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ORIGINAL RESEARCH ARTICLE

Deep ResNet 18 and enhanced firefly optimization algorithm for on-road vehicle driver drowsiness detection

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ABSTRCT

The driver drowsiness detection (DDD) technology is based on vehicle safety, and this system prevents many accidents and deaths that occur due to driver drowsiness. As a result, it is monitored and detected when vehicle drivers become drowsy. The DDD method, which is aided by AlexNet and deep learning models, has limitations such as vanishing gradients and overfitting issues as the depth of the model increases. The enhanced firefly optimisation algorithm has solved the problem of lower optimisation exploration. The National Tsing Hua University Driver Drowsiness Detection (NTHU-DDD) dataset's input image contains individual groups of female and male drivers of various vehicles. The Min-max normalisation method is a general method for normalising data. The convolutional neural network (CNN) is used to extract features from input images and images classified by the neural network. ResNet 18 refers to the deepest of the convolutional neural network's 18 layers. A network of pre-trained models can be used to classify the model classified by the 1000 image objects. The state-of-the-art Hierarchical Deep Drowsiness Detection (HDDD) model with Support Vector Machine (SVM) assistance has an effective high dimensional space. The CNN-EFF-ResNet 18 models have a high accuracy of 91.3%, while the HDDD method has a higher accuracy of 87.19% than the ensemble and Pyramid Multi-level Deep Belief (PMLDB) methods in DDD.

Keywords: AlexNet; convolutional neural network; driver drowsiness detection; enhanced firefly optimization; ResNet 18

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1. Introduction

The use of driver sleepiness detection to avoid accidents has resulted in a considerable number of fatalities in the modern technology based on the safety of automobiles. Different types of characteristics are used by the driver drowsiness detection method to determine drowsiness. The driving simulator's performance of SVM, K-NN, and artificial neural network (ANN) classifiers based on the detection of driver drowsiness was employed in the model. Physiological measurements, information-based vehicles, and behavioural data can all be used in the detection process[1–3]. For physiological data like electrocardiograms (ECG), electroencephalograms (EEG), and blood pressure, the first model can be presented. The second model can identify the driver-vehicle interaction as well as speed, wheel, breaking, and acceleration. The third model has made use of computer vision techniques that can gauge the driver's condition using the deployed cameras[4–6]. The drowsy drivers reported quick steering wheel corrections, longer departures from the desired trajectory, and reduced speed limits. The model generally used multistep and frame based approaches, and the driver drowsiness detection is the most acceptable method of three dimensional (3D) for feature learning of spatiotemporal[7].

The drowsiness driver detection methods are generally utilized in two methods such as support vector machine and network neural. The deep learning method is used by CNN to generate maps of features for the process of learning. The model assisted by the LSTM method take the advantages of frames between temporal data[8]. Vehicle usage is globally increasing and human beings have many deleterious experiences, such as accidents, traffic, fatalities, losses in financial and injurious. The machine learning techniques used in the model such as support vector machine (SVM) and k-nearest neighbor (KNN), The deep learning network based on classification of image such as, VGGNet, AlexNet and ResNet models[9]. The model-assisted by using the plot recurrence technique and overlapped windows time can be converted data into image. The model-assisted by the vehicular ad-hoc networks (VANETs) effort to prevent the danger of the accident by detecting more data. The information on the driver, vehicle, and environment can increase driving safety, the distraction of the driver resources involves events or persons outside or inside the car, objects drinking or eating, and utilize cell phones or vehicle in other technologies[10]. The main contribution of the research paper described given below:

1) The deep learning models based on enhanced firefly optimization algorithm applied for the driver drowsiness detection. The model has solved the problems of lower exploration of local searching issues.
2) The CNN is used to extract the features from the input image and features of images classified by the neural network. The advantages of the CNN model have a wide range of extracted relevant features and provide high accuracy.
3) The ResNet 18 model using the classification process and selected searches of enhanced firefly optimization. The model solves the vanishing gradient issues due to the mapping of identified.

The organization of the research paper detailed as follow: Section 2 describes the recent research paper of deep learning based CNN models in the literature review, section 3 describes the enhanced firefly optimization methodology, the simulation setup described in the section 4, the result section described in the section 5. Finally, section 6 describes the conclusion of the research paper.

