Schlachter, T., MingDe, L. et al., "Deep learning for liver tumor diagnosis part I: development of a convolutional neural network classifier for multi-phasic MRI". *European radiology*, 29(7), 2019, pp. 3338-3347.
39. Jianhua, L. and Zhiheng, W., "A Hybrid Sparrow Search Algorithm Based on Constructing Similarity". *IEEE Access*, 9, 2021, pp. 117581-117595.
40. Mahdi, A., Talatahari, S. and Gandomi, A. H., "Fire Hawk Optimizer: A novel metaheuristic algorithm". *Artificial Intelligence Review*, 56(1), 2022, pp. 1-77.
41. Cheng, Y., Kui, H., Jun, W., Haiping, Z. and Xinyu, S., "A convolutional neural network based degradation indicator construction and health prognosis using bidirectional long short-term memory network for rolling bearings". *Advanced Engineering Informatics*, 48, 2021, 101247.
42. Refaat, K. S., Ding, K., Ponomareva, N., and Ross, S., "Agent Prioritization for Autonomous Navigation". *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Macau, China, 2019, pp. 2060-2067.
43. Guofa, Li, Shenglong, Li, Shen, Li, Yechen, Qin, Dongpu, Cao, Xingda, Qu, and Cheng, Bo, "Deep reinforcement learning enabled decision-making for autonomous driving at intersections". *Automotive Innovation*, 3(4), 2020, pp. 374-385.
44. Jaiswal, S. and Mohan, C. B., "A Survey: Privacy and Security to Internet of Things with Cloud Computing". International Journal of Control Theory and Applications, 10(1), 2017, pp.1-14