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An effective lane changing behaviour prediction model using optimized CNN and game theory

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ABSTRACT
Accurately predicting lane changes, a crucial driving activity for preventing accidents and ensuring driver safety, is addressed in this study. An innovative predictive model that integrates game theory for precise lane change intention detection and an optimized Convolutional Neural Network (CNN) for trajectory prediction is proposed in this study. The CNN's efficiency is enhanced through metaheuristic optimization of both the convolution and fully connected layers using the Whale Optimization Algorithm (WOA). Emphasizing robust data processing, a Wiener filter is applied for pre-processing, and the Cascaded Fuzzy C means (CFCM) technique is employed for segmentation. The resulting Whale Optimization Algorithm-based CNN (WOA-CNN) effectively forecasts the trajectory of lane-changing vehicles. Validation of the proposed approach in Python demonstrates exceptional accuracy, reaching 96.5%. This study showcases the effectiveness of the WOA-CNN model in advancing the prediction accuracy of lane-changing behaviour, contributing to enhanced driver safety and accident prevention.

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KEYWORDS
WOA-CNN; CFCM; weiner filter; game theory; lane change prediction

1. Introduction

Traffic accidents are mainly caused by the reckless and negligent nature of human drivers, especially in the form of over speeding, over taking, fatigue, distractions, rash driving and drunken driving. Moreover, eighteen percent of the traffic accidents are mainly due to lane changing, which is a prominent driving activity in terms of motorway driving. The lane changing process executed without caution results in an angled clash, side swap or rear end [1,2]. The process of lane changing is considered to be the most serious factor in terms of road safety, since it is the cause of many accidents, which ultimately impairs traffic flow stability. Technologies such as lane departure and blind spot warning systems are successful in preventing accidents only if the driver is capable of accurately using the turn signal lights [3]. Thereby the application of autonomous smart vehicles [4] has gained immense prominence in recent times because it overcomes human based driving errors. However, in order to enhance the commercialization of smart vehicles, ensuring safety in lane changing is deemed necessary [5].

A lane changing cycloid reference trajectory based double-layer steering controller is proposed in [6] for studying vehicle collision avoidance behaviour. In [7], the issues persisting around vehicle motion tracking are studied by developing a PID tracking controller, but its tracking accuracy is very low. The driving behaviour of drivers was studied by the scholars of the University of Michigan Transportation Research Institute by collecting the headway data of thirty-six driving elements [8]. The recognition and training processes were accomplished with the application of a Neural Network. This is one of the earliest known studies conducted for predicting driver behaviour, but its efficiency is limited due to the shortcomings in data and technology. The rapid technological advancements seen in the field of sensors and communication have in turn increased the availability of high qualityvehicle data. Additionally, connected vehicle technology aids in the creation of an environment where the concerned vehicles collaborates and function together by integrating factors such as sensing capabilities, processing power, vehicle-to-road communications and vehicle-to-vehicle communications [9–11]. The use of historical data in some of the recent behaviour prediction approaches is detrimental to its ability to alert the drivers about potential threats. Thus, the development of a real-time accurate networking data-based methods helps in prompt and precise determination of lane changing (lateral operation). Moreover, for accurate lane change prediction, the determination of lane changing intention, along with accurate trajectory estimation is deemed necessary. Recently, the application of deep learning techniques [12–14] for trajectory prediction has become increasingly popular. Many algorithm models such as

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the machine learning algorithm model, game theory model [15,16] and Hidden Markov Model (HMM) are used for resolving issues of evaluation, prediction and identification. In [17], Neural Networks are used for lateral motion prediction and it is possible to extend this to predicting lane change using SVM. The Long Short-Term Memory (LSTM) [18] technique is also prominently used for trajectory prediction; however, the most promising approach is to use CNN [19] for the prediction of lane change.

Existing methods for predicting lane-changing behaviour in the context of traffic accidents and autonomous driving suffer from several shortcomings. Firstly, the accuracy of trajectory prediction is often limited. These limitations can hinder the effectiveness of existing models in real-world scenarios where precise trajectory forecasting is crucial. Additionally, technologies such as lane departure and blind spot warning systems heavily depend on the driver's use of turn signals, introducing a reliance on human behaviour that may not always align with system requirements. Earlier studies also faced efficiency challenges due to limited data and technological constraints, impacting the overall efficacy of predicting driver behaviour. Some recent behaviour prediction approaches relying on historical data may introduce delays in responding to immediate threats, and integrating diverse algorithm models can pose challenges in terms of complexity and efficiency. These shortcomings underscore the need for more advanced, accurate and real-time methods to improve the reliability of lane-changing predictions and enhance overall road safety. By understanding and overcoming the shortcomings of existing methods, the survey aims to pave the way for the development and deployment of more effective and reliable lane-changing prediction systems, ultimately advancing road safety in the era of autonomous driving.

The primary focus of this study revolves around predicting lane-changing behaviour, a critical aspect of driving activity with significant implications for road safety and autonomous vehicle systems. The integration of Game Theory models the strategic interactions between vehicles during lane changes, capturing the decision-making dynamics of each vehicle as rational players in a game scenario. Furthermore, the study introduces an Optimized Convolutional Neural Network (CNN) enhanced by the Whale Optimization Algorithm (WOA) to improve trajectory prediction accuracy. The study's notable contribution lies in the synergy between Game Theory and Optimized CNN, combining strategic decision modelling with advanced trajectory prediction capabilities. This integration offers a holistic approach to understanding and forecasting lane-changing intentions, crucial for autonomous driving and road safety. The results of the study demonstrate the effectiveness of the proposed approach, which significantly contributes to the body of knowledge in the field of intelligent transportation systems and enhances the understanding of predictive modelling for complex driving behaviours.

2. Proposed system description

A predictive model for identifying a vehicles lane changing intention is proposed in this research work. The game theory is used for intention identification and a Stackelberg game model is developed by combining the data about the distance, acceleration, speed, lane number, etc. of the vehicles involved. The environmental intermittencies and data variations in the conventional lane changing model are resolved by obtaining dynamic interactions among vehicles. Moreover, it is also capable of identifying whether the current environmental condition is suitable for lane changing. The structure of the proposed predictive model for lane change detection is given in Figure 1. Moreover, here a wiener filter is used for pre-processing the input data owing to its capability of delivering an image of pristine quality with no variation in the image structure. The segmentation process is subsequently carried out using CFCM. The segmentation process is carried out in two stages using CFCM. For the predictive model to be effective in identifying the lane changing behaviour of a vehicle, an intention detection and trajectory prediction model is considered necessary. Thereby, a WOA-CNN is used for trajectory prediction in this work. The kernel of the convolution layer and the weights of the fully connected layer are optimized using whale optimization algorithm. Finally, the WOA-CNN successfully predicts the trajectory in which the vehicle intends to change lanes. It identifies if the vehicle is moving to the left lane or right lane or if it is staying in the current lane. Game Theory, with its focus on strategic interactions, models the decision-making dynamics between vehicles during lane-changing maneuvers. It considers each vehicle as a rational player making choices to maximize its payoff, taking into account the potential actions of others. On the other hand, the Optimized CNN, enhanced through metaheuristic techniques like WOA, serves as a powerful predictive engine. The CNN is adept at learning intricate spatial features from data, and the optimization algorithm fine-tunes its convolution and fully connected layers for improved performance. The integration of these two approaches aligns strategic decision-making, captured by Game Theory, with the precision and efficiency of CNN-based trajectory prediction. This amalgamation enables the model to not only comprehend the strategic aspects of lane changing but also optimize its predictive capabilities, resulting in a robust and accurate system for anticipating lane-changing intentions in real-world driving scenarios.