2. Literature review

This study reviews the recent research methods as mentioned in this section. The CNN-based deep learning models are mostly utilized in drowsiness detection.

Dua et al.[11] proposed four types of deep learning models such as ResNet, FlowImageNet, VGG-FaceNet and AlexNet. The model utilizes detecting drowsiness and utilizes the input in the RGB videos for drivers. The model activation method tackles limitations such as vanishing descents gradient issues and overfitting. The model addresses the challenges such as computational complexity and computational cost is high. The AlexNet has the problems like difficulty of all features scanning process, decreasing depth. The model-assisted by the ANFIS model has the problem of increasing the computational cost due to learning of gradient and structure of complex.

Moujahid et al.[12] developed the four types of models such as classification and feature selection of subset, feature selection of multi scale multi-level feature extraction (MSML) using for face description, Pyramid-multi level and face detection and alignment. The model-assisted by the histogram oriented gradient overcome the limitation of rotation of image is more sensitive and delay in computation speed for large-scaled images during object diagnosis The model tackles the issues of integration of initial and aggregation contextual. The model assisted by the principal component analysis (PCA) has the limitations such as losses of information, reduction of dimensionality and independent attributes have decrease interpretable.

Wijnands et al.[13] proposed 3D neural network utilizes for monitoring real-time driver drowsiness based on platforms of mobile. The model-assisted by the ImageNet solves the problem of images within border boxes of labeling or all labeling each pixel. The model-assisted by the graphical processing units (GPU) tackles the issues of massive information including processing is parallel. The model has the limitations of unexpected changes could not be identified utilizing measures of subjective.

Jamshidi et al.[14] developed phases of a temporal and spatial split with deep networks contains the hierarchical system for hierarchical deep drowsiness detection (HDDD). The model utilized by ResNet to identify the faces of the drivers, the condition of lighting, and the drivers' glasses-wearing or not. The model-assisted by the long short term memory (LSTM) addresses the disappearance gradient issues in neural recursive networks and tackles the issues of complex problems. The model-assisted by the multi-layer perceptron has the limitations to involve more parameters as connected fully and depending on training and the LSTM has the overfitting problem easily and vanishing gradient.

Shahverdya et al.[15] developed the 2D convolutional neural network (CNN) based on the recurrence plot method created images for driving signals. The detecting of the behavior of driver utilizing the effective method for the deep learning algorithm. The method has utilizing signals of driving, involving gravity, acceleration, speed, throttle and revolutions per minute (RPM) identify to five methods The model-assisted by the gaussian mixture model (GMM) tackles the issues of one classification issue and inference problem and k-nearest neighbors (KNN) has the problems such as more inefficient computational, dimension of number is high. The model-assisted by the intelligent transportation system has the issues such as cost of maintenance high and mixed traffic utilize for very challenging.

3. Proposed method

Numerous steps are included in the proposed method, such as the NTHU-DDD dataset input image, preprocessing min max normalisation, feature extraction, feature selection, and classification procedure. Normalisation approach based on Minmax normalisation, Convolutional neural network (CNN) based feature extraction process, enhanced the firefly optimization based feature selection process, and ResNet 18 model-based classification process. The proposed work is depicted in **Figure 1**.

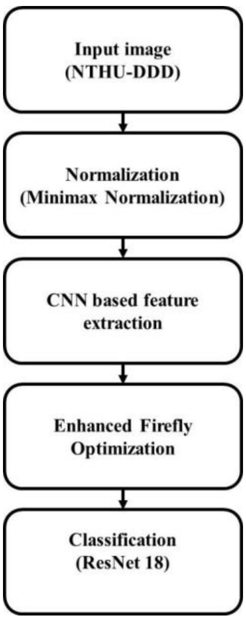

Figure 1. The block diagram of the proposed method.

NTHU-DDD dataset: The NTHU-DDD dataset[16] was derived from a video dataset of driver drowsiness detection, which included 36 people of various ethnic groups. Normal driving, weak blink rate, yawning, falling asleep, and burst out laughing are among the five types of classes. The evaluation dataset contains 4 subjects with 20 video clips (173, 259 frames), the train dataset has 18 subjects with 360 video clips (722, 223 frames), and the test dataset has 14 subjects with 70 clips (736, 132 frames). The videos are 640 × 480 pixels in size, without audio, and 30 frames per second in AVI format.

