

LANE MISBEHAVIOR DETECTION USING MULTI-LAYER PERCEPTRON WITH THE AID OF BACK PROPAGATION ALGORITHM

Mr.SIVAKUMAR.T¹, Dr.L. MANJUNATHA RAO²

¹Research Scholar-MCA Program, Dr.Ambedkar Institute of Technology, Bengaluru.

²Professor, MCA Program, Dr.Ambedkar Institute of Technology, Bengaluru

Abstract - With the proliferation of the Advanced Driver Assistance System, Lane-line misbehavior detection is an essential procedure nowadays. In this letter, novel feature selection and classification approaches are incorporated. In most cases, a median filter is used to remove the image's noisy components submitted in an image. After eliminating the noisy content in an image, binary whale optimization (BWOA) is introduced for selecting a relevant set of features to make ease the classification process. In this context, Multi-layer perceptron-based back propagation is introduced for detecting misbehavior activities attained in the lane-line image. The proposed system's performance is evaluated based on accuracy and error function.

Key Words: Multi-layer perceptron, Back Propagation, Lane-line, Misbehaviour detection, Whale optimization.

1. INTRODUCTION

The Advanced Driver Assistance System (ADAS) is playing a major role in driving and transportation in this digital environment which is automotive, flexible, and improved the experience of driving. In recent days, plenty of accidents are carried out due to the carelessness of the driver [1]. The ADAS is helping to minimize the workload of drivers and also ensures safety. When the hazardous circumstance occurs, the ADAS alert the driver or takes an effective role by functioning require corrective action to evade an accident [2]. This system utilizes some technologies such as radar, computer vision methods, image sensors, and global positioning. In this system, lane line detection is the most important factor to lead the vehicles towards the appropriate path [3]. Moreover, the lane line detection method is helpful to realize the current path condition and the driver can able to get ready for various road trends in advance [4]. This method is performed in terms of the various lane line kind marks such as Broken white line, Continuous white line, Double continuous yellow line, Continuous yellow line, and shattered yellow line. Still, it requires rectifying some challenges and they are, blockages, interference, and defects of lane line mark [5]. Therefore, lots of researches are conducted to overcome these challenges with the help of various traditional techniques. Here, machine learning techniques are playing a massive part to overcome these challenges [6, 7].

In recent decades, machine learning algorithms are widely utilized techniques for various applications like the medical

field, automation, image processing, etc. Machine learning algorithms are performed based dataset which contains the information about the correspondent application [8, 9]. Moreover, this machine learning technique is categorized into four types and they are named unsupervised learning, Reinforcement learning, Supervised Learning, and Semi-supervised learning [10]. Supervised machine learnings are utilizing characterized experience or information for performing which is mostly utilized for the applications of classification, Regression, and Forecasting [11]. Unsupervised machine learnings can identify the correlations and relationships with the help of investigating the input data. These techniques are mostly implemented for the clustering and dimension reduction process [12]. Semi-supervised machine learnings are similar to supervised learning still this method utilizes both characterized and uncharacterized. Reinforcement machine learning methods are concentrating on organized information which provides the algorithm along with a set of activities, parameters, and outputs. From these categories, the supervised machine learning algorithm is widely utilized due to its advantages in real-world estimation [13].

Several techniques existed for supervised machine learning algorithms and they are named as Naïve Bayes (NB), Linear regression (LR), Random Forest (RF), K-nearest neighbor (KNN), Multilayer perceptron (MP), Support vector machine (SVM), etc. [14]. The performance of the machine learning techniques is developed in recent decades still the performance level is required to improve to achieve a high accuracy level in the process [15]. The enhancement of the machine learning techniques' performance is executed by the hybridization method. Hybridization is the process of integrating two or more learning algorithms to minimize the drawbacks of each algorithm and increase the performance of the process. Therefore, lots of researchers are utilizing this hybridization method for their research works in recent days. This is motivating the present work to propose a novel hybrid learning method for detecting lane line misbehavior. The proposed technique is performed based on image processing for detecting the lane line misbehavior with high accuracy level.

2. Literature review:

Xinxin Du, et al [16] have offered a novel technique in terms of Robust vision to detect the lane line and vehicle localization.