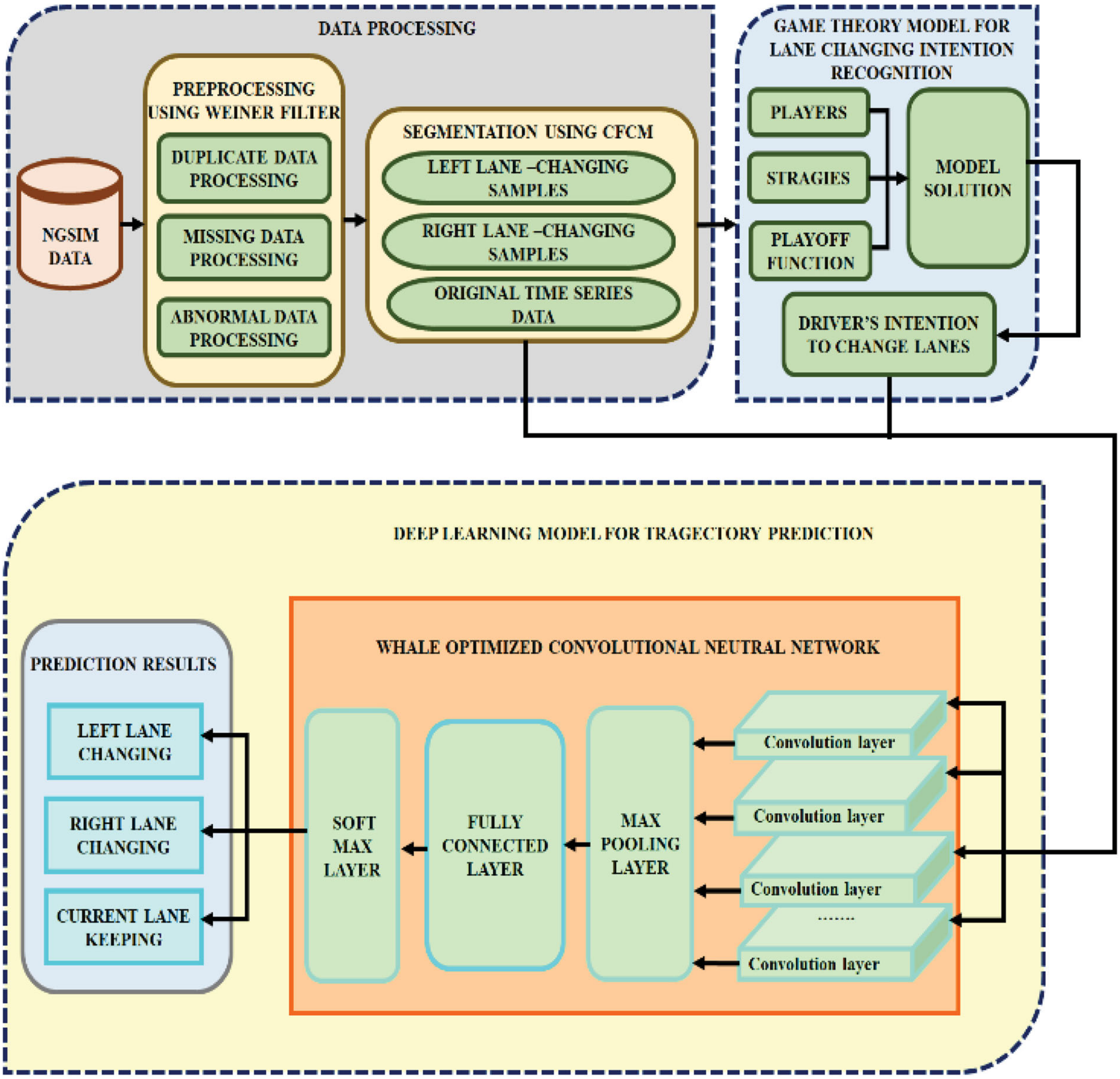

Figure 1. Structure of the proposed predictive model for lane changing.

3. Proposed system modelling

3.1. Image preprocessing using weiner filter

The irrelevant noise components in the input data are removed using wiener filter, thus ensuring that an image of enhanced quality is obtained for further processing. The wiener filter is an effective filter in terms of elimination of high frequency elements and noises along with significant minimization of mean square error. Its ability to deliver an image of utmost clarity without any variation in the image structure, accredits to its choice as an effective filter for pre-processing. This statistical approach based low pass filter is an adaptive filter that obtains optimum balance in bias-variance trade off. In a neighbourhood, it estimates the variance and mean and subsequently for lower variation applies stronger smoothening and for higher variation applies minimal smoothening. The error measure is given as,

$$e^2 = E\left\{(f - \hat{f})^2\right\} \tag{1}$$

where, the estimated image and uncorrupted image are specified as $\hat{f}$ and f respectively, while the expected value of argument is specified as $E\{.\}$. Thus by determining quadratic error function minimum value, the estimated image $\hat{F}(u, v)$ is obtained.

$$\hat{F}(u, v) = \left[\frac{H^*(u,v)S_f(u,v)}{S_f(u,v)|H(u,v)|^2 + S_f(u,v)} \right] G(u, v) \tag{2}$$

The above equation is derived in the frequency domain and both the image and noise are assumed to have a zero mean along with being uncorrelated. Here u, v represent the spatial frequency variables used in the Fourier domain. Moreover, liner function is used for degradation of estimated image intensity levels. The transform of degraded image and degradation function are specified as $G(u, v)$ and $H(u, v)$ respectively, $H^*(u, v)$ is the complex conjugate of $H(u, v)$. The non-degraded image's power spectrum is,

$$S_f(u, v) = |F(u, v)|^2 \tag{3}$$

$$\hat{F}(u,v) = \left[\frac{1}{H(u,v)}\frac{|H(u,v)|^2}{|H(u,v)|^2 + S_\eta(u,v)/S_f(u,v)}\right] \times G(u,v) \tag{4}$$

where, the noise power spectrum is represented as,

$$S_\eta(u,v) = |N(u,v)|^2 \tag{5}$$

Here, $N(u,v)$denotes the Fourier transform of the noise in frequency domain. For images that are affected by constant power additive noise, the application of wiener filter is the most preferred solution. The pre-processed images obtained as output from wiener filter then undergo segmentation using CFCM.

3.2. CFCM based image segmentation

The pre-processed input is segmented using CFCM, where clusters c is based on the minimization of a quadratic function. The following definition gives the optimal solution to minimize:

$$J_{FCM} = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m ||x_k - v_i||_A^2 = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m d_{ik}^2 \tag{6}$$

Here the input datas are specified as x_k and is given by $k = 1, 2, 3, \ldots, n$, the centroid or prototype value is represented as v_i, cluster element as i where $i = 1, 2, \ldots, c$, d_{ik}denotes distance between x_k and v_i, fuzzy membership function as $u_{ik} \in [0, 1]$ and fuzzification parameter as $m > 1$. Since FCM employs a probabilistic partition, any input vector x_k fuzzy memberships with respect to courses satisfies the probability constraint $\sum_{i=1}^{c} u_{ik} = 1$. The optimum values are found by iterations utilizing zero gradient criteria and Lagrange multipliers, and are then estimated as follows:

$$u_{ik}^* = \frac{d_{ik}^{-2/(m-1)}}{\sum_{j=1}^{c} d_{jk}^{-2/(m-1)}} \quad \begin{matrix}\forall\, i = 1\ldots c\\ \forall\, k = 1\ldots n\end{matrix} \tag{7}$$

$$v_i^* = \frac{\sum_{k=1}^{n} u_{ik}^m x_k}{\sum_{k=1}^{n} u_{ik}^m} \quad \forall\, i = 1\ldots c \tag{8}$$

Here, u_{ik}^* denotes the optimal fuzzy membership value whereas v_i^* denotes the optimal centroid of clusters. As part of the FCM algorithm's alternating optimization approach, Equations (7) and (8) are performed alternately until cluster prototypes settle. This criterion for terminating compares the sum of the norms of variations of prototype vectors v_i inside the most recent iteration with a minimal threshold value set ε.

3.2.1. Cascaded fuzzy C-Mean

The fundamental objective of the FCM cascaded algorithm is to efficiently separate homogeneous zones in the volume. Further, it separates aberrant from normal images using decision support based on earlier information. FCM frequently positions the cluster prototypes in regions with a high density of adjacent input vectors. In order to offer accurate clustering, it should be able to initialize a cluster prototype in close vicinity to each of these accumulation sites in the 4D colour space. Evidently, this is untrue. Even if we managed to accomplish this in some way, the hundreds of clusters and millions of input vectors, make clustering a very computationally intensive process. The suggestion is to perform FCM in two steps in order to prevent this scenario. The first stage assists in eliminating the majority of input data, namely those vectors that are far from the full range of abnormal intensities that stored in an image. Only extracted features with intensities that are somewhat similar to the affected patterns are present in the second stage. To distinguish between abnormal clusters and normal clusters, the second stage's cluster prototypes are individually examined.