3.1. Preprocessing using Min-max normalization

The preprocessed the input data is to reduce the noise and missing data. The Min-max normalization method using the following Equation (1), the normalized in the feature range [0, 1].

$$v' = \frac{v - min_A}{max_A - min_A} \tag{1}$$

where, feature A contains maximum and minimum values of the max_A and min_A. The normalized and original values of the features, A is indicated by v_o and v respectively. This method can be mentioned by the above equation that features minimum and maximum values that are 0 and 1 mapped to, respectively. The normalized data indicates that the output of v' value.

3.2. Feature extraction using convolutional neural network

The pre-processing of data for extracted features using various types of convolutional neural networks. CNNs[17] rely heavily on max pooling, convolutional, and connected to full layers. The input layer shape must be similar to the input data. The output layer shape must be similar to the training data. The hidden layer is located between the output and input layers. Next step advances to the convolutional layer. The normalised data shows that the output v' value of the CNN method was applied to the input.

Batch normalization: On a group of mini-batch data, normalised data distribution is used to limit variance and mean in the range [0, 1]. This method is used to reduce overfitting issues. The techniques are used to improve learning speed, with the technique being 17 times faster than the technique alone.

Convolutional layer: An ANN-based network is the convolutional neural network. It contains a layer of fully connected and spatial data that does not take this into account. The input image that convolutional layers can handle is as follows (the pixels with distant and close values are processed in different ways). The convolutional layers use the previous layer's data image to convolute various filters. The most common convolution function is to swap the location filters with S pixels. The letter S refers to the number of strides. The correction is the result of the filter's learning process.

Pooling layer: The average or maximum values in the pixels HH are presented. The number of H is generally referred to as stride in the max-pooling layer. These layers' output images of size by transverse and longitudinal transform into input images by 1/H. This layer makes no changes to the image channels. The maximum values reported by the function of max pooling; the variance in low sensitivity sites inside complex cells in the primary visual cortex. This layer enables the model to have a strong and little variation in image locations of objects.

Dropout layer: Nodes in the CNN can be eliminated using the dropout approach throughout the training phase of the specific probability. During the testing phase, all nodes were used. The model avoids unit removals and unit changes during the training phase. The model-assisted method is used to reduce overfitting problems.

Fully connected layer: The fully connected layer is made up of various units. The units in the previous layer's output signals are weighted, and all the units for added, the bias is a previous layer in the addition and weighted signal is attached with a constant, and thereafter given to the activation function. The activation function employed by the rectified linear unit. The input values are returned as the same input values whether zero return or more than return zero and when the input values are whether equal to zero or zero less than (i.e., $y = max\ (x, 0)$) here output value and input value indicated are *y* and *x* respectively. The extracted features indicate that the output value of *y*.

3.3. Enhanced firefly optimization—Feature selection

The extracted feature undergone for the output value of *y* applied to the input of firefly algorithm[18] is the most developed heuristic optimization method and this algorithm encouraged by the expressing the character of fireflies. FA algorithm has three steps. The first step of the FA is referred to as pseudocode. The second step contains two elements like intensity of light variance and attractiveness of formulation. The third step firefly of the brightness. The related to the objective of the concept issues given by described below as Equations (2)–(4).

The reduce the attractiveness and intensity of light and increasing source in the distance, the attractiveness and intensity of light variation must be exactly function can be reduced. For example, intensity of light describes can be:

$$I(r_{ij}) = I_0 e^{-\gamma r_{ij}^2} \tag{2}$$

FA is a parameters of the coefficient *c* can be referred to as absorption of light, in order to r_{i_j} firefly of the distance between the values are j and i at x_j and x_i respectively, this method described by cartesian distance $rij = k_{x_i x_{j_k}}$. The proportional between firefly's attractiveness and light intensity can be described by

$$\beta(r_{ij}) = \beta_o e^{-\gamma r_{ij}^2} \tag{3}$$

in that β_o is a attractiveness in $r = 0$. Conclude, the attracted firefly to the probability of another firefly, *j* is a referred to as firefly very (brighter) attractive, described by,