The presented technique utilized the ridge detector to pool the lane line pixels. After that, the noises from the pixels were removed by implementing an efficient noise filtering mechanism. The capturing of each lane line that existed in the image was validated with the help of a modified sequential Random sample consensus. At last, the accuracy of the lane detection was enhanced by the parallelism reinforcement method. The experimental results were demonstrated that the presented technique was performed well for lane line detection and vehicle localization. Fang Zheng, et al [17] have developed an algorithm in terms of Hough transform to detect lane line which was recognized the lane line directly in the environment of Hough space. The presented work utilized an image dataset that was performed with Hough transform and it was confirmed to the length and angle traits, intercept traits, and parallel traits were chosen in the Hough space. Those traits were directly transformed into the lane line equations. The experimental results were proved that the presented technique was recognizing the lane lines effectively. Jingwei Cao, et al [18] have suggested the lane detection algorithm for autonomous vehicles to identify dynamic environments and complex road conditions. The presented technique utilized inverse perspective transformation and region of interest extraction to attain the aerial view of the lane. Thereafter, the third-order B-spline curve model-based lane line fitting was performed with the help of a random sample consensus algorithm, and also the fitting validation and curvature radius estimation were conducted over the curve. The analysis results were proved that the suggested technique was detecting the lane effectively. Minho Lee, et al [19] have designed a novel deep learning-based lane following technique for autonomous ground vehicles. The presented technique was utilized an improved convolutional neural network to compute the right and left lane lines' 6 coefficients through the help of two quadratic functions. The whole process was performed based on the surround-view of a vehicle image. The investigation results were showed that the presented technique was able to drive the vehicle autonomously and steadily without any lane distraction.

Qin Zou, et al [20] have combined recurrent neural network (RNN) and convolutional neural network (CNN) for the lane prediction process. In the presented technique, the CNN was applied for gathering the data of each frame and holding the time-series properties. Thereafter, the feature learning and lane prediction was performed by implementing RNN. The experimental results were showed that the implemented technique effectively detected the lane and also managed complex situations. WEI-JONG YANG, et al [21] have employed deep learning techniques to attain robust lane detection. The presented technique was advanced from the Lane Net model which was performed based on semantic segmentation concepts with the help of the encoder's multilevel features. Moreover, it was improved the binary segmentation and minimized the embedding branches of the pixel. The outcomes were proved that the suggested lane detection network was performed well for lane detection with better accuracy. Jun Li,

et al [22] have also executed two kinds of neural networks like multi-task recurrent neural network (RNN) and convolutional neural network (CNN) for lane detection in traffic scenes. In the presented technique, the information in the traffic scenes was gathered by implementing multi-task CNN and the lane boundaries were automatically detected by utilizing RNN. Suvarna Shirke, et al [23] have presented a Deep CNN for discovering the lane based on bird images. The presented technique utilized a hybrid optimization technique for enhancing the accuracy level and attaining optimal weight. The optimization technique modified the earthworm optimization algorithm (EWA) through the traits of the Crow Search Algorithm (CSA) which was called the Earth worm-crow search algorithm (EW-CSA). The experimental results were showed that the presented technique was performed well for the lane detection process with high accuracy.

3. Research Methodology:

Lane-line misbehavior detection is an essential process nowadays to discriminate the normal and misbehavior activities. Initially, input lane-line images intersected with the open-source technology is used to collect automobiles. The collected images may have different distortions so initially; the image enhancement procedure is incorporated. After that, for selecting a relevant set of features from the pre-processed outcome, the binary whale optimization approach is introduced. Finally, to differentiate both the normal and misbehavior activity from lane-line images, MLP based BP algorithm is presented.

The complete architecture of the proposed methodology is revealed in Fig.1. Based on mentioned procedure, the input image is recognized by two different classes namely misbehavior and normal activity. The proposed approach is applied in the Python programming platform which is investigated by statistical measurements such as precision, error, F-measure, accuracy, and recalls. The detailed process of the proposed methodology is presented in the upcoming sections.

3.1 Image quality enhancement using a median filter

The data acquisition phase is done in the initial step by collecting input lane-line images. Primarily, a median filter is applied to eliminate noisy contents present in an input image. While processing input images directly to the misbehavior prediction model, the proposed system lacks in attaining accurate outcomes. Henceforth noise reduction and quality enhancement steps are essential steps to be incorporated in computer vision applications. With the aid of a non-linear noise destruction method named median filter, the original image gets improved. Following this procedure, edges get preserved and exact pixels of each image found in the lane-line image are obtained. By taking the median value of neighbor pixels, each pixel value tends to be replaced and is mathematically solved using the following equation,

$$I_{(x,y)} = \text{median}(J_{m,n} : (m,n) \in l) \quad (1)$$

Where l estimates the neighborhood location of an image at (x, y) . The noise-destructed lane-line images are obtained for the further feature analysis process.

3.2 Lane-Line Feature Selection using BWOA

The problem of finding redundant information systems has been attracted by many researchers. The expensive basic solution is only applicable in the simple dataset for the problems such as creating all feasible subsets, discovering a subset, and reclaiming those through the least function value. Maximum only one redundant is needed, in traits rarely one subset is used to minimize the dataset, thus discovering the rest of all the estimations is pointless. For the FS problem, the current subset is described by the binary vector which is the solution. In the subset randomly a small number altering of embers that leads the WOA's specific version is perturbed a subset. The objective function is measuring the solution which includes redundant traits or not. In addition, between the computational burden and efficiency of attribute extraction, the accuracy of classification or other criteria is considered the best trade-off. In this paper, BWOA is employed to choose the traits for the best traits combination and achieve optimum solution capably.