In the first stage, the entire set of extracted features is applied with fuzzy c-means. The clusters vary between 8 and 16. At the moment when the first stage is ready, the features are classified into c-clusters and the clusters are specified as prototype v_i. The decision support system examines each of these cluster prototypes independently before determining whether or not it suspects them of carrying abnormalities in the image. The latter stages do not include clusters whose centroid vector is far from the intensity of the image. At this point, the decision support typically preserves up to three clusters attained from first FCM. The second step of cascaded FCM uses the remaining n' features, or more accurately, the collection of extracted features that represent them, as input data. Next time, the FCM is applied with c' clusters varying between 8 and 16. The decision-support system rechecks final cluster prototypes. This time, any clusters with prototypes close to affected intensities will be classified as positive, while all others will be classified as negative. The components of fuzzy changes from stage to stage, which is denoted as m and m' the exponents used in the first and second stages.

3.2.2. FCM initialization

The prototype activation of FCM algorithm is extremely important, especially in multi-dimensional problems. In general, it is best to try positioning initial cluster prototypes far from one another, perhaps in input vector accumulation areas. High variability between various runs is produced by input vectors that were chosen randomly. So a stable solution requires a deterministic rule. An initial of 16 sets of potential cluster seeds with 4-dimensional hypercube is produced by the algorithm. The scalar data of FCM clustering $\log(x_1^{(d)}), \log(x_2^{(d)}) \ldots \log(x_n^{(d)})$ is accomplished in every $d\epsilon\{T1, T2, T1C, FLAIR\}$ dimension. The output obtained using two prototypes clusters is specified as

$v_1^{(d)}$ and $v_2^{(d)}$.

$$w_{1\ldots16} = \begin{bmatrix} v_1^{(T1)} or v_2^{(T1)} \\ v_1^{(T2)} or v_2^{(T2)} \\ v_1^{(T1C)} or v_2^{(TIC)} \\ v_1^{(FLAIR)} or v_2^{(FLAIR)} \end{bmatrix} \tag{9}$$

The representation of average square distance is expressed by,

$$\Delta(w_i) = \sum_{k=1}^{n} x_k - w_i^2 \tag{10}$$

Here, x_k indicates the input data point and w_i indicates i^{th} prototype of cluster seed. For each stage of cascaded FCM, potential cluster seeds w_i, $i = 1, 2, \ldots 16$ are organized in ascending order depending on $\Delta(w_i)$ values, and the initial cluster prototype is assigned as first c seeds.

3.3. Game theory model for lane-changing intention prediction

The game theory model is used for predicting the intention of the driver to change lanes and active lane-changing behaviour is examined in this study. Game theory, rooted in the analysis of strategic interactions among rational decision-makers, proves to be a suitable framework for modelling the intricate decision-making dynamics involved in lane-changing scenarios. By treating each vehicle as a rational player making decisions to maximize its payoff, the model captures the complex interplay of factors influencing lane-changing behaviour. This background sets the stage for a more nuanced understanding of the dynamics at play, paving the way for a predictive model that goes beyond conventional approaches, thereby contributing significantly to the domain of intelligent transportation systems. The adoption of this model for lane-changing intention prediction presents notable advantages in the realm of road safety and autonomous driving systems. Game theory excels at modelling the strategic interactions and decision-making processes of multiple intelligent entities, such as vehicles on the road. By framing lane-changing as a strategic game, the model accounts for the dynamic interplay between vehicles, acknowledging that each decision impacts others. The inclusion of payoff considerations, particularly related to safety and spatial factors, enhances the accuracy of predicting lane-changing intentions by evaluating the perceived benefits and risks for each vehicle. Furthermore, the model's adaptability to changing environments and encouragement of collaborative decision-making contribute to a more harmonized approach to lane changing, fostering safer and more efficient driving scenarios. Overall, the game theory model provides a comprehensive framework that considers the intricacies of multi-agent decision-making, contributing to the advancement of predictive models for lane-changing in autonomous and connected vehicle environments. This model entails three factors including the players, their techniques and the corresponding payoffs of those techniques. In this model all the players are assumed to be intelligent and it aims to increase the profit of every player in response to a specific strategy devised by the opponent. The players (drivers) are not subjected to strict restrictions and they base their decisions in accordance with the knowledge obtained by monitoring neighbouring vehicles. While making a decision about changing lanes, the driver has to consider the position of the leading vehicle (V3) in its lane, leading (V2) and the trailing vehicles (V1) in the adjacent lane in addition to the position of his/her own vehicle (SV) as seen in Figure 2. Among all these vehicles, the one with the highest impact on the position of SV is V1, so it is assumed that both of them are in game relationship. The two options that are available for SV are to either remain in the current lane or shift to the adjacent lane.

3.3.1. Lane-change behaviour

The four phases that make up a vehicle's lane-change behaviour are described as follows.

- Generation of Lane Change Intention:

This phase involves the initiation of a driver's intention to change lanes. Drivers decide to change lanes based on various factors, such as traffic conditions, speed, the behaviour of surrounding vehicles and the driver's destination. In the presented model, the generation of lane change intention is implicit in the decision-making process initiated by SV. SV considers information from neighbouring vehicles, such as V1, V2, and V3, to determine whether a lane change is warranted.

- Judgment of Lane Change Conditions:

Drivers assess the feasibility and safety of changing lanes during this phase. Critical factors include the positions and behaviours of surrounding vehicles, the available space in the target lane, and the current speed of the subject vehicle. The game model explicitly considers safety and spatial conditions in the determination of payoffs (U_{safety} and U_{space}). The decision-making process involves evaluating the time headway, spatial distance, and potential impact on safety during a lane change.

- Selection of Lane Change:

Once a driver decides to change lanes, they need to choose the specific lane and execute the maneuver. The driver considers the desired lane, the relative speed

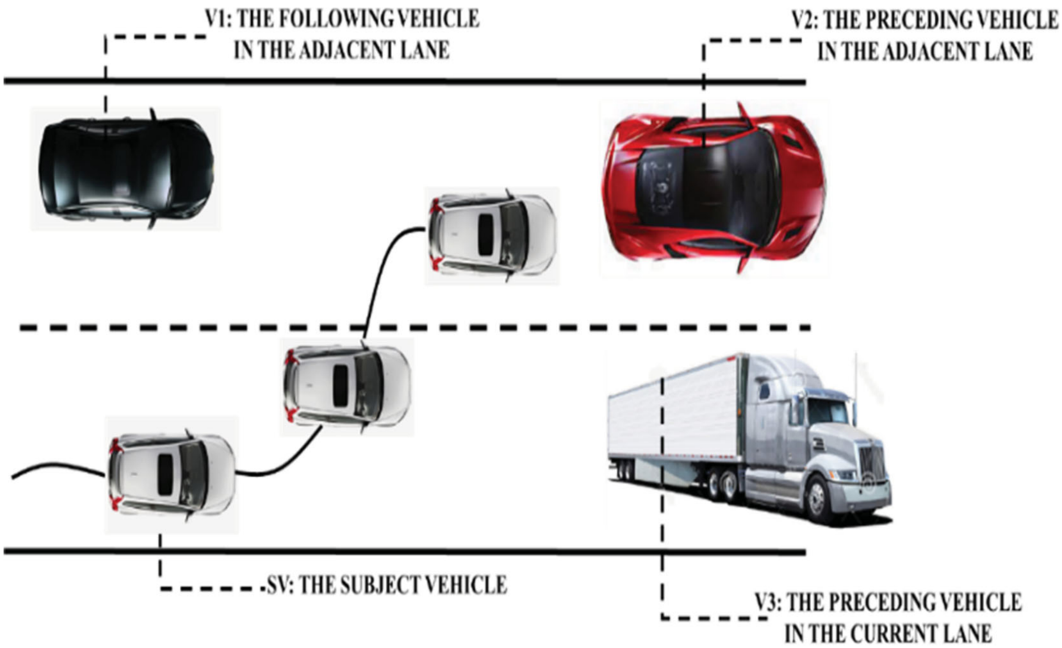

Figure 2. Schematic representation of lane changing vehicles.

of vehicles in the adjacent lanes, and the gap between vehicles for a safe lane change. While not explicitly stated, the model inherently involves the selection of lane change through the decisions made by the SV and V1. The optimization process aims to find the optimal strategy for both SV and V1, influencing the selection of lane change actions.