$$\Delta x_i = \frac{\beta_{o^{e^{-\gamma r^2}ij}(x_j^t - x_i^t)}}{D} + \alpha\varepsilon_i, \qquad x_i^{t+1} = x_i^t + \Delta x_i \tag{4}$$

where number of generation is a t, vector of random is a ε_i (β_o, the gaussian random vector in that deviation of standard and mean respectively 1 and 0) and parameter of the randomization is a. The initial step of right hand side provides the fireflies between the attraction and the another step is the movement of random. The firefly easily attracted to the brighter fireflies and moving for randomly. The above equation specified, which parameter must be set for the user a, c, b_0 and the ε_i is the distribution to utilize the FA, and in order to mention that two limits of *c* is large or small.

(a) if *c* techniques zero, the constants are brightness and attractive, and simultaneously, the fireflies can be sighted by other all fireflies. In case, the reverts to the FA–PSO.

(b) if *c* techniques ∞, The brightness and attractiveness technique zero, and short sighted of the all the fireflies or a foggy can be fly at environment, randomly moving. In case, the reverts to the FA-random search pure algorithm.

Thus, the FA has the generally depends on the two limits. The upcoming section discussed the effectiveness of the FA is a tackling the truss optimization issues. The feature selection process indicates that the output value of Δx_i.

3.4. ResNet 18-classification

The feature selection undergone for output value of Δx_i applied to the input value of ResNet 18[19] presents the topic of residual learning. The deep learning based ResNet 152, it is compared to that AlexNet and VGG-FaceNet are deeper to 8 & 20 times respectively, and low complexity of computational. Described below as Equations (5) and (6).

When the same of the output and input dimensions, the numerical equation of output values function can be:

$$Z = F(x(input), \{w_k\}) + x(input) \quad (5)$$

when the different of the dimensions, the numerical equation of output values function can be described below:

$$Z = F(x(input), \{w_k\}) + w_s x(input) \quad (6)$$

where, w_k indicates that are w is a weight related with k is a k-th layer. The tasks of the image classification are used to ResNet has the 101 layers, 50 layers, and 152 layers generated error decrease the percentage. ResNet provides better performance in tasks of localization and recognition of images. The classification process indicates that the output values Z.

The convolutional neural architecture contains input image, convolutional layer, pooling layer, dropout, fully connected layer and extracted features as shown in **Figure 2**.

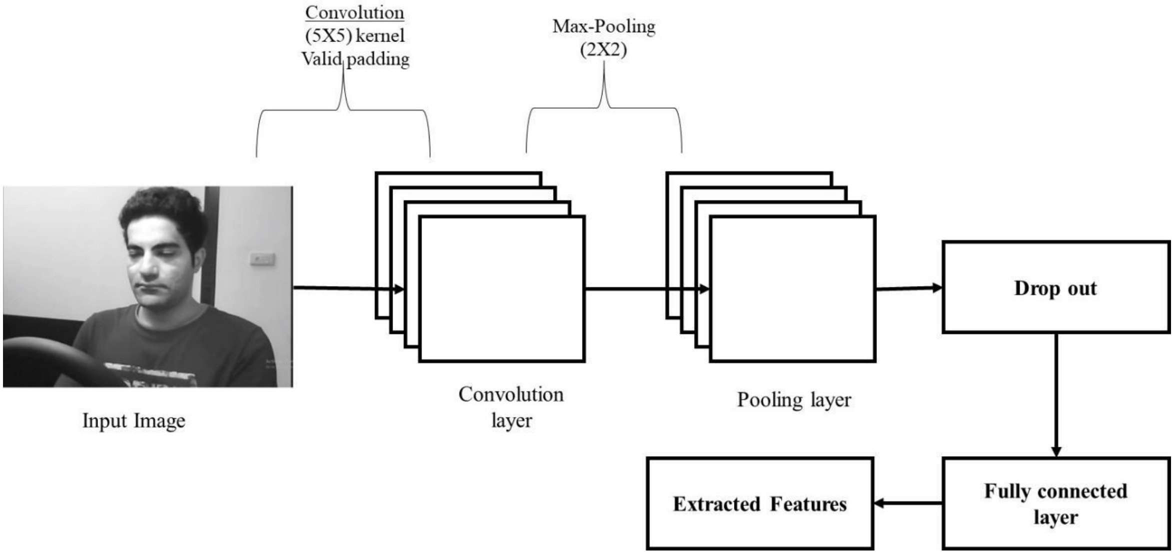

Figure 2. CNN architecture.