This work introduces a new novel algorithm which is the binary WOA algorithm because of simple and useful to discover global solutions in WOA. In addition, for the Feature Selection (FS) problem, this algorithm is to enhance the discovering the best solutions, that have precision and reliability. The range of the agents or in binary version the whale's position is 0 to 1. Preserving the proposed algorithm is the principal purpose of this algorithm as same as the simple original WOA. The bubble-net hunting approach for humpback whales is known as WOA's humpback whale hunting method in which within the shrinking circle and with a spiral-shaped path, the humpback whales are swim around the prey and create bubbles. To select between the spiral model and the shrinking encircling mechanism, the probability of imitation behavior in WOA is 50% and then this proposed BWOA change this probability in search space for the spiral model into 40% to provide further intensification.

The Swarm based optimization technique of the global strategy is the Whale Optimization Algorithm (WOA). Here the search agents are represented by the population of the candidate solutions which exist in the WOA. The search agents can be denoted as,

$$S^* = \{s_1^*, s_2^* \dots, s_k^*\} \quad (2)$$

For the specific optimization problem's candidate solution is represented as the location of the search agent. The objective function of the WOA is F_{obj}^* . Each search agents have position

vector art at any point of time, which is denoted as x_i^* and associated with search agents. Amid the search agents S^* concerning the objective function F_{obj}^* is represented as the S_{best}^* this is the best level that search agents have visited up to the current level

Process:

For the search space dimension is represented as M^* in addition to N^* is the search agents consist of the swarm.

$$\text{Swarm}^* = \{S1^*, S2^*, \dots, SN^*\} \quad (3)$$

Where S_i^* , in the search space all search agents are denoted as,

$$x_{i1}^*, x_{i2}^*, \dots, x_{iM}^*, \quad i = \{1, 2, \dots, N\} \quad (4)$$

WOA which consist of three stages they are listed below,

Process of Encircling the Prey

Process of Exploitation Phase

Process of Exploration Phase

3.2.1 Process of Encircling the Prey

Initially, the search agents take the encircle process which means the search agents used to define the best solution's location and encircle it. Furthermore, using the objective function found the current best solution. The current best candidate solution is the best-obtained solution, thus it's close to the optimal solution. Other search agents adjust their positions in the direction of the best candidate solution after receiving the best candidate solution. The updated position of the search agents is,

$$d^* = |c^* \cdot x^*(t^*) - x(t^*)| \quad (5)$$

$$x(t^* + 1) = x^*(t^*) - A^* \cdot d^* \quad (6)$$

Where t = Current Iteration number, A^* and c^* = Coefficient vectors,

x^* = Best candidate solution's position vector. x = Current search agent's position vector,

$||$ = Used values are absolute in nature.

$$A^* = 2 \cdot a^* \cdot R \cdot a^* \quad (7)$$

$$c^* = 2 \cdot Rq^* \quad (8)$$

During execution, α^* which is decreased from 2 to 0. In addition, R = Random vector which is a range of 0 to 1.

3.2.2 Process of Exploitation Phase

After the process of encircling the prey, the exploitation process is done. The attack mechanism of the humpback whales is inspiring this phase which is also known as a bubble-net mechanism. In the humpback whales modeling the bubble-net behavior consists of two types of mechanisms.

Mechanism of Shrinking Encircling:

Reducing the value of α^* which means the value of α^* is decreased from 2 to 0 linearly leads to modeled this mechanism. Moreover, the value of the A^* is in the range of $-\alpha^*$ to α^* .

Mechanism of Spiral Updating Position:

The distance between the calculation of the best search agent and the estimation of the current search agent is done in this mechanism. In addition, the spiral shape movement of the humpback is represented by the spiral equation. The spiral equation is given below,

$$x(t^* + 1) = d_g^* \cdot e^{BL} \cdot \cos(2\pi L) + x^*(t^*) \quad (9)$$

$d_g^* = |x^*(t^*) - x(t^*)|$, The distance between the location of best and current search agent location,

B = Constant, L = Arbitrary Number, in between -1 to 1.

Furthermore, to choose between these two mechanisms here is 50% probability, so it is using both mechanisms. The exploitation phase is represented as,

$$x(t^* + 1) = \begin{cases} x(t^* + 1) = x^*(t^*) - A^* \cdot d^* & \text{if } p^* < 0.5 \\ d_g^* \cdot e^{BL} \cdot \cos(2\pi L) + x^*(t^*) & \text{if } p^* \geq 0.5 \end{cases} \quad (10)$$

p^* = Random number ranges from 0 to 1.

3.2.3 Process of Exploration Phase:

This is the last phase of this WOA, where randomly the search agents search the best solution over the search space, and the changed search agents' position is revised concerning the other agent's position. When moving the search agents left from the reference search agent, the value of A^* is either more than 1 or less than 1.

$$d^* = |c^* \cdot x_{rand} - x| \quad (11)$$

$$x(t^* + 1) = x_{rand} - A^* \cdot d^* \quad (12)$$

The above equations are the numerical model of the exploration phase.