- Implementation of Lane Change:

This phase involves the actual execution of the lane change maneuver by the driver. The driver needs to smoothly merge into the target lane, adjusting speed and position to ensure a safe transition. The continuous circulation of information between SV and V1 represents an ongoing interaction until both players reach a satisfactory outcome. This can be seen as the implementation phase, where decisions are communicated and adjusted iteratively until equilibrium is reached. Table 1 lists out the lane changing intention recognition features.

Table 1. Lane-changing intention recognition feature.

Lane-changing intention recognition feature	Description
Generation of Lane Change Intention	Initiation of a driver's intention to change lanes based on factors such as traffic conditions, destination, and surrounding vehicle behaviour.
Judgment of Lane Change Conditions	Assessment of the feasibility and safety of lane changing, considering factors like time headway, spatial distance, and potential impact on safety.
Selection of Lane Change	Decision-making on the specific lane to change into, considering factors like desired lane, relative speeds, and the gap between vehicles for a safe maneuver.
Implementation of Lane Change	Execution of the lane change maneuver, involving the actual transition into the target lane, adjusting speed, and ensuring a smooth merge.
Game Theory Model Integration	Implicit consideration of these features through the Stackelberg game model, where SV and V1 iteratively make decisions based on safety and spatial considerations.

3.3.2. Lane-changing recognition model

The Lane-Changing Recognition Model aims to integrate the principles of game theory to accurately recognize when a driver intends to change lanes. The explanation of the key components and considerations related to the Lane-Changing Recognition Model are given below:

- Data Input:

The model takes input data from various sensors and sources, including information about the SV and surrounding vehicles (e.g. V1, V2, V3). This data typically includes details such as distance, acceleration, speed, lane number and environmental conditions.

- Game Theory Integration:

The recognition model integrates game theory principles, particularly the Stackelberg game model, to model the decision-making process among intelligent players (drivers). The players' decisions are influenced by factors like safety payoffs, spatial distance and strategic interactions.

- Decision Variables:

The Lane-Changing Recognition Model considers decision variables introduced by the SV during the lane-changing process. These variables are part of the optimization problem within the Stackelberg game model.

- Continuous Interaction:

The Lane-Changing Recognition Model acknowledges the continuous circulation of information between SV and V1 until both players reach satisfaction in the game. This ongoing interaction reflects the iterative nature of the decision-making process.

- Recognition Features:

The model considers recognition features related to the generation of lane change intention, judgment of lane change conditions, selection of lane change and the continuous process of implementation. These features are essential for accurately identifying and predicting lane-changing behaviour.

- Output Prediction:

The Lane-Changing Recognition Model outputs predictions regarding the likelihood of a lane change, the preferred direction of the lane change (left or right), or the decision to stay in the current lane. These predictions are based on the optimized strategies derived from the game theory model.

If vehicle V1 predicts the lane changing decision of SV, it has the choice of either deaccelerating or accelerating or remain staying in its present lane. Equation (11) is used to express the strategic space of these drivers,

$$\begin{aligned} SV &: \Phi_1 = \{C: \ changelanes, \ S: stay\}, \\ V1 &: \Phi_2 = \{K: \ keepstate, \ D: deceleration, \\ &\qquad A: acceleration\} \end{aligned} \tag{11}$$

Here "Φ" signifies the strategic space available, "τ" denotes the distinct choices made by the vehicles, and "U" and "u" represent the benefits accrued to the SV and V1, respectively, from their selected strategies. Specifically, "U_{11}" is the benefit to the SV for opting to change lanes, while "u_{11}" is the benefit to V1 for maintaining its current state. Both vehicle operators aim to optimize their outcomes by making informed choices that maximize their benefits, which is a fundamental principle in game theory. The determination of these benefits in this study hinges on evaluating safety and spatial considerations, represented as U_{safety} and U_{space}, respectively. Table 2 represents the payoff matrix and

Table 2. Payoff matrix.

SV	V1: Keep (K)	V1: Decelerate (D)	V1: Accelerate (A)
Change Lane (C)	U_{11}, u_{11}	U_{21}, u_{21}	$U_{31} u_{31}$
Stay in Lane (S)	U_{12}, u_{12}	U_{22}, u_{22}	U_{32}, u_{32}

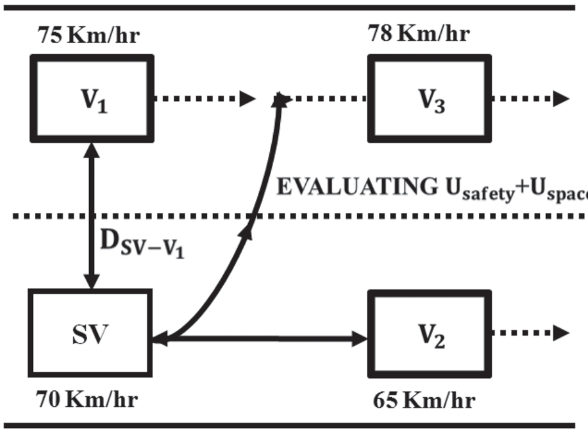

Figure 3. A sample illustration of vehicle track parameters.

Figure 3 indicates a sample illustration of vehicle track parameters.

During lane-changing process, the payoff obtained for being safe is,

$$U_{safety} = \begin{cases} \frac{2|T(t)|-T_{min}(t)}{T_{min}(t)}, & -T_{min}(t) \le T(t) \le T_{min}(t) \\ 1, & else \end{cases} \tag{12}$$

Where, the time headway during lane changing between the current vehicle and the competing vehicle is specified as T (t), the minimum safe time headway that ensures the safety of the concerned drivers is specified as $T_{min}(t)$.

$$T_{min}(t) = min(T_{initial}, T_a) \tag{13}$$

where, $T_a = 3$, and the headway between V1 and V2 at time t is specified as $T_{initial}$. In order to prevent accidents, a headway of at least 3s has to be maintained. During lane changing process, the payoffs with respect to the spatial distance is represented as U_{space},

$$U_{space} = \begin{cases} \frac{2|D(t)|-D_{min}(t)}{D_{min}(t)}, & -D_{min}(t) \le D(t) \le D_{min}(t) \\ 1, & else \end{cases} \tag{14}$$

Where, the conflicting vehicle's spatial distance is specified as D (t), $D_{min}(t)$ is the minimum safe distance that needs to be maintained between the subject vehicle and the conflicting vehicle at time t. At normal driving conditions, the minimum safe distance required to be maintained is,

$$\begin{aligned} D_{min}(t) = max \Bigg(& \int_0^t \int_0^\lambda (a_{V1}(\tau) - a_{SV}(\tau)) d\tau d\lambda \\ & + (\nu_{V1}(0) - \nu_{SV}(0))t \Bigg) \end{aligned} \tag{15}$$

Where, the vehicle V1's longitudinal velocity and acceleration are specified as ν_{V1} and a_{V1} respectively, while the longitudinal velocity and acceleration are specified as ν_{SV} and a_{SV} respectively. The total payoff is estimated

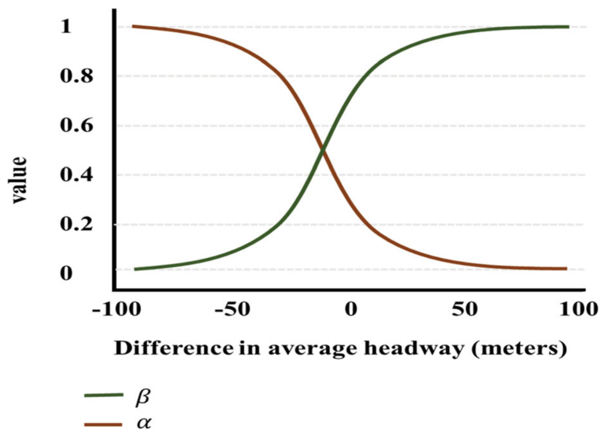

Figure 4. Space payoff and safety payoff weight coefficients.

as,

$$U_{total} = \alpha U_{safety} + \beta U_{space} \quad (16)$$

Here, the weight coefficients are referred as α and β. The driver's space headway over the entire road section is compared to the other vehicle's average space headway within a 100-meter range and then a sigmoid function is used to process the space headway difference to obtain each driver's space weight coefficient. It is estimated as,

$$\beta = \frac{1}{1 + e^{-(|l-l_{ave}|/20)}} \quad (17)$$

Here, the target vehicle's average headway is represented as l and the average headway of nearby vehicles is specified as l_{ave}. The weight coefficients are represented as functions of difference in Figure 4. The optimal strategy is obtained by introducing the estimated total payoff in the game model. On analysing the driving environment, the SV initially gives decision variables during lane changing. On the basis of these decision variables, the vehicle V1 provides an optimal response and returns the decision to SV. The continuous circulation of information takes place untilsatisfaction is reached by both players of the game.