4. Simulation setup

Simulated setup in this section includes metrics, datasets, system requirements, and parameter settings, which are explored further below.

Metrics: The metrics employed in the driver drowsiness detection approach include accuracy, sensitivity, and specificity[20,21], which are described as Equations (7)–(9) below.

$$Accuracy = \frac{TP + TN}{P + N} \quad (7)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (8)$$

$$Specificity = \frac{TN}{TN + FP} \quad (9)$$

Dataset: The NTHU-DDD dataset was derived from a video dataset of driver drowsiness detection, which included 36 subjects of various ethnicities. Driving normal, blink rate slow, yawning, falling asleep, and burst out laughing are among the five types of classes. The obtained dataset is divided into three datasets such as:

- Evaluation dataset
- Train dataset
- Test dataset

The evaluation dataset contains 4 subjects of 20 video clips (173, 259 frames), while the train dataset comprises 18 subjects of 360 video clips (722, 223 frames), and test dataset comprise 14 subjects of 70 clips (736, 132 frames). The videos are the pixel size in 640 × 480, without audio to AVI format per second of 30 frames. The sample images are shown in below **Figures 3** and **4**. The images of the same circumstance (bare face at night) and various positions, various circumstances but in the same positions.

Figure 3. The sample frames of same circumstances (bare face at night) and various actions (combine non drowsy and drowsy state).

Figure 4. The sample frames of various circumstances (glasses wearing at night, bare face at night, glasses wearing, sunglasses wearing and bare face) and same actions (drowsy state).

The divided into four parts in the training dataset. Described subject states below as:

- Drowsy
- Non-drowsy
- Head nodding
- Yawning

The drowsy states are mentioned like as drowsy, head nodding and yawning, the subsampled at a 1/10th rate has a training set to decrease the size of the training data.

System requirement: The DDD method used for the system requirements described below as:

- Intel i7
- GPU–6GB
- RAM-16GB
- Windows 10, 64-bit OS

Parameter setting: The DDD method used for the parameter settings consists of CNN and ResNet 18 models described below as:

- Epoch-8
- Learning rate-0.01
- ReLU activation function
- Adam optimizer

5. Result

This results section includes a comparison of CNN-EFF-ResNet 18 models with individual standard CNN models and individual ResNet 18 models using the DDD method. CNN-EFF-ResNet 18 is compared to other deep learning techniques like AlexNet, GoogleNet, RCNN, and FasterRCNN in the DDD method. In the DDD method, the CNN-EFF-ResNet 18 deep learning model and optimisation algorithms ResNet 18, WOA, GOA, and FA are compared. In the DDD method, the ensemble technique, PMLDP, and HDDD based on the CNN method are compared to CNN-EFF-ResNet 18.

Table 1 and **Figure 5** compare CNN-EFF-ResNet 18 to standard CNN and ResNet 18 models using the DDD method. The CNN model's benefits include a wide range of applicable characteristics and high accuracy. The issue with local optima is resolved by the enhanced firefly optimisation algorithm, which also increases exploration. The vanishing gradient issue is resolved by the ResNet 18 model due to identifying mapping. The CNN-EFF-ResNet 18 model combination used in the DDD method has high accuracy (91.3%), sensitivity (92.1%), and specificity (92.5%). In comparison to the CNN model, the ResNet 18 model has higher values for accuracy (82.5%), sensitivity (80.2%), and specificity (81.5%).

Table 1. Quantitative analysis.