Algorithm 1

Parameters Initialization:

Input Parameters: No. of humpback whales = N^* , No. of variables = n^* , No. of Iterations = t^* , Max. No. of Iterations = max_{Iter} .

Output Parameters: Optimal position = x^* . Best fitness = $F(x^*)$.

Initialization of the binary population for the number of humpback whales;

While ≠ Stop conditions **do**

for $i \leftarrow 1$ to N^* **do**

Fitness of the i^{th} agent is calculated;

if $F(x_i) \leq F(x^*)$ **then**

fix current fitness value by x^* and update the best leader so far;

end

if $t^* > max_{Iter}/3$ **then**

From the best leader x^* is selected randomly;

End

Update A^* , α^* and c^* ;

Random number generation L in between the -1 to 1 range and p^* is in between the 0 to 1 range.

for $d^* \leftarrow 1$ to n^* **do**

if $p^* < 0.4$ **then**

if $|A^*| < 1$ **then**

#Mechanism of Shrinking encircling preys

d^* search agents' position is revised concerning to best solution;

else

#Mechanism of Search of preys

d^* search agents' position is revised concerning to random agent;

end

else

#Spiral bubble net attacking

d^* search agent's spiral position is revised;

end

end

end

end

Give x^* as the minimal reduct.

Mechanism of shrinking encircling preys:

In the BWOA, like in the WOA, the best candidate solution is deemed the target prey, and the remaining search agents improve their locations in the BWOA. In equation (4) into new value range by converting step values which are in 0 to 1 as follows,

$$tf_i^* = \left| \alpha^* \cdot \arctan\left(\frac{\pi}{3} A^* d^*\right) + \beta_1^* \right| \quad (13)$$

α^* = Constant value; which is equal to $\frac{3}{\pi}$;

β_1^* = The new parameter is added to avoid tf_i^* is equal to zero in the case of $x^*(t^*)$ and $x(t^*)$ are zeros.

The new position of the BWOA depends on equation (5) in WOA. The new updating position of BWOA,

$$x(t^* + 1) = \begin{cases} 1 - x^*(t^*), & Rd_1^* < tf_i^*; \\ x^*(t^*), & \text{Otherwise,} \end{cases} \quad (14)$$

Rd_1^* = Random number which is consistently shared in the range 0 to 1.

Mechanism of Spiral bubble net feeding maneuver:

Between the position of prey and whale, the spiral equation is used to copy the helix-shaped movement of humpback whales. Equation 9 is described by another transfer function in BWOA as follows,

$$tf_i^{'*} = \frac{|\arctan(s_i^* + \beta_2^*)|}{4} \quad (15)$$

$$s_i^* = d_8^* \exp(BL) \cos(2\pi L) \quad (16)$$

s_i^* = Walk step derived from equation 9.

β_2^* = Constant value;

In addition, divided by 4 is maintain the $tf_i^{'*}$ value in the range of 0 to 0.5. Then the below calculation is denoted the upgrading the i^{th} whale position or trait of spiral bubble net feeding

$$x(t^* + 1) = \begin{cases} 1 - x^*(t^*), & Rd_1^* > \gamma^*, tf_i^{'*} = \frac{\beta_2^*}{4}; \\ x^*(t^*), & Rd_2^* > tf_i^{'*}; \\ x(t^*), & \text{Otherwise,} \end{cases} \quad (17)$$

Rd_2^* = Uniformly distributed number [0,1];

γ^* = The parameter which makes the difference in results and updates current solution if in current population more than one of the same solutions.

3.2.4 Prey search:

In BWOA, using the transfer function, for arbitrarily chosen search feature rather of best search feature the search agent revised when the A^* is greater than 1. The position of the i^{th} whale on randomly chosen search features is given as follows,

$$x(t^* + 1) = \begin{cases} 1 - x_{rand}, & Rd_3^* < tf_i^* \\ x_{rand}, & \text{otherwise} \end{cases} \quad (18)$$

Rd_3^* = The random number consistently shared in-between range 0 to 1;

x_{rand} = Random whale from the population.

For finding the optimum solution, add the new procedure to BWOA to improve the search performing and improve the new solution quality through the goal of shifting to a provide hope research field centered on the best solutions that have been shown. More than one optimal solution is available for the solution of the feature selection problem. The memory structure is used in the implementation of this procedure

which means they visited best solutions (short-term= considering the best solution's recent set). The best solution set is represented as l_{best}^* and m^* is the length of this set. In suboptimal regions maybe stick to the approach which is the traits of poor quality during the search. Furthermore, apply this procedure after the one by third of maximum iterations, so that the best optimal solution gets. The best solution x^* is selected by BWOA in l_{best}^* as the set of minimum traits at the end of the search.

