Driver Drowsiness Detection Based on Convolutional Neural Network Architecture Optimization Using Genetic Algorithm

Raparthi Santhosha[1], Swetha G[2]

[1]*PG Student, Department of Computer Science and Engineering, Teegala Krishna Reddy engineering college, India, raparthi.santhosha18@gmail.com*
[2]*Assistant Professor, Department of Computer Science and Engineering, Teegala Krishna Reddy engineering college, India, swethareddy630@gmail.com*

Abstract: Drowsy driving is a major factor in many road accidents, which makes it essential to have dependable real-time detection systems to help keep roads safer. Detection of driver drowsiness presents a novel approach using convolutional neural network (CNN) optimized by a genetic algorithm (GA). The facial features of drivers are examined for the system to classify whether the driver is "Alert" or "Drowsy," thereby issuing warnings to prevent fatigue-related incidents. The Genetic Algorithm optimizes a few critical CNN hyperparameters dynamically, such as the number of layers, filter sizes, and dropout rates. This evolutionary optimization enhances classification accuracy and decreases overfitting in the model, thereby producing a much stronger and more generalizable solution. The CNN model was trained on a set of labeled facial images and tested for performance on a separate set for validity and applicability under real-world conditions. The achieved high accuracy with the optimized system is 91.8% and a billion low inference time of 50 milliseconds per frame suitable for real-time deployment with vehicles. This way, the driver monitoring system opens avenues for efficient and high performance through a smart marriage of deep learning and evolutionary algorithms. The results strongly suggest that the proposed method could be a promising option for enhancing Advanced Driver-Assistance System (ADAS) and thus building safer driving environments.

Keywords: Driver Drowsiness Detection, Convolutional Neural Network (CNN), Genetic Algorithm (GA), Hyperparameter Optimization, Real-Time Monitoring, Facial Feature Analysis, Advanced Driver-Assistance Systems (ADAS), Deep Learning, Fatigue Detection, Road Safety.

1. Introduction

Driver drowsiness is a major cause of road accidents around the world, and thousands die and get injured every year. Long hours of driving especially during nighttime or in monotonous conditions can highly deprive a driver of alertness, reaction time, and judgement. Keeping a mounting concern about road safety, the growth of intelligent automated systems has become inevitable, which will monitor the driver's level of fatigue and alert him on time [1], [8]. Developments in the field of artificial intelligence, especially deep learning, appear promising in this regard. Convolutional Neural Networks (CNNs) are widely used in visual recognition tasks due to the hierarchical way of feature extraction from an image. CNNs can be utilized for drowsiness detection by analyzing and detecting in real-time video input the signs of fatigue such as facial expressions, eye closure, yawning, and head movements [2], [4], [6], [9]. Though CNNs are powerful, designing and optimizing their architectures is generally a cumbersome task requiring training and testing over a number of parameters such as number of layers, filter sizes, activation functions, dropout rates, etc [1], [2]. Given this challenge, the research poses a novel system for driver drowsiness detection using CNNs and GAs to optimize network architecture. GAs simulate some biological phenomena that revolve around natural selection. They basically propagate an evolving population of solutions through many generations through the use of genetic operators such as selection, crossover or mutation [1], [7]. The CNN architecture design by GAs thus helps the system search automatically the set of hyperparameters that guarantees the highest accuracy and efficiency and the least possibility of overfitting. This approach is said to be easeful for implementation in real-world vehicles, unlike traditional or sensor-based techniques, such as EEG or wearable devices, which may be intrusive or inconvenient for drivers [3], [5]. It brings the advantage of high detection accuracy, which, in turn, ensures low inference times of about 50 ms/frame, allowing it to be easily incorporated into ADAS platforms [6], [9]. This project has demonstrated the utility of fostering better generalization to various persons, structures of