A Hybrid PFO-GA Approach for Robust and Efficient Driver Drowsiness Detection Using CNNs

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ABSTRACT

Driver drowsiness detection plays a pivotal role in modern intelligent transportation systems by improving road safety and reducing accidents caused by sleepiness at the wheel. However, real-world detection is challenging due to variations in driver behavior, lighting conditions, occlusions, and environmental noise. To address these challenges, a hybrid optimization method combining Polar Fox Optimization (PFO) and Genetic Algorithm (GA) is proposed to effectively fine-tune convolutional neural network (CNN) hyperparameters for drowsiness detection. The tuned CNN models focus on two key inputs—facial expressions and eye state classification—which are critical indicators of fatigue. The PFO-GA optimizer autonomously adjusts parameters such as the learning rate, number of filters, kernel size, and dropout rate, aiming to maximize detection performance. Using k-fold cross validation and standard evaluation metrics, the optimized model achieved an accuracy of 93.4 %, precision of 93.49 %, recall of 93.4 %, F1-score of 93.4 %, and AUC of 96.67 %, demonstrating strong reliability under real driving conditions. An end-to-end automated pipeline covering preprocessing, model training, validation, logging, and visualization is also implemented to ensure reproducibility and efficiency. By maximizing the F1-score, the PFO-GA framework balances false positives and false negatives, yielding timely and accurate drowsiness alerts suitable for safety-critical applications.

Keywords: Driver Drowsiness Detection, Convolutional Neural Networks (CNN), Polar Fox Optimization (PFO), Genetic Algorithm (GA), K-Fold cross-validation

INTRODUCTION

Driver fatigue is one of the leading contributors to road accidents worldwide, causing thousands of deaths and injuries each year. Studies indicate that drowsiness impairs both cognitive and motor functions, resulting in slower reaction times, poor decision-making, and an increased likelihood of vehicle collisions [1]. Crashes associated with fatigue tend to be more severe than other types of accidents due to delayed responses and diminished situational awareness. According to the National Highway Traffic Safety Administration (NHTSA), drowsy driving accounts for approximately 23–25% of all road accidents in the United States, claiming over 4,000 lives annually [2]. Many drivers fail to accurately gauge their own fatigue levels, which leads to reduced alertness and a higher probability of crashes. These alarming statistics highlight the urgent need for reliable and efficient driver drowsiness detection systems to mitigate fatigue-related incidents.

In response to this challenge, researchers have developed multiple detection strategies, broadly classified into physiological, behavioral, and vehicle-based approaches. Physiological methods rely on biosignals such as electroencephalogram (EEG), electrooculogram (EOG), and heart rate variability (HRV) to assess fatigue levels. Although these systems provide valuable insight into the driver's physical state, their practical application is limited by the invasiveness and discomfort caused by wearable sensors. Moreover, their accuracy in real-world driving scenarios can be compromised by environmental factors such as temperature changes and motion artifacts [3]. Behavioral approaches, on the other hand, analyze visual cues including facial expressions, eye closure duration, yawning frequency, and head movement patterns to determine signs of drowsiness. However, Vehicle-based approaches aim to study driving habits, such as lane drifts, steering maneuvers, and braking patterns. With recent breakthroughs in artificial intelligence and deep learning, the performance of these approaches has been significantly enhanced, enabling real-time drowsiness detection with high accuracy [4], [5]. Deep learning architectures, particularly CNNs, Recurrent Neural Networks (RNNs), and hybrid architectures, have shown great promise in detecting drowsiness through image and video processing. Facial micro-expressions and eye states can be very accurately identified using CNN-based models. The temporal dependencies of drowsiness patterns can be understood through Long Short-Term Memory (LSTM) networks and Transformer-based architectures. Multimodal approaches with behavioral and physiological signals have been explored to achieve higher accuracy [6], [7]. Facial feature variability, lighting conditions, occlusions, and computational costs are the issues that must be addressed and implemented in real-world scenarios [8]. When drivers allow distractions, the chances of their being involved in an accident are high; hence, it is important to examine the seriousness of the accident to prevent it from happening [9]. With the use of the images recorded [10], the segments of the video analyzed [11], and potholes detected on the route [12], one can learn about accidents that occur when people are not wearing helmets.