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
CNN	80.3	79.7	78.6
ResNet 18	82.5	80.2	81.5
CNN-EFF-ResNet 18	91.3	92.1	92.5

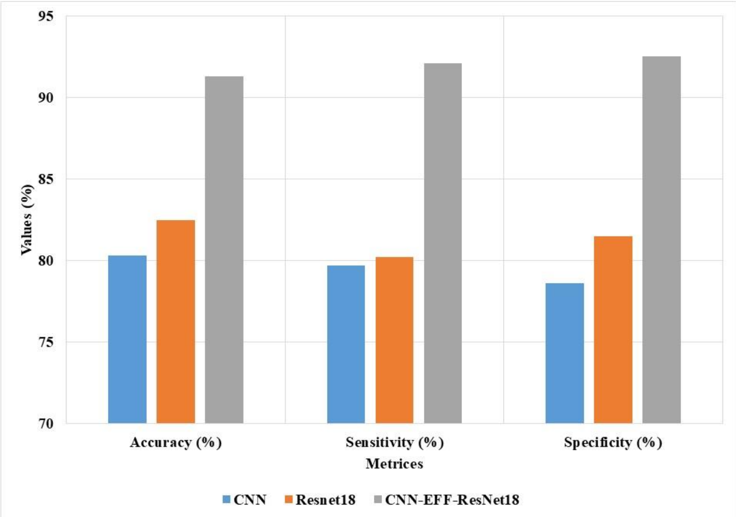

Figure 5. Quantitative analysis of the driver drowsiness detection.

As shown in **Table 2** and **Figure 6**, CNN-EFF-ResNet 18 is compared with deep learning techniques like AlexNet, GoogleNet, RCNN, and FasterRCNN. Because AlexNet model has overfitting and vanishing gradient issues, the GoogleNet model performs better than AlexNet model. Since FasterRCNN uses a selective search model to generate fields of interest, it performs better than the RCNN model. The CNN-EFF-ResNet 18 model combination used in the DDD method has high accuracy (91.3%), sensitivity (92.1%), and specificity (92.5%). The GoogleNet model outperforms the combination of the AlexNet, RCNN, and FasterCNN models in terms of accuracy (86.2%), sensitivity (84.9%), and specificity (83.5%).

Table 2. Comparative analysis of the deep learning methods using in the DDD method.

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
AlexNet	84.54	82.9	82.2
GoogleNet	86.8	84.9	83.5
RCNN	83.9	82.4	81.8
FasterRCNN	85.45	83.45	82.23
CNN-EFF-ResNet 18	**91.3**	**92.1**	**92.5**

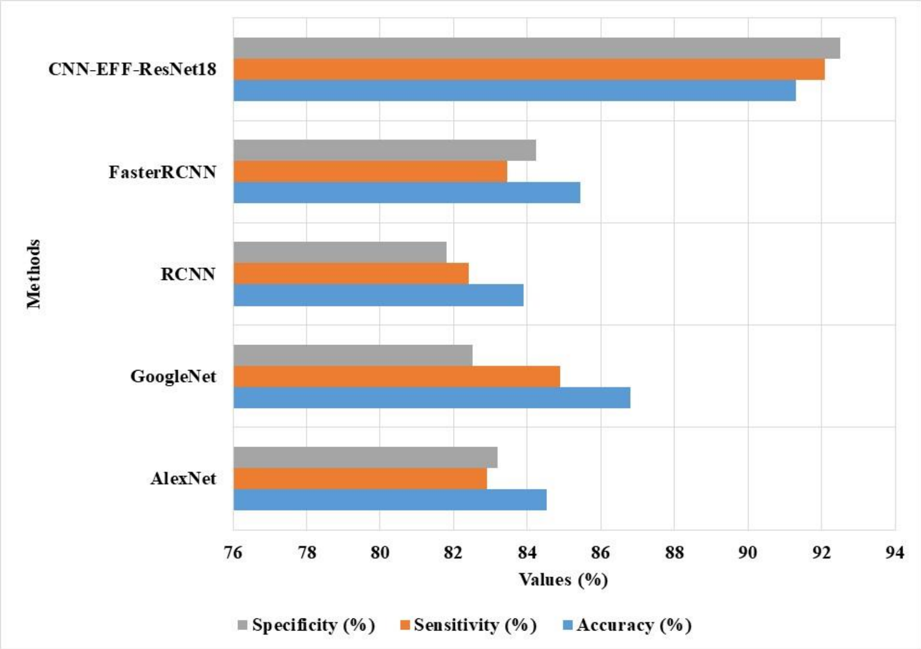

Figure 6. Deep learning methods in the DDD method.