The optimization problem of this Stackelberg game model at perpetual equilibrium is expressed as,

$$\begin{cases} \tau_1^* = argmax(U(\tau_1, \tau_2)), \tau_2 \in \Phi_2^{'}(\tau_1), \tau_1 \in \Phi_1 \\ \tau_2^* = argmax(u(\tau_1^*, \tau_2)), \tau_2 \in \Phi_2 \\ \Phi_2^1(\tau_1) \triangleq \{\tau_2^{'} \in \Phi_2 : u(\tau_1, \tau_2^{'}) \\ \qquad \geq u(\tau_1, \tau_2) \forall \tau_2 \in \Phi_2, \tau_1 \in \Phi_1\} \end{cases} \quad (18)$$

Equation (18) is subject to $v_{SV}, v_{V1} \geq 0$ and $a_{min} \leq a_{SV}, a_{V1} \leq a_{max}$. Moreover, the decision of SV and V1 is represented as $\tau_1 \in \Phi_1$ and $\tau_2 \in \Phi_2$ respectively. The set of choices available for V1 is specified as $\Phi_2'(\tau_1)$. The best decisions of both V1 and SV are specified as τ_2^* and τ_1 respectively. The payoff values of every decision and current decision are used to determine the probability of lane changing.

3.4. Trajectory prediction using whale optimization algorithm based CNN (WOA-CNN)

After predicting the lane changing intention using the game theory model, the lane changing trajectory is predicted using WOA-CNN. The WOA-CNN is effective in extracting the important lane changing related data segments. The utilization of Trajectory Prediction using WOA-CNN offers a significant advantage in enhancing the accuracy and efficiency of trajectory forecasting in the context of lane-changing. The integration of WOA optimizes both the convolutional layer and fully connected layer of the CNN, contributing to improved model performance. WOA, as a metaheuristic algorithm, aids in finding optimal solutions by simulating the social behaviour of whales. This optimization technique enhances the learning capabilities of the CNN, allowing it to better capture complex patterns and dependencies in the trajectory data. The algorithmic optimization not only bolsters the accuracy of trajectory predictions but also facilitates quicker convergence, making it well-suited for real-time applications in autonomous driving. This approach demonstrates the potential to significantly advance the capabilities of trajectory prediction systems, ultimately contributing to safer and more reliable autonomous vehicle navigation.

The structure of WOA-CNN is given in Figure 5. In order to improve the accuracy of CNN in trajectory prediction, the WOA is used for tuning the kernel values of the convolution layer and optimizing the weights of the fully connected layer. Game theory focuses on strategic interactions between players, while optimization, in this work, is applied to enhance the efficiency of the CNN model. Both contribute to the overall effectiveness of the lane-changing prediction system but operate at different levels of decision-making and problem-solving. Game theory models the strategic decisions of intelligent entities, whereas optimization fine-tunes parameters to improve the performance of CNN. The visual cortex cells of the human brain are the inspiration behind the development of this effective supervised learning approach. Moreover, it is structured in such a way that each of its layers is completely connected to its adjacent layers. It is one of the most preferred choices in many applications, owing to its capacity to resolve the issue of overfitting as well as its swift high dimension feature detection capability.

The convolution layer, max pooling layer, fully connected layer and softmax layer, together constitutes the CNN architecture. The prominent input features required for trajectory prediction are extracted in the convolution layer. The kernels (weights) of this layer are optimized using WOA. The maxpooling layer aids in the minimization of calculation complexity, without compromising any vital information. It mainly minimizes the computational complexity by reducing the

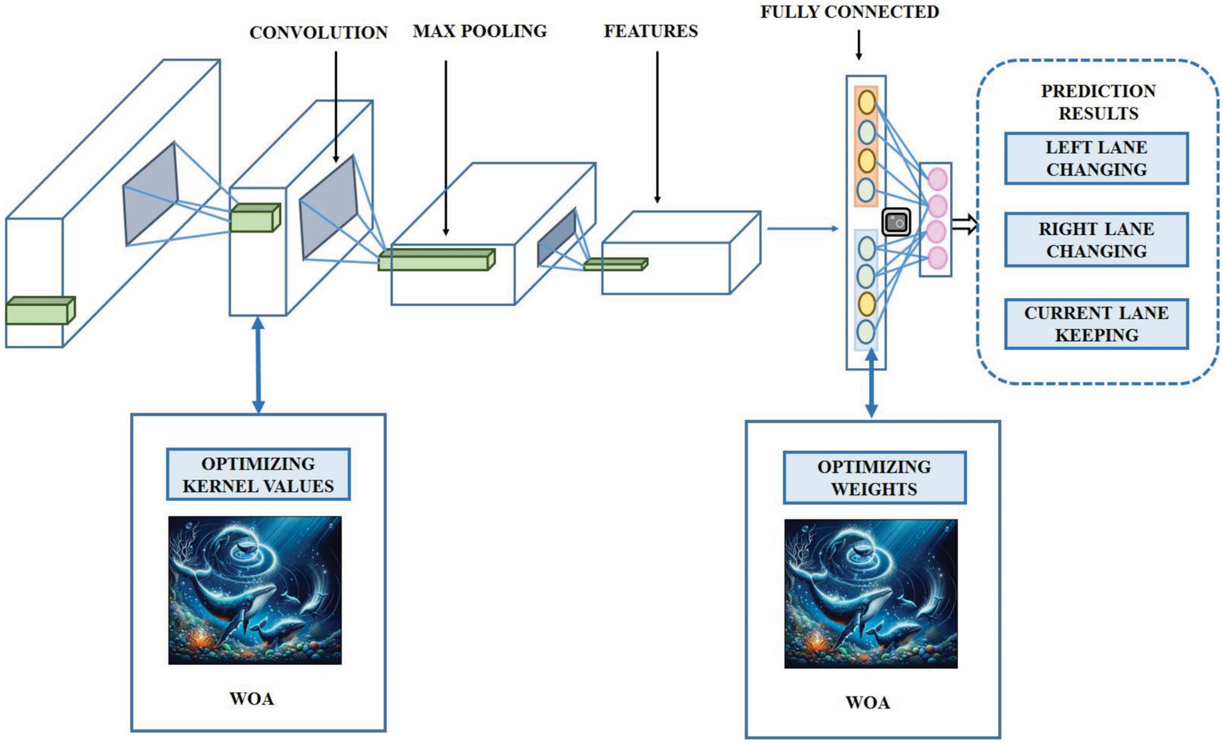

Figure 5. WOA-CNN architecture.

dimension of its prior layer's output. After undergoing a series of convolution and max pooling layers, the final output obtained from these layers is flattened and provided as input to the fully connected layer. This layer is effective in predicting the best label for describing the given input and its weights are tuned using WOA. Finally, the trajectory of lane changing vehicle is predicted by the softmax layer.