Conversely, computer vision-based methods have gained prominence as non-intrusive and scalable solutions for identifying driver fatigue. These approaches analyze visual cues such as facial expressions, eye movement patterns, yawning frequency, and head orientation to assess real-time drowsiness levels [13]. The introduction of deep learning has further improved their performance, enabling precise and automated detection of fatigue. The integration of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) allows for the extraction of both spatial and temporal information from continuous video streams, thereby increasing the reliability of fatigue recognition systems [14].

Despite these advancements, CNN-based models still encounter limitations related to variations in illumination, facial occlusions, and inter-individual differences in facial structure. Object detection algorithms such as YOLO have proven effective in minimizing road accidents by identifying relevant objects in real-world images [15], [16]. More recently, Graph Convolutional Networks (GCNs) have opened new research avenues by leveraging spatial dependencies among facial landmarks for drowsiness analysis. Unlike traditional CNNs that primarily capture localized spatial information, GCNs can model interrelationships among multiple facial regions, resulting in improved feature representation and classification precision [17]. Furthermore, multi-modal fusion strategies have been introduced to combine data from facial expressions, head pose, and blinking patterns, offering a more comprehensive and robust understanding of driver fatigue across diverse driving conditions.

To address the challenges of model optimization, a hybrid optimization framework combining Polar Fox Optimization (PFO) and the Genetic Algorithm (GA) is proposed. This framework automatically fine-tunes crucial CNN hyperparameters, including the learning rate, filter count, kernel size, and dropout rate. A specialized CNN architecture was developed for both facial expression and eye-state classification—key indicators of drowsiness—and optimized through the PFO-GA process. The model's robustness was validated using k-fold cross-validation and multiple evaluation metrics to ensure consistent performance. By maximizing the F1-score, the system effectively reduced both false positives and false negatives, thereby improving the accuracy of drowsiness alerts. Additionally, a fully automated end-to-end training pipeline was implemented, encompassing data preprocessing, model training, validation, performance logging, and visualization, which enhanced both reproducibility and overall efficiency.

The subsequent sections of this work are organized as follows: Section 2 examines the current literature on the detection of driver sleepiness. Section 3 presents our suggested model along with its essential components. Section 4 delineates experimental findings and a comparative evaluation with established methodologies. Ultimately, Section 5 culminates with insights and prospective research avenues.

RELATED WORK

The study on driver drowsiness detection has progressed considerably through the use of sophisticated deep learning methods, multi-sensor integration, and attention-based mechanisms, thereby improving detection precision and reliability. Different methodologies have been investigated to address the real-time monitoring challenge of drivers' vigilance, with a strong focus on physiological, behavioral, and vehicular data. One utilizes ECG and auto encoders with self-attention for R-R interval analysis, a crucial measure of heart rate variability that can indicate drowsiness. This approach provides a robust physiological monitoring system [18]. The Deep Alert Driver Vigilance System is another system that utilizes deep neural networks to identify facial features and patterns in eye movements for the detection of effective micro sleep and drowsiness-related cues [19]. Transfer learning has also been utilized, where pre-trained deep learning models were fine-tuned to enhance drowsiness detection with minimal computational burden. Thus, deployment is feasible in embedded automotive platforms [20]. Several approaches to classify distraction driver detection systems using various data mining techniques have been proposed [21], and a corresponding mechanism has been developed [22].

Multi-sensor fusion has also been researched, where vision-based monitoring inputs are combined with heart rate sensor inputs and steering pattern inputs to enhance detection robustness, particularly in heavy vehicle applications involving prolonged driving, as it increases the likelihood of fatigue [23]. Due to the voice recognition [24], self-motivation in driving [25], and predicting the weather condition using NN [26]. By observing the driver's facial expressions, the system can easily identify stress [27], and an ML model [28] was developed.