3.3 Lane-line misbehavior detection using MLP_BP

Typically, for detecting the misbehavior activity of vehicles, lane-line images with the interaction of vehicles are considered in the proposed system. The proposed model incorporates a new framework named Multilayer Perceptron integrated through the back propagation algorithm (MLP_BP). The MLP framework contains three layers: an input layer, a hidden layer, and an output layer that processes labeled data. The weight values present in the network model are tuned based on the BP training model. The output error function of the hidden layer cannot be estimated due to the unknown actual measure. That's why the back propagation-based training model is adopted in the proposed system for classification purposes. The input of MLP is a total number of selected features acquired from proposed meta-heuristic values. The focus of this study is to discriminate both the misbehavior and normal activity of vehicles present in the lane-line image. Each selected feature is divided to get its representative level in discriminating between misbehavior and non- misbehavior activity. The steps followed in the network model is detailed as follows,

Primarily, the MLP_BP network model takes input and yield target as t . Each neuron present in the learning algorithm incorporates the summation of weight function and is mathematically formulated as follows,

$$b_k = \sum_j x_{kj} y_j \tag{19}$$

Here the weight term represents the connection among node k and j . The output of the preceding node is denoted as y_j . The summation function present in the above equation is converted to a sigmoid form of activation function and is formulated as follows,

$$y_k = \tanh(b_k) \tag{20}$$

The above equation is determined for getting the activation output y_k in the node k . The further step is to evaluate the error function using the output estimated function z_j and the target function t_j . The back-propagation model δ' is incorporated in the proposed network model for choosing the

weight values and to get δ_k the derivative function of each hidden layer and is formulated as,

$$\delta_j = z_j - t_j \tag{21}$$

$$\delta_k = h'(b_k) \sum_j x_{kj} \delta_j \tag{22}$$

With the aid of the backpropagation algorithm, the obtained output is equated with the estimated and target output by which the error function is evaluated. The back-propagation model updates the minimal error function to the network model by updating weight values. Henceforth, the outcome achieves very closer to the estimated or target outcome. The procedure gets repeated until the final iteration and the error gets minimized.

4. Results and Discussion

A detailed explanation of the outcomes is discussed in this section. The major focus of this study is to detect the lane line misbehavior of the vehicles. The suggested approach is implemented in the python tool, in addition, compared with the present approach to prove the suggested method is more perfect than the other techniques. Furthermore, this portion evaluates the performing metrics of the proposed MLP-BP approach in terms of accuracy, precision, F-Measure, recall, and Loss function through existing techniques. The below section explained the performance matrices of this approach.

4.1. Performance Metrics

This segment describes the proposed model's performing metrics, some metrics are validated and tested. The evaluation of the performance metrics taken for the suggested and present analysis are elaborated and mathematically represented as follows,

Accuracy - The term of accuracy is described as the amount of misbehavior detection made correctly. The mathematical representation is below,

$$\text{Accuracy} = \frac{tp+tn}{tp+fp+fn+tn} \tag{23}$$

Precision - Precision is defined as the detection of positive class values by the proposed model accurately. The equation for the precision is given below,

$$\text{Precision} = \frac{tp}{tp+fp} \tag{24}$$

Recall - The sensitivity or measure recall is defined as the correctly detected misbehavior and non-misbehavior data by the proposed approach. The formula for the recall is as follows,

$$\text{Recall} = \frac{tp}{tp+fn} \tag{25}$$

F-measure – F-measure means the computation of mean value using accuracy and recall which provides the F-measure. It varies from 0 (worst performance) to 1 (highest performance). The formula for F-measure is as follows,

$$F - measure = \frac{2 \times (recall \times precision)}{recall + precision} \quad (26)$$

Loss – This is one of the quality metrics which helps to detect the performance of the detection model. In addition, it is calculated through the error function.

According to the above standard formulas, these statistical measures are evaluated. For each measure, the whole performance of suggested and present techniques is computed and offered in the subsequent section.

4.2. Analysis of performance metrics for proposed and existing approaches:

The performance metrics of the proposed and existing techniques are discussed in the below table. The evaluated performance metrics are accuracy, precision; recall, F-Measure, and Loss of the suggested and existing are listed. Furthermore, the Manoeuvre Assessment for Reliable Verification of Mobility Data (MARV-X) Particle Filter (PF-MDS), and Context-aware-data-centric misbehaviour scheme (CA-DC-MDS) are considered the existing methods. Table 1 illustrates the performance comparison of the performance metrics of the proposed and existing techniques.

Table 1: Performing comparison of the proposed and existing methods

Predictive methods	Performance of Classifier				
	Accuracy	Precision	Recall	F-Measure	Loss
PF-MDS	0.8321	0.8302	0.8123	0.8065	0.4025
MARV-X	0.8654	0.8545	0.8456	0.8263	0.3826
CA-DC	0.8902	0.8865	0.8695	0.8512	0.3562
Proposed Method (MLP+BP)	0.9194	0.8958	0.8722	0.8907	0.2793

In table 1, For the proposed method (MLP+BP), 0.9194 is the accuracy, 0.8958 is the precision value, 0.8722 is the value of the recall, 0.8907 is the F-Measure value and 0.2793 is the loss of the proposed method. For the Context-aware-data-centric misbehavior scheme (CA-DC-MDS) method, 0.8902 is the accuracy value, 0.8865 is the value of the precision, 0.8695 is the recall value, 0.8512 is the F-measure value and 0.3562 is loss value. For Man oeuvre evaluation for Reliable Verification of Mobility Data (MARV-X) method, 0.8654 is the accuracy, 0.8545 is precision, 0.8456 is the recall, 0.8263 is F-measure and 0.3826 is loss value. In addition, for Particle Filter (PF-

MDS) method, 0.8321 is the accuracy value, 0.8302 is the precision value, 0.8123 is the recall value, 0.8065 is the F-Measure, and 0.4025 is the loss value.