3.4.1. Whale optimization for convolution layer and fully connected layer

The hunting technique used by the whales is the inspiration behind the development of WOA [19]. It is an evolutionary technique; hence it aims at identifying the global optimum solution using a random population set. The term candidate solution is an alternate term referring to the population set. The WOA continuously improves and updates its solution, till the optimal value is obtained. Its distinct way of creating rules and updating solutions, sets it apart from other available meta-heuristic approaches. The hunting technique of whale, which influenced the development of WOA, involves trapping their prey in a bubble net before hunting. The mathematical representation of the bubble net is,

$$X(t+1) = \begin{cases} X^*(t) - ADp < 0.5 \\ D'e^{bl}cos(2\pi t) + X^*(t)p \geq 0.5 \end{cases} \quad (19)$$

$$D' = |CX^*(t) - X(t)| \quad (20)$$

$$A = 2ar - a \quad (21)$$

$$C = 2r \quad (22)$$

Where, the terms r and p refers to random constants within [0, 1] and the random constant within [−1, 1] is given as l. The number of iterations is represented by t and the distance for the best solution is given by D'. $X(t+1)$indicates the updated position of the whales in the population at the next iteration $(t+1)$, $X^*(t)$ denotes the current best known position, A is the parameter that determines the distance of a whale from its prey, D denotes a random vector that is uniformly distributed in the range [0,1], b is the parameter that influences the shape of the bubble net, p denotes a random number between 0 and 1, C indicates a constant parameter that influences the distance calculation. A random population is initially considered and for every iteration, the solutions are updated in order to mathematically model bubble net hunting and prey encircling. Here, in order to heighten the accuracy of CNN in trajectory prediction, the filter values are tuned in both the convolution layer and fully connected layer using WOA. The parametric optimization is achieved by providing the WOA with orderly arranged weights and filter values. The weights are given to the module containing the replica of the model, where the fitness or accuracy is evaluated by copying each weight. The entire process is given in the form of a flowchart in Figure 6. In order to make the algorithm more compatible with CNN, the following modifications were made:

- The single point in space is replaced with n-dimensional individual length.

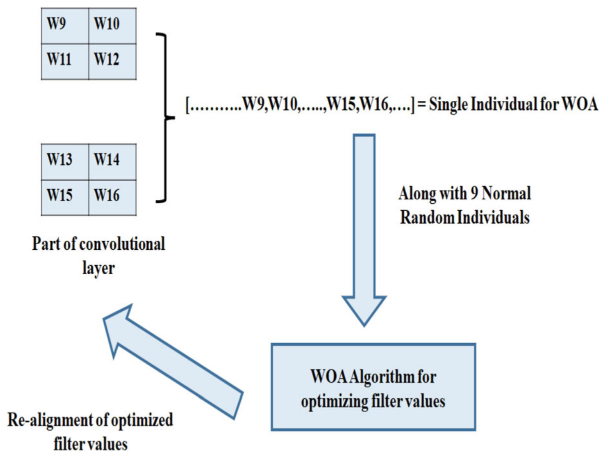

Figure 6. Work flow of WOA optimization.

- The parameters are transformed into an n-dimensional array and the individual size controls the value of n.
- The forward network evaluation is contained within the objective function.

The flowchart of the WOA-CNN is given in Figure 7. Thus, the trajectory of lane changing is predicted successfully using WOA-CNN. The proposed concept makes significant contributions to the entire lane-changing process by enhancing the following aspects.

- **Desire to Change the Current Lane** – The integration of game theory into the model allows for a more nuanced understanding of the drivers' decision-making process when considering a lane change. By incorporating strategic interactions between drivers, the model captures the desire to change lanes as a result of optimizing payoffs, considering safety, and spatial distance.
- **Target Lane Selection** – The proposed model contributes to target lane selection by utilizing the WOA to optimize both the convolutional and fully connected layers of the CNN. This optimization process enhances the efficiency of the CNN in predicting trajectories, thereby aiding in the precise selection of the target lane.
- **Ensuring Lane Change Feasibility** – Through the utilization of a Wiener filter for pre-processing and CFCM technique for segmentation during data processing, the proposed model addresses environmental intermittencies and data variations. This ensures that the lane change process is executed in consideration of the surrounding conditions, making it more feasible and safer.
- **Decision to Change Lane Based on Gap Acceptance** – The game theory model explicitly incorporates payoffs related to safety (U_{safety}) and spatial distance (U_{space}) during the decision-making process. The consideration of these payoffs contributes to a more informed decision to change lanes based on gap acceptance. The optimization of the game model helps in determining the optimal strategy for

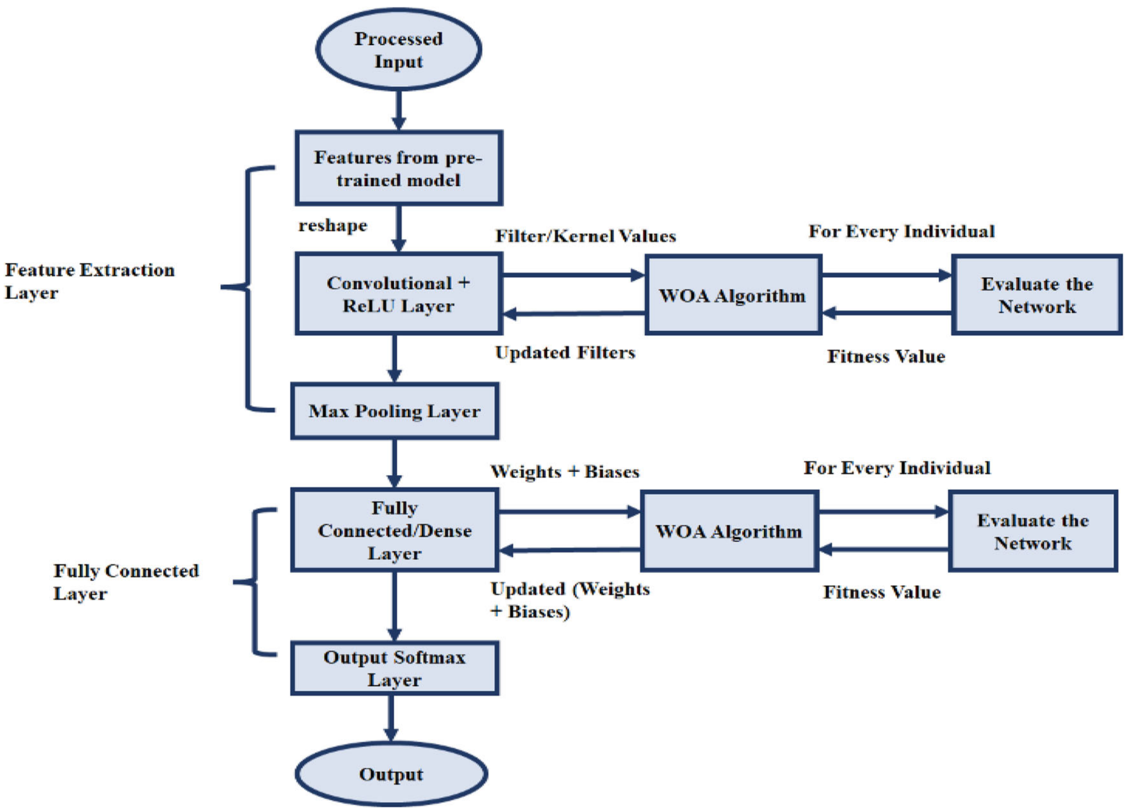

Figure 7. Flowchart of WOA-CNN.

both the subject vehicle and the competing vehicle, leading to improved decisions related to gap acceptance.

Generally, autonomous vehicles operate in dynamic environments where interactions with other vehicles are crucial. Integrating game theory allows autonomous vehicles to make strategic decisions considering the actions of other intelligent entities on the road. The use of optimized CNN is beneficial for processing sensor data and predicting lane-changing trajectories accurately. This contributes to the decision-making process by providing a reliable understanding of the surrounding environment, enabling the autonomous vehicle to anticipate and respond to lane-changing intentions. In autonomous driving, continuous learning and adaptation to changing road conditions are essential for effective decision-making. The optimization component contributes to the adaptability of the autonomous system.

4. Results and discussion

In order to ensure the accurate detection of lane changing behaviour, the selection of a proper dataset is crucial. Accordingly, a dataset including high quality time series data on continuous vehicle states is preferred, while also taking into account the interactions of vehicles with one another. The selected dataset is also required to have several vehicle states such as, acceleration, speed and coordinates. Thereby, the Next Generation Simulation (NGSIM) is selected as the dataset in this work. The dataset includes data about 2706 cars and the statistical description of the dataset is provided in Table 3. The simulation model for the proposed work is developed in Python and the effectiveness of the proposed approach in detecting vehicle lane changing behaviour is ascertained.