This modality fusion technique significantly enhances system precision by minimizing dependence on a single modality and mitigating limitations such as occlusions or insufficient lighting conditions [29]. These advancements collectively enhance road safety by promoting preventive interventions and alerts, thereby reducing accident hazards associated with driver sleepiness. The combination of sophisticated AI algorithms, physiological data, and embedded systems marks a paradigm towards intelligent transportation systems, laying out opportunities for real-time, effective, and precise driver alertness monitoring. In addition to drowsiness detection, RF technology with lane detection is investigated for highway cruise control, enhancing lane-keeping quality and driver monitoring precision [30]. Potholes are also detected using machine learning (ML) models [31]. A novel framework was employed to enhance object detection performance using the YOLO algorithm for various detection applications [32].In addition, a hybrid deep learning model that integrates CNNs with ConvLSTM and YOLO (You Only Look Once) shows better performance in proactive risk prediction by observing both spatial and temporal driving habits [33]. This multimodal fusion technique significantly enhances the accuracy of hazard detection, providing real-time notifications that enable drivers to make timely interventions.

Although the systems are remarkable in terms of accuracy and dependability, they also suffer from issues such as low-light performance problems, occlusions, and data synchronization complexities in multi-sensor systems. Overall, these advancements in AI-based driver monitoring offer promising solutions for enhancing road safety, reducing accidents, and paving the way for intelligent transportation systems.

Table 1. Literature Review

Ref	Year	Models Used	Results	Limitations
[34]	2023	Various ML & DL models (CNN, SVM, LSTMs, Random Forest)	Overview of existing techniques and their effectiveness	Lacks experimental results; focuses on literature review
[35]	2024	CNN + LSTM Hybrid Model	Improved accuracy compared to traditional approaches	Requires high computational resources
[36]	2024	Quantum SVM, Quantum Neural Networks	Claims enhanced accuracy and efficiency	Implementation complexity; lacks real-world validation
[37]	2024	Vision Transformer (ViT)	High accuracy in detecting drowsiness using vision-based features	Needs large-scale data for effective generalization
[38]	2021	Various tested ML models (SVM, RF, Decision Trees)	Evaluate regulatory compliance and effectiveness	Limited scope; focuses on policy rather than new detection techniques
[39]	2023	Convolutional Neural Network (CNN)	Effective in detecting drowsiness and distraction	Prone to false positives in real-world conditions
[40]	2023	Support Vector Machine (SVM), Decision Trees, KNN	Detects drowsiness based on behavioral patterns	Performance varies with individual differences
[41]	2023	Deep Neural Networks (DNNs) for biosignal classification	High accuracy in controlled conditions	Requires intrusive biosignal monitoring
[42]	2024	CNN, RNN, LSTM, and Autoencoders applied to EEG data	Compares the performance of different DL models	EEG data collection is complex and not easily deployable
[43]	2024	CNN, LSTM, Transfer Learning	Promising accuracy in predicting drowsiness	Requires large labelled datasets
[44]	2023	Dilated Convolutional Neural Network (DCCNN)	Higher accuracy in eye state recognition	Performance is dependent on dataset quality
[45]	2024	CNN + Genetic Algorithm	Optimized CNN architecture with improved efficiency	Computationally expensive optimization
[46]	2023	Lightweight CNN, Facial Landmark Detection	Real-time, cost-effective solution	Limited accuracy under extreme conditions
[47]	2023	SVM, Random Forest, Decision Trees, KNN	High accuracy with behavior-based feature extraction	Limited generalization to real-world settings
[48]	2024	CNN, Eye Aspect Ratio (EAR)	Effective mobile-based drowsiness detection	Performance is affected by smartphone camera quality and lighting

In Table 1, a comprehensive review of the existing literature was conducted to provide an understanding of the current research landscape. This in-depth analysis enabled us to identify several critical gaps, which are outlined below, that facilitate further exploration of potential solutions.