As shown in **Table 3** and **Figure 7**, the CNN-EFF-ResNet 18 deep learning model and optimisation algorithms such as ResNet 18, WOA, GOA, and FA are compared with each other using the DDD method. High complexity and an overfitting issue are two limitations of the ResNet 18 deep learning model. The GOA performs better than WOA because WOA has a slow rate of convergence, is vulnerable to local optimum formation, and has poor accuracy. Because FA has the local optima problem, requires more computational time due to its complexity, and has a slow convergence rate, the ACO algorithm performs better than FA. The CNN-EFF-ResNet 18 model combination used in the DDD method has high accuracy, sensitivity, and specificity values of 91.3%, 92.1%, and 92.5% respectively, whereas the ant colony optimisation algorithm has higher values of accuracy, sensitivity, and specificity of 88.4%, 85.9%, and 86.5% than the combination of ResNet 18, WOA, GOA, and FA models.

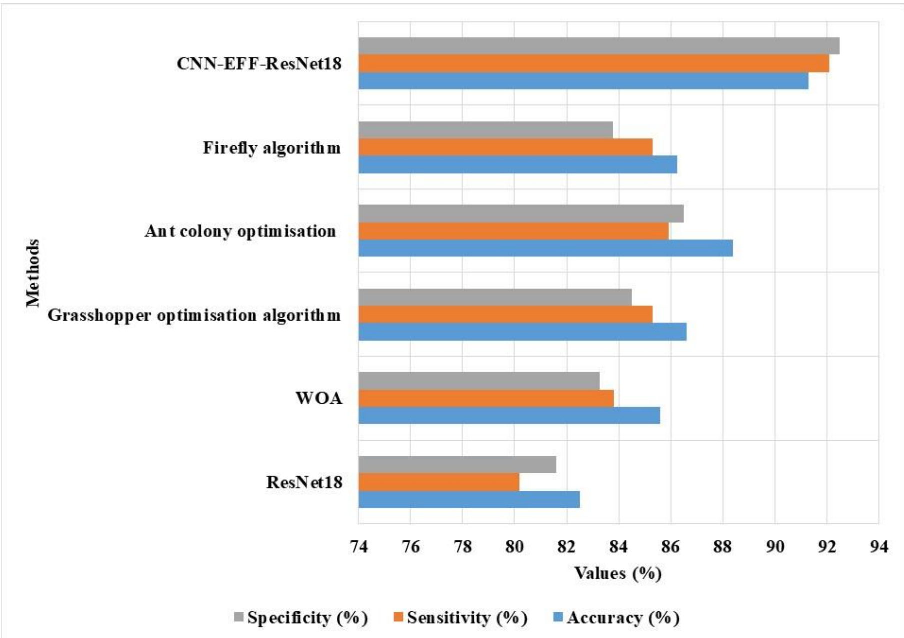

Figure 7. Optimization algorithm using in the driver drowsiness detection method.

Table 3. Optimization algorithm using in the comparative analysis of the driver drowsiness detection method.

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
ResNet 18	82.5	80.2	81.6
Whale optimization Algorithm (WOA)	85.6	83.8	83.25
Grasshopper optimization algorithm (GOA)	86.6	85.3	84.5
Ant colony optimization (ACO)	88.4	85.9	86.5
Firefly algorithm (FA)	86.23	85.3	83.76
CNN-EFF-ResNet 18	91.3	92.1	92.5

Comparative analysis

The comparative analysis of the existing methods such as ensemble method, PMLDB and HDDD methods are compared with CNN-EFF-ResNet 18 in DDD method.

As shown in **Table 4** and **Figure 8**, the CNN method based ensemble technique, PMLDP, and HDDD are compared to CNN-EFF-ResNet 18 in the DDD method. The negative axis on the inactive as a means of providing zero values and the inability of zero to differentiate are two limitations of the ensemble algorithm assisted by the ReLU function. The limitations of the PMLDB model, which is supported by the SVM and PCA model, include imbalanced classes, data loss, and reduced dimensionality. The HDDD model, which the LSTM supports, has drawbacks like overfitting and memory requirements during training. The accuracy of the DDD method, which combines the CNN-EFF-ResNet 18 models, is high (91.3%). The HDDD model, however, outperforms the ensemble and PMLDB model combination by 87.19% in terms of accuracy.