4.3. Comparison of Performance metrics

This section detailly explained the comparison for the performing metrics of the proposed and existing methods such as CA-DC-MDS, MARV-X, and PF-MDS. For analyzing the proposed detection system, primarily confusion matrix is generated for the taken source code dataset based on statistical measures. To show the clarity of the proposed based detection of lane line misbehavior in-vehicle, its obtained results of training and validation process for the taken dataset are graphically displayed in the following figures. The performance parameters of the proposed and existing approaches, like accuracy, precision, recall, f-measure, and loss, are compared in the following figures.

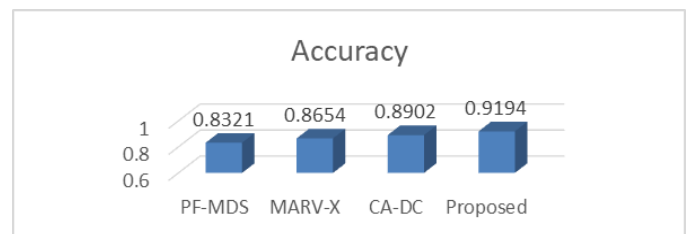


Figure 1: Accuracy of proposed and existing methods

From the analysis, it can be stated that the proposed technique achieves a good prediction rate. The above figure furnishes the good accuracy for detecting the lane line misbehavior of the vehicle in earlier stage using proposed attribute selection with MLP model integrated with BP. For instance, when the number of iterations gets increases, accuracy also gradually increases. Figure 1 demonstrates the comparison of the accuracy of the proposed and existing such as CA-DC-MDS, PF-MDS, MARV-X, and. For the proposed technique, 0.9194 is the accuracy value is better than the other existing techniques. For CA-DC, 0.8902 is the accuracy, 0.8654 is the accuracy of the MARV-X, and 0.8321 is the accuracy of the PF-MDS. The proposed method is more accurate than the other techniques, according to the analysis.

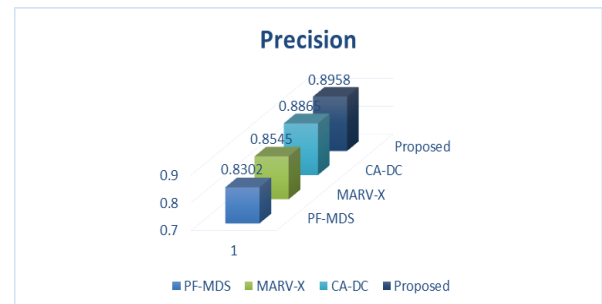


Figure 2: The exactness of proposed and existing methods

The precision similarity of the proposed and existing methods is illustrated in figure 2. Furthermore, 0.8958 is the precision value of the proposed method, 0.8865 is the precision for CA-DC, 0.8545 is for MARV-X, and 0.8302 is for PF_MDS. The proposed method's precision value is better than the existing techniques. Figure 3 demonstrates the recall comparison, for the proposed method, 0.8722 is the value of the recall, 0.8695, 0.8456, and 0.8123 are recall values of the existing approaches such as CA-DC, MARV-X, and PF-MDS. The recall of the proposed is greater than the other techniques.

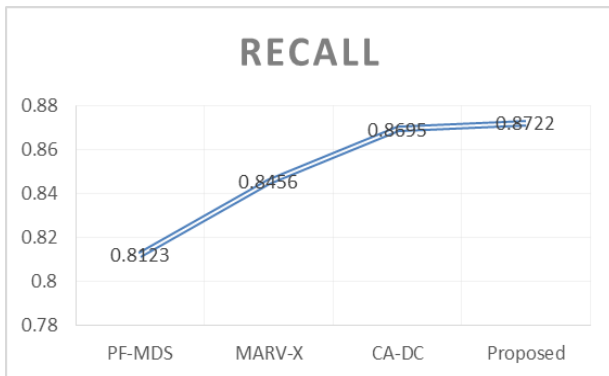


Figure 3: Recall of the proposed and existing methods

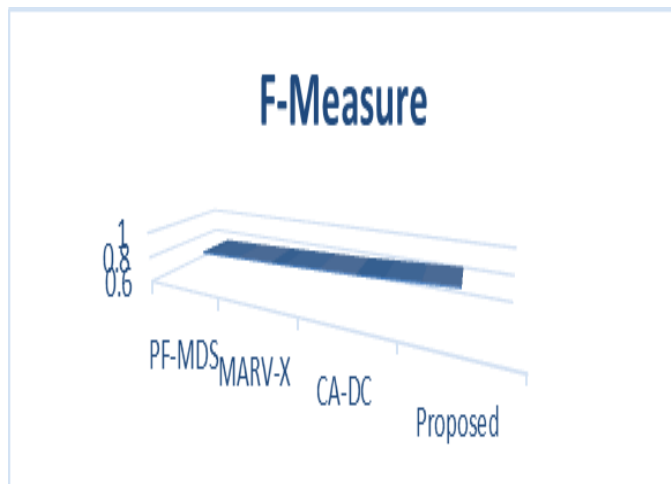


Figure 4: F-Measure of the proposed and existing method.