GAPS identified

1. Manual and Suboptimal CNN Hyperparameter Tuning: Most existing CNN-based drowsiness detection systems rely on manual or trial-and-error methods for selecting hyperparameters, such as the learning rate, number of layers, and batch size, resulting in suboptimal model performance and prolonged training times.

2. Inadequate Model Generalization across Drivers: Current models tend to overfit specific datasets and fail to generalize across drivers with different facial structures, lighting conditions, or driving environments due to insufficient validation mechanisms.

3. Poor Precision and Recall in Drowsiness Detection: Detection systems often struggle with high false-positive or false-negative rates due to weak feature extraction and imbalanced training, which limit the system's ability to reliably differentiate between drowsy and alert states.

METHODOLOGY

OBJECTIVES

1. Automate the CNN hyperparameter tuning process using the Polar Fox Optimization–Genetic Algorithm (PFO-GA), enhancing model performance and reducing manual intervention.
2. To implement k-fold cross-validation and comprehensive performance metrics (accuracy, precision, recall, and F1-score) to ensure robust model generalization across varied driver datasets and environmental conditions.
3. To design an optimized CNN architecture that maximizes precision and recall**,** enabling early and reliable detection of driver drowsiness with minimal false alarms.

DATASET

The dataset used for drowsiness detection is taken from Kaggle [49]. It provides a diverse collection of images capturing different states of drivers, including natural and drowsy conditions, making it suitable for developing deep learning (DL) and machine learning (ML) models for drowsiness detection. The dataset consists of a total of 7,342 images, categorized into two classes:

- Drowsy: 3,566 images (2,809 for training, 757 for testing)
- Natural: 3,776 images (3,050 for training, 726 for testing)

The images used to train the model are located in the training folder, while the images used to evaluate the model's performance are located in the testing folder. These two primary folders make up the dataset. All images have undergone preprocessing steps, including image framing from videos, face region detection, grayscale conversion, and resizing to 48x48 pixels. These steps enhance feature extraction and computational efficiency. The dataset is valuable for researchers and developers aiming to build accurate drowsiness detection models.

PROPOSED MODEL

Data Preparation

The images are loaded, and meaningful features, such as edges, curves, and textures, are extracted using image processing techniques or pre-trained models. Self-normalizing Neural Networks (SNNs) utilizing the SELU activation function, which automatically normalize pixel values during training. Instead of applying manual normalization before feeding images into the model, SNNs maintain the mean and variance of activations within an optimal range as data passes through the network. This self-normalization occurs when inputs are correctly initialized and passed through dense layers with SELU activations, ensuring stable learning without the need for explicit normalization layers. As a result, this technique enhances model robustness to the varying lighting conditions and contrast levels commonly found in real-world lane detection scenarios.

Initialization

Potential solutions are randomly initialized, and a CNN model uses each solution's hyperparameters to compute a fitness value (e.g., validation accuracy) and the top-performing candidate's best set of hyperparameters.

FPO Optimization Loop

In the FPO optimization cycle, the algorithm continually optimizes hyperparameter solutions within a predetermined number of iterations ($t \leq Tmax$). The candidate solutions are modified with each iteration based on the FPO equation, which mimics natural processes such as light absorption and energy transfer in the Fenna–Matthews–Olson system. The modified solutions are subsequently assessed using trained CNN models and evaluated based on their performance, typically in terms of training accuracy. If any new solution is better than the current best (XBest), it replaces it, thus providing continuous improvement towards an optimal hyperparameter set.

GA Tuning Loop

In the GA tuning loop, candidate hyperparameter sets are evolved using principles inspired by natural selection. First, solutions with high fitness are selected as parents for reproduction. These parents undergo crossover, combining parts of their configurations to create new offspring solutions. Finally, these new candidates replace the least fit solutions in the population, ensuring that each generation moves closer to an optimal set of hyperparameters. Figure 1 illustrates the sequential process for applying PFO + GA, followed by hyperparameter tuning of the CNN for the final classification.