On the basis of the vehicle ID, the dataset is preprocessed using weiner filter and segmented using CFCM. The coordinate distribution of vehicles in every lane is computed in order to estimate the centre line of every lane. Then, in accordance with the vehicle trajectory from the centre line, the lane changing of vehicles is determined. Moreover, a sample is obtained by slicing the vehicle's lane changing behaviour segment. Finally, from 1243 vehicles, 1698 samples are obtained as the verification and training sample sets. Among the total samples, 1188 samples are left lane-changing and 510

Table 3. Dataset statistical description.

Variable	Max	Min	Standard Deviation	Mean
Time headway (s)	29.42	0	2.09	2.74
Space headway (m)	52.68	0	9.43	19.76
Acceleration (m/s^2)	2.36	−3.12	1.39	0.06
Speed (m/s)	29.15	0	4.16	9.25

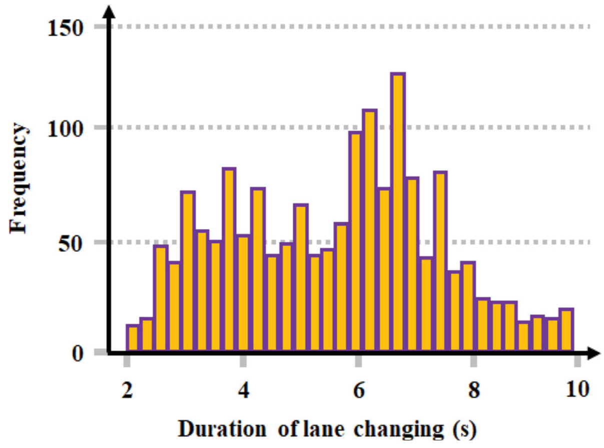

Figure 8. Lane-changing duration.

samples are right lane changing. Figure 8 illustrates the duration of the segments, from which it is observed that almost every vehicles travelled away from the centre line of one lane and towards the centre line of the adjacent lane within 3-7s. During lane changing, the acceleration and speed of the vehicle are illustrated in Figure 9.

After undergoing the wiener filter based preprocessing and CFCM based segmentation, the obtained processed data is subsequently sent for training. Initially, the vehicles within a specified range (100m), that have an impact on the SV are identified according to the relative position and ID of the SV. Then, for every vehicle the payoff value is determined using game theory model. The vehicle lane changing possibility, which is obtained as an output of the game theory model is added to the vehicle driving state data as a data dimension.

Figure 10 represents the comparison for game theory model with respect to average speed and number of passed vehicles in which the game theory aids in the generation of improved outputs. The segmented samples and lane changing possibility data are given as input to the WOA-CNN. Among the total samples, the verification samples are 30%, while the training samples are 70%. The WOA-CNN predicts lane changing behaviour in real time. Moreover, the input given to the WOA-CNN includes the game theory model output, steering angle, headway, time headway, longitudinal acceleration, longitudinal velocity, lateral acceleration and lateral velocity. The convolution step is unity and the kernel is 3×3 matrix in the convolution layer. Furthermore, the batch size is 8, the time step is three and the learning rate is 0.001. The WOA is used to optimize the model. An outstanding prediction accuracy of 96.5% is obtained as seen in Figure 11(b).

The effectiveness of the game theory in improving the accuracy of CNN in determining lane changing behaviour is also verified. Hence, the proposed model is validated for its accuracy without the application of

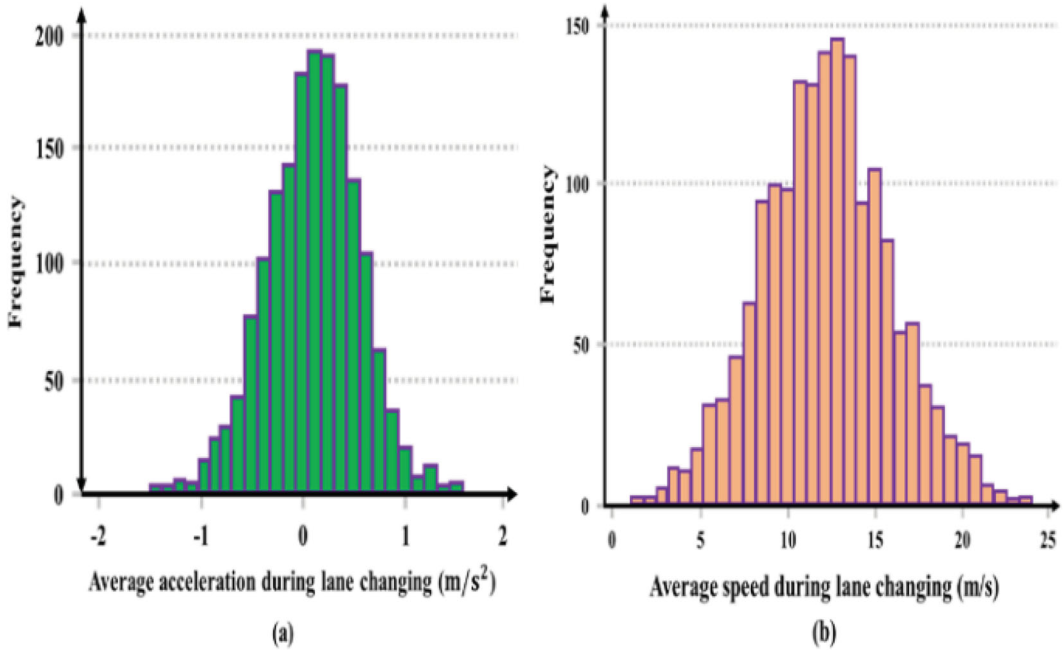

Figure 9. During lane changing (a) Acceleration and (b) Speed.

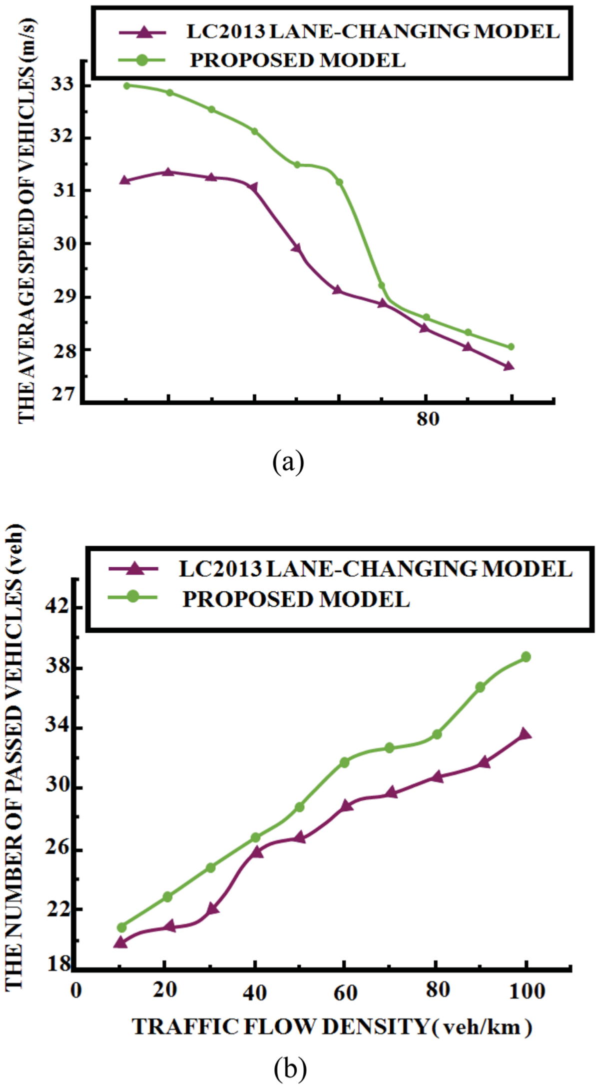

Figure 10. Comparison of game theory model for (a) average speed (b) number of passed vehicles.

game theory. From Figure 12, it is noted that the prediction accuracy of WOA-CNN reduces substantially to around 86% without the application of game theory. Thus, it is concluded that the game theory significantly heightens the accuracy of the deep learning technique in predicting lane changing.