Figure 4 demonstrates the F-Measure of the suggested and present methods such as CA-DC, MARV-X, and PF-MDS. The proposed has a high F-measure value which is 0.8907. The others are 0.8512, 0.8263, and 0.8065 for CA-DC, MARV-X, and PF_MDS.

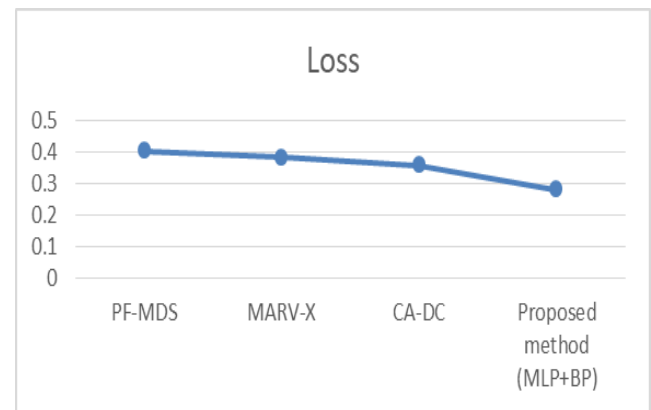


Figure 5: The loss of the proposed and existing methods the loss achieved by proposed attribute selection with MLP model attains minimum detection error and is shown in the above figure. Here, when the iteration is raised, the detection error of the proposed solution decreases. As a result, it is found that the suggested system improves accuracy and error function. Figure 5 demonstrates the comparison of the loss of the suggested method and present approaches such as CA-DC, MARV-X, and PF-MDS. For the proposed method, 0.2793 is the loss value, 0.3562 is the loss of the CA-DC, 0.3826 is the loss of the MARV-X, and 0.4025 is for PF-MDS.

Figure 6 demonstrates that the processing time of the proposed and existing methods. The processing time of the suggested method is 7.5 secs, in addition, to the existing methods, 9 secs for CA-DC, 15 secs for MARV-X, and 27 for PF-MDS.

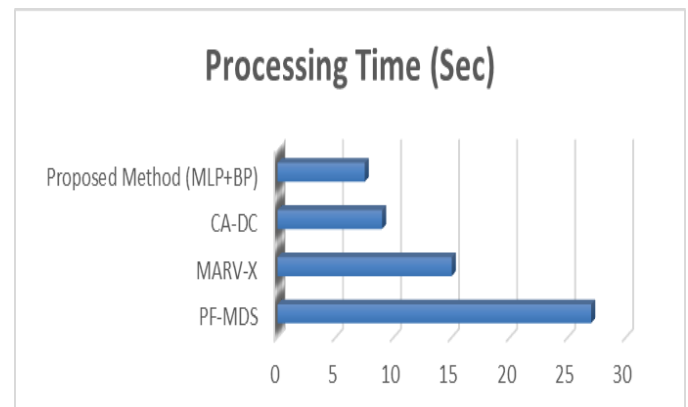


Figure 6: The processing time of the proposed and existing techniques. When the loss acquired is reduced, then automatically the system performing will get enhanced this is fine recognized truth. The above fact by sustaining the proposed system works well by receiving the least loss value. Thus, from the analysis, it is resolved that general performing is enhanced sufficiently for discovering lane line misbehavior of vehicles. From the overall analysis, it is concluded that the suggested MLP attains the best solution for the prediction system due to the incorporation of the optimization procedure. From the achievable outcome, it is proven that selected

attributes are most appropriate in detecting the lane line misbehavior of the vehicles.

CONCLUSIONS :

The principal aim of the proposed system is to discover the misbehavior activity acquired from the original lane-line image. The median filter is adopted to eliminate the noisy information contained in an image. The filtered outcome image is processed to the feature selection phase whereas a binary whale optimization algorithm is introduced to get the binary features. This tends to make the classification process easier. For categorizing the normal and misbehavior activity from the lane-line image, MLP_BP is proposed by minimizing the error function. The performance measures exhibit the proposed methodology in an effective manner.