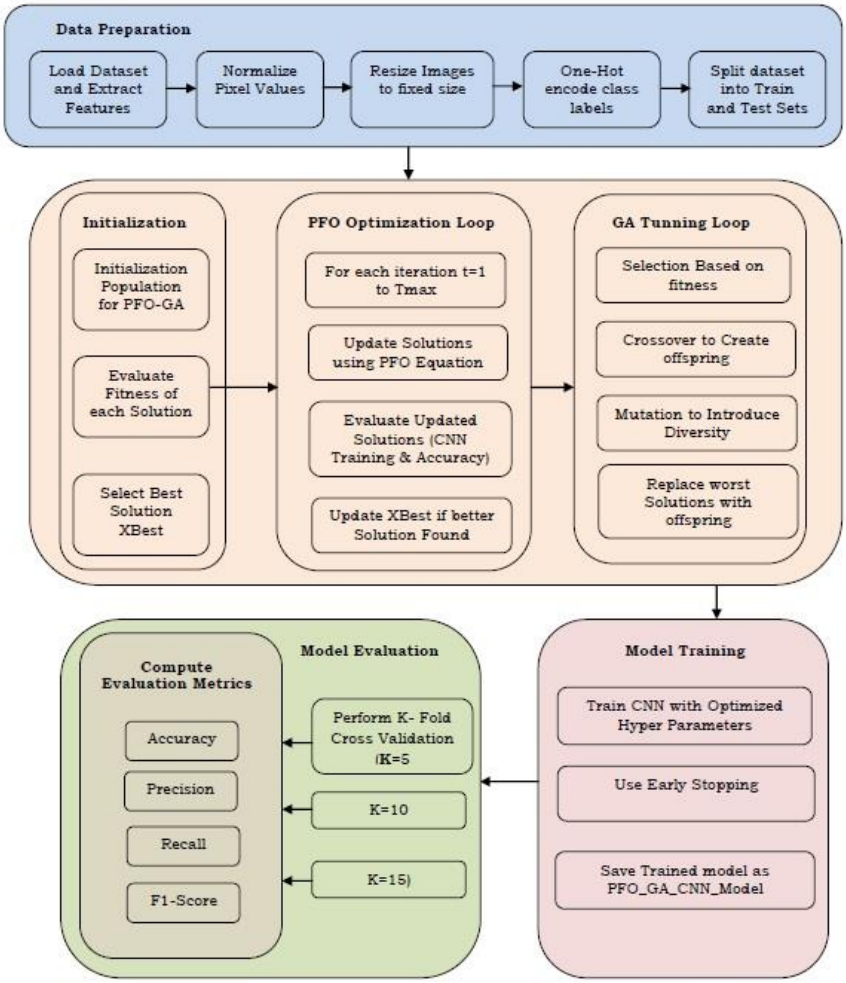

Figure 1. PFO + GA + CNN architecture

Model Training

The final CNN model is trained using the optimal hyperparameters identified through the FPO-GA optimization process. This fine-tuned configuration trains the lane detection model to achieve high accuracy and generalization. Early stopping is employed by monitoring the validation loss during training; if no improvement is observed over a set number of epochs, training halts to prevent overfitting. Once the model achieves optimal performance, it is saved as FPO_GA_CNN_Model for future use in real-world lane detection applications.

Model Evaluation

Perform K-Fold Cross Validation:

Evaluate model stability using K-fold CV (e.g., K=5, 10, 15). The data is split into K parts, each used once as a test set.

Algorithm: PFO + GA + CNN

Step 1: **Data Preprocessing**

i. Load dataset D and extract features.
ii. The pixel values can be normalized in the range of [0,1] as:

a. $X' = \frac{X}{255}$

b. This helps with convergence during training.

where X: Original image pixel value, X′: Normalized image pixel value

iii. Resize images to a fixed size (H, W, C)=(128,128,3).

iv. For categorical classification, we one-hot encode the class labels

v. Next, this dataset is divided into training (80%) and testing (20%) sets.