Table 4. Driver drowsiness detection method accuracies.

Methods	Accuracy (%)
Ensemble[11]	85
PMLDB[12]	79.84
HDDD[14]	87.19
CNN-EFF-ResNet 18	91.3

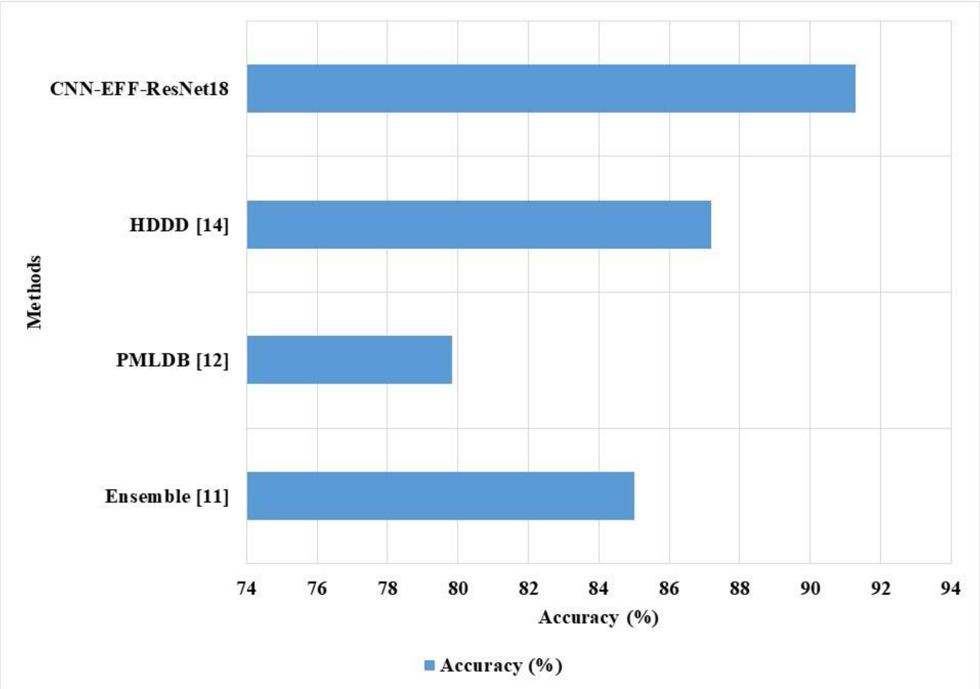

Figure 8. Accuracy of the driver drowsiness detection system.

6. Conclusion

The driver drowsiness detection (DDD) technology is based on the safety of cars and this system reduces many accidents and deaths that occur due to driver drowsiness. As a result, it is monitored and identified when drivers gets drowsy. The LSTM-assisted model has the drawbacks of overfitting and disappearing gradients, and requires more memory to train. Lower exploration of optimisation problems has been resolved by the enhanced firefly optimisation technique. The ACO is constrained by factors including phase of slowdown, exploitation rate, exploration rate, and convergence speed. Due to the mapping of identified, the model with help from the ResNet 18 model resolves the vanishing gradient problems. The effective dimensional space is high for the state-of-the-art HDDD model assisted by SVM method. In comparison to ensemble and PMLDB methods in DDD, the CNN-EFF-ResNet 18 models have a high Accuracy of 91.3%, while HDDD method has an accuracy of 87.19%. The existing WOA model has drawbacks such slow convergence, poor precision, and difficulty with easily entering local optimums. The future goal of this research is to improve driver drowsiness detection through the use of transfer learning-based convolutional neural networks.

Author contributions

Conceptualization, SN and S; methodology, SN and S; software, SN and S; validation, SN and S; formal analysis, SN and S; investigation, SN and S; resources, SN and S; data curation, SN and S; writing—original draft preparation, SN and S; writing—review and editing, SN and S; visualization, SN and S; supervision, SN; project administration, SN and S. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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