REFERENCES:

- [1] Qiu, S., Rachedi, N., Sallak, M. and Vanderhaegen, F., 2017. A quantitative model for the risk evaluation of driver-ADAS systems under uncertainty. Reliability Engineering & System Safety, 167, pp.184-191.
- [2] Lin, T.C., Ji, S., Dickerson, C.E. and Battersby, D., 2018. Coordinated control architecture for motion management in ADAS systems. IEEE/CAA Journal of Automatica Sinica, 5(2), pp.432-444.
- [3] Sun, Q., Zhang, H., Li, Z., Wang, C. and Du, K., 2019. ADAS acceptability improvement based on self-learning of individual driving characteristics: a case study of lane change warning system. IEEE Access, 7, pp.81370-81381.
- [4] Son, J., Yoo, H., Kim, S. and Sohn, K., 2015. Real-time illumination invariant lane detection for lane departure warning system. Expert Systems with Applications, 42(4), pp.1816-1824.
- [5] Li, J., Shi, X., Wang, J. and Yan, M., 2020. Adaptive road detection method combining lane line and obstacle boundary. IET Image Processing, 14(10), pp.2216-2226.
- [6] Chen, T., Chen, Z., Shi, Q. and Huang, X., 2015, June. Road marking detection and classification using machine learning algorithms. In 2015 IEEE Intelligent Vehicles Symposium (IV) (pp. 617-621). IEEE.
- [7] Bailo, O., Lee, S., Rameau, F., Yoon, J.S. and Kweon, I.S., 2017, March. Robust road marking detection and recognition using density-based grouping and machine learning techniques. In 2017 IEEE winter conference on applications of computer vision (WACV) (pp. 760-768). IEEE.
- [8] Gyawali, S. and Qian, Y., 2019, May. Misbehavior detection using machine learning in vehicular communication networks. In ICC 2019-2019 IEEE International Conference on Communications (ICC) (pp. 1-6). IEEE.
- [9] Kamel, J., Ansari, M.R., Petit, J., Kaiser, A., Jemaa, I.B. and Urien, P., 2020. Simulation framework for misbehavior detection in vehicular networks. IEEE transactions on vehicular technology, 69(6), pp.6631-6643.
- [10] Zhang, C., Chen, K., Zeng, X. and Xue, X., 2018. Misbehavior detection based on support vector machine and Dempster-Shafer theory of evidence in VANETs. IEEE Access, 6, pp.59860-59870.
- [11] Sharma, P. and Liu, H., 2020. A Machine-Learning-Based Data-Centric Misbehavior Detection Model for Internet of Vehicles. IEEE Internet of Things Journal, 8(6), pp.4991-4999.
- [12] Wahab, O.A., Mourad, A., Otrok, H. and Bentahar, J., 2016. CEAP: SVM-based intelligent detection model for clustered vehicular ad hoc networks. Expert Systems with Applications, 50, pp.40-54.
- [13] Kim, J., Kim, J., Jang, G.J. and Lee, M., 2017. Fast learning method for convolutional neural networks using extreme learning machine and its application to lane detection. Neural Networks, 87, pp.109-121.
- [14] Jahangiri, A. and Rakha, H.A., 2015. Applying machine learning techniques to transportation mode recognition using mobile phone sensor data. IEEE transactions on intelligent transportation systems, 16(5), pp.2406-2417.
- [15] Kim, I.H., Bong, J.H., Park, J. and Park, S., 2017. Prediction of driver's intention of lane change by augmenting sensor information using machine learning techniques. Sensors, 17(6), p.1350.
- [16] Du, X. and Tan, K.K., 2016. Vision-based approach towards lane line detection and vehicle localization. Machine Vision and Applications, 27(2), pp.175-191.
- [17] Zheng, F., Luo, S., Song, K., Yan, C.W. and Wang, M.C., 2018. Improved lane line detection algorithm based on Hough transform. Pattern Recognition and Image Analysis, 28(2), pp.254-260.
- [18] Cao, J., Song, C., Song, S., Xiao, F. and Peng, S., 2019. Lane detection algorithm for intelligent vehicles in complex road conditions and dynamic environments. Sensors, 19(14), p.3166.
- [19] Lee, M., Han, K.Y., Yu, J. and Lee, Y.S., 2019. A new lane following method based on deep learning for automated vehicles using surround view images. Journal of Ambient Intelligence and Humanized Computing, pp.1-14.
- [20] Zou, Q., Jiang, H., Dai, Q., Yue, Y., Chen, L. and Wang, Q., 2019. Robust lane detection from continuous driving scenes using deep neural networks. IEEE transactions on vehicular technology, 69(1), pp.41-54.

[21] Yang, W.J., Cheng, Y.T. and Chung, P.C., 2019. Improved lane detection with multilevel features in branch convolutional neural networks. *IEEE Access*, 7, pp.173148-173156.

[22] Li, J., Mei, X., Prokhorov, D. and Tao, D., 2016. Deep neural network for structural prediction and lane detection in traffic scene. *IEEE transactions on neural networks and learning systems*, 28(3), pp.690-703.

[23] Shirke, S. and Udayakumar, R., 2020. Hybrid optimisation dependent deep belief network for lane detection. *Journal of Experimental & Theoretical Artificial Intelligence*, pp.1-13.