Step 2: Initialize Population for PFO-GA

A. Randomly generate PP solutions (each representing a CNN hyperparameter set):

$X_i = \{F_i, k_i, D_{r_i}, n_i, B_i\}$

Where $F_i$is Filter size, k_i is Kernel size, $D_{r_i}$is Dropout rate, n_i is the number of neurons,

B_i is Batch size

B.Return the fitness, which can be calculated as the accuracy of the CNN trained with those parameters:

$$Acc = \frac{C_p + C_n}{C_p + C_n + I_p + I_n}$$

C. Choose the best solution, Xbest, with the maximum accuracy.

The use of random initialization helps prevent premature convergence of PFO and GA on suboptimal paths.

Step 3: Perform Polar Fox Optimization (PFO)

For each iteration t (from 1 to T_{max}):

***A.* Using the PFO equation to update each solution**:

$$X_i^{t+1} = X_i^t + \alpha \cdot \left(X_{best}^t - X_i^t\right) + \beta \cdot \epsilon$$

Where:$X_i^t$is the solution at iteration *t,* $X_i^{t+1}$is the Best solution found at iteration *t,* T_{max} is the Maximum number of iterations for PFO. The α parameter controls the movement of foxes towards the best solution, β adds random exploration, ϵ is a positive constant-sized small perturbation, which can be determined from the context of diversification

B. Evaluate updated solutions using CNN training and accuracy computation.

C. If a better solution exists, update X_{best}.

PFO balances exploration (searching the entire environment) and exploitation (locally converging on environmental optima), emulating the movement of actual Arctic foxes.

Step 4: Use Genetic Algorithm (GA) for Tuning

***A.* Selection:** The selection of the parent is based on fitness (accuracy ranking).

***B.* Crossover:** Create new offspring with:

$X_{mutated} = \frac{X_{parent1} + X_{parent2}}{2}$

$X_{parent1}, X_{parent2}$ are Selected parents based on fitness, $X_{mutated}$ is the offspring created via crossover and mutation.

Mutation: Change the offspring to avoid an early convergence:

$X_{mutated} = X_{child}$

Where δ is a random perturbation.

C. Replace the worst solutions with new offspring.

GA enhances exploration by introducing diversity while leveraging the best solutions.

Step 5: Train the Final Optimized CNN Model

- i. Train the CNN with the optimized hyperparameters on the full training set Dtrain.
- ii. Use early stopping to prevent overfitting.
- iii. Finally, save the trained model as PFO_GA_CNN_model. h5.

Training the CNN with optimal parameters ensures higher accuracy and efficiency.

Step 6: Cross-Validation and Evaluation

- i. Perform **K-Fold Cross-Validation** (K=5, 10, 15).
- ii. Compute evaluation metrics:
  - a. **Accuracy**: $Acc = \frac{C_p+C_n}{C_p+C_n+I_p+I_n}$
  - b. **Precision**: $Pre = \frac{C_p}{C_p+I_p}$
  - c. **Recall**: $Rec = \frac{C_p}{C_p+I_n}$
  - d. **F1 Score**: $F1 = 2 * \frac{Pre*Rec}{Pre+Rec}$

Where, $\boldsymbol{C_p}$: Correctly predicted positive cases, C_n: Correctly predicted negative cases, $\boldsymbol{I_p}$: Incorrectly predicted positive cases, $\boldsymbol{I_n}$: Incorrectly predicted negative cases.

The images in the dataset are preprocessed by resizing them to a fixed shape of (128, 128, 3) and normalizing their pixel intensities to the [0, 1] range, which supports quicker convergence. One-hot encoding is applied to the class labels, and the dataset is then divided into training and test sets. When an input is provided as an image, it undergoes a systematic pipeline to be classified correctly via a hybrid optimization-augmented CNN model. To enhance the performance of the CNN, a hybrid approach combining Polar Fox Optimization (PFO) and Genetic Algorithm (GA) is employed. It begins with the random generation of sets of CNN hyperparameters, which are ranked according to model accuracy. PFO progressively optimizes these parameters by replicating the behavior of the Arctic. GA then continues to maximize diversity using selection, crossover, and mutation. After the optimal hyperparameters are discovered, the CNN is trained with these hyperparameters and saved as a model. Regarding evaluation, the model is validated under K-Fold Cross-Validation, and its performance is assessed through accuracy, precision, recall, and F1-score. Ensure the model has excellent predictive performance and generalizes well to new images.