Moreover, the proposed model only takes 0.15s in advance to warn the neighbouring vehicles about lane changing. The time taken by the proposed approach to predict lane changes is illustrated in Figure 13. Other existing works are also analysed using the same dataset for their prediction accuracy and the obtained results are tabulated in Table 4.

From Table 4, it is noted that the proposed approach using game theory and WOA-CNN is effective in predicting the lane changing behaviour of the vehicles with comparatively higher accuracy.

Table 5 compares the accuracy of the proposed lane-changing prediction model with existing approaches found in the literature. The accuracy percentages represent the effectiveness of each method in accurately predicting lane-changing behaviours in driving scenarios. The proposed model outperforms these existing approaches, showcasing a significantly higher accuracy of 96.5%. This indicates the superior predictive capabilities of the novel approach, which combines game theory, optimized CNN and advanced data processing techniques. The higher accuracy suggests that the proposed model is more adept at precisely identifying lane-changing intentions and predicting trajectories, contributing to enhanced driver safety and accident prevention compared to the reviewed methods.

Table 6 provides a comprehensive performance evaluation of the proposed lane-changing prediction

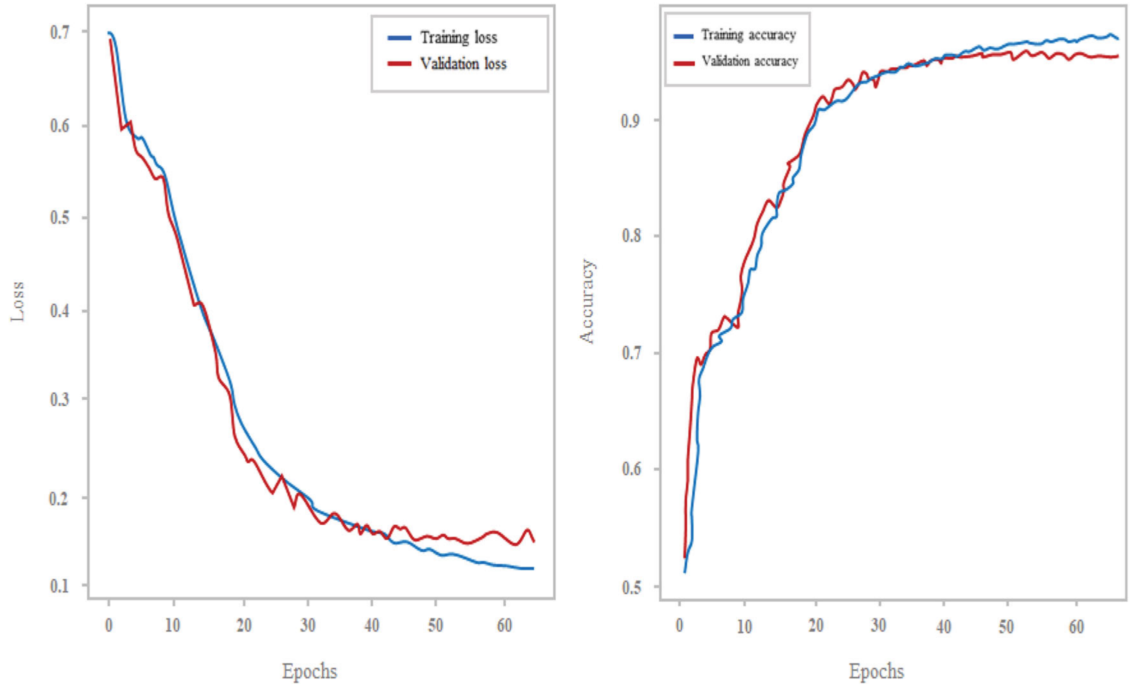

Figure 11. WOA-CNN (a) Loss function and (b) Prediction accuracy.

Table 4. Comparison of different approaches.

Algorithm		RBFNN	BPNN	CNN	LSTM	CNN-LSTM	LSTM-CNN	WOA-CNN
Hidden Layers	1	2	2	1	2 + 1	1 + 1	1	
Parameters	473	90	47068	167200	90058	176804	186500	
Prediction Accuracy (%)	Without game theory	75.21	73.79	78.25	81.08	81.52	83.76	86.38
	With game theory	85.76	84.76	88.31	92.06	92.78	94.43	96.50

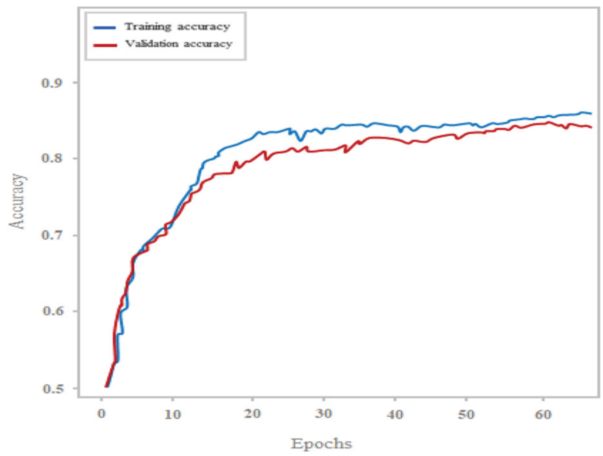

Figure 12. WOA-CNN prediction accuracy in the absence of game theory.

Table 5. Comparison of accuracy with existing approaches.

Methods	Accuracy (%)
[20]	94.6
[21]	93.5
[22]	87.4
[23]	83
Proposed	96.5

model compared to existing approaches. The evaluation metrics include Precision, Recall and F1-score, which collectively assess the model's ability to make

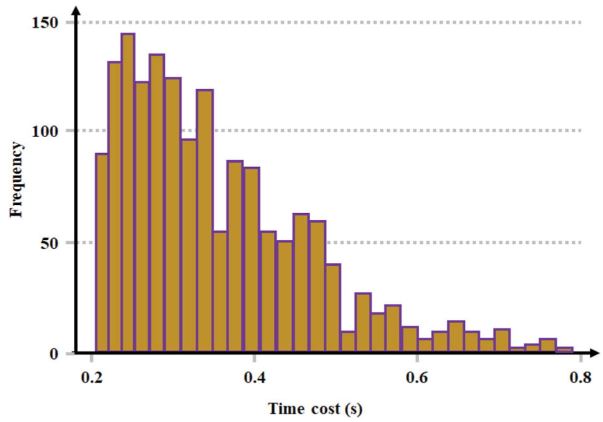

Figure 13. Accurate result prediction time cost.

Table 6. Performance evaluation with existing approaches.

Methods	Precision	Recall	F1-score
[22]	0.927	0.880	-
[23]	0.85	0.85	0.85
Proposed	0.972	0.97	0.97

accurate predictions while considering false positives and false negatives. The proposed model excels in all evaluated metrics, with a Precision of 0.972, Recall of 0.97, and an F1-score of 0.97. These results highlight the superior performance of the proposed approach in accurately identifying lane-changing intentions and predicting trajectories. The higher Precision indicates fewer false positives, while the higher Recall suggests fewer false negatives, resulting in an overall balanced and effective model. The F1-score, which considers both Precision and Recall, reinforces the robustness of the proposed model in comparison to the reviewed methods.

5. Conclusion

A prediction model for accurate determination of the lane changing behaviour of vehicles is proposed in this work, since lane changing behaviour is considered to be the major cause of several road accidents. The proposed model comprises game theory for lane changing intention prediction and WOA-CNN for lane changing trajectory detection. By combining both the intention and vehicle driving state, an accurate prediction of lane changing is accomplished. The deep learning approach of CNN is optimized using WOA and the proposed model is tested using the NGSIM dataset. The entire approach is validated for its effectiveness using Python. An excellent prediction accuracy of 96.5% is obtained, which accredits the significance of the proposed approach in determining the lane changing behaviour of vehicles. Moreover, the proposed approach exhibits comparatively better performance than other available algorithms in predicting lane changing behaviour for the same dataset. Thereby, it is possible to greatly reduce the probability of road accidents caused by lane changing using the proposed approach. Further exploration and refinement of this concept could involve enhancing the model's adaptability to dynamic and complex traffic scenarios, including factors like varied weather conditions, diverse road types, and interactions with pedestrians. Furthermore, investigating the scalability of the proposed approach for large-scale deployment and its compatibility with emerging autonomous vehicle technologies would be crucial.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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