RESULT ANALYSIS

Figure 2 presents the comparative results between the standard CNN model and the PFO-GA optimized CNN for facial images in drowsiness detection. Each row includes the original image, the true class label, and predictions from the CNN and the PFO-GA-optimized CNN. Prediction confidence scores were also displayed. These visual comparisons highlight how the PFO-GA optimized model improves classification reliability, particularly in ambiguous or borderline cases.

The instances shown in Figure 2 show that the PFO-GA optimized CNN model outperforms the baseline CNN in all cases, particularly among the misclassified ones. For instance, on the second row, the baseline CNN misclassifies a 'DROWSY' sample as 'NATURAL' with a confidence of 0.73. In contrast, the PFO-GA model correctly classifies it as 'DROWSY' with a higher confidence of 0.89. Similarly, for both 'NATURAL' instances in the second-to-last and last rows, the CNN model misclassifies them as 'DROWSY.'

In contrast, the PFO-GA model correctly classifies them as 'NATURAL' with confidence levels of 0.98 and 0.99, respectively. These observations further solidify the usefulness of applying the PFO-GA hybrid optimization method in fine-tuning the hyperparameters of the CNN, thereby improving the model's robustness and accuracy.

Figure 2: Performance between Baseline CNN and PFO-GA Optimised CNN on Facial Drowsiness Detection.

The CNN model with the specified hyperparameters is validated across various folds, and the corresponding evaluation metrics are recorded. In Table 2, we can see the outcomes of k-fold cross-validation with k = 5, 10, and 15.

Table 2. PFO-GA ON CNN Evaluation Metrics

Total Folds	Accuracy	Precision	Recall	F1 Score	ROC AUC
5	0.934	0.935	0.934	0.934	0.967
10	0.925	0.928	0.925	0.925	0.965
15	0.929	0.931	0.929	0.929	0.966

The results in Table 2 demonstrate that the Hybrid PFO-GA approach significantly enhances CNN performance across multiple evaluation metrics. The model maintains high accuracy, precision, and recall across different cross-validation folds, reinforcing the effectiveness of meta-heuristic optimization in CNN hyperparameter tuning. To test the stability and generalization capability of the model proposed, k-fold cross-validation was done using varying values of k (5, 10, and 15). The obtained accuracies are depicted in Figure 3, drawn from Table 2.

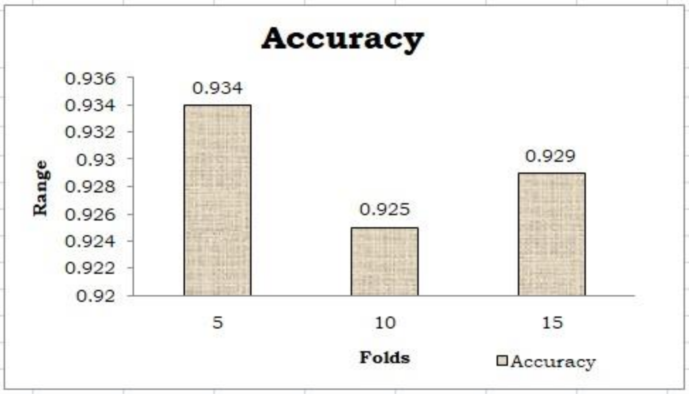

Figure 3: Evaluation metrics of PFO+GA ON CNN

From Figure 3, it can be observed that the accuracy decreased slightly with the increase in folds, standing at 92.5 for 10 folds and 92.9 for 15 folds. It appears that 5-fold cross-validation yielded the best results for training and validation on the dataset.

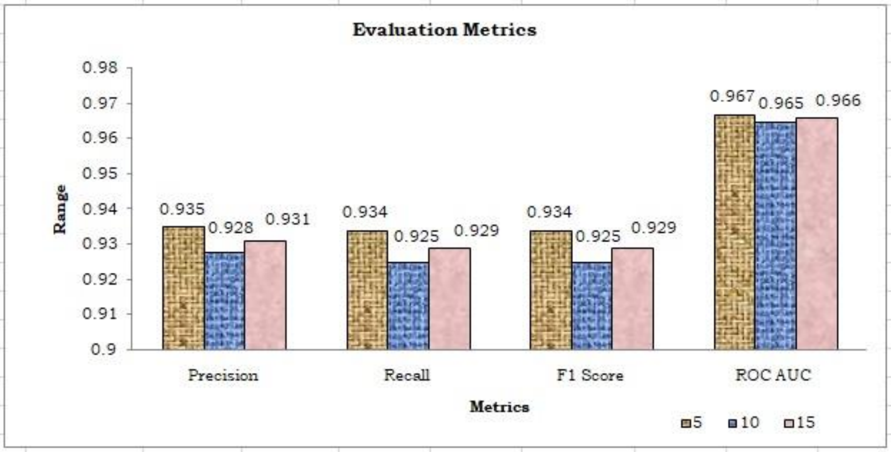

Figure 4: Evaluation metrics of PFO+GA ON CNN

Figure 4 represents the evaluation metrics of PFO+GA. By leveraging the strengths of PFO and GA, this method enables CNNs to achieve superior classification accuracy while minimizing the need for manual hyperparameter tuning. The domain with extensive hyperparameter tuning is impractical due to high computational costs.

Table 3. Comparison with Previous Models

[Ref]	Model Used	Accuracy
[20]	CNNs, VGG16, VGG19, GAN, MLP	Accuracy < 90%
[34]	CNN, LSTM, GRU, CNN-LSTM	89.4%
[32]	SVM, RF, AdaBoost, KNN, MLP	90.31%
[36]	DCCNN	91.25%
[50]	VGG16, VGG19, AlexNet	91.34%
[51]	CNN, CNN-LSTM	92.84%

	PFO+GA + CNN	93.4%

Table 3 summarises the performance of various driver drowsiness detection models from different research studies. The models are evaluated primarily based on their accuracy. As Table 3 illustrates, some of the models in the literature fall short of the proposed model's accuracy rate of 93%. This underscores the competitiveness and robustness of the proposed approach in detecting real-time drowsiness.

CONCLUSION

This work efficiently addressed some key challenges of driver drowsiness detection systems by hybridizing Polar Fox Optimization (PFO) and Genetic Algorithm (GA) to undertake automated CNN hyperparameter tuning. The PFO-GA eliminates the time-consuming, trial-and-error-based parameter selection procedure, resulting in significant time savings in the optimization process for key hyperparameters, such as learning rate, number of filters, kernel size, and dropout rate. This automated tuning process takes special care in solving the problem of manual and non-optimal CNN hyperparameter tuning, resulting in more efficient and precise model structures. Furthermore, using k-fold cross-validation and comprehensive performance metrics ensures robust model generalization across various driver datasets and diverse environmental conditions. This drastically reduces the risk of overfitting, enabling the model to learn and adapt to various facial structures, illumination conditions, and driving styles of drivers, thereby eliminating the common generalization challenges of traditional methods.

Additionally, the enhanced CNN architecture proposed via the PFO-GA approach showed markedly improved precision and recall, with notable results of 93.4% accuracy, 93.49% precision, 93.4% recall, 93.4% F1-score, and 96.67% AUC. These findings validate the model's ability to effectively differentiate between drowsy and alert states, thereby reducing false alarms and enhancing the early detection of drowsiness. Generally, this study presents a holistic solution to the key issues of manual tuning, poor generalization, and low detection reliability, opening the way for more effective and responsive driver drowsiness detection systems. Additional work would involve investigating the fusion of multimodal information, such as heart rate and driving behavior, to enhance the robustness and accuracy of detection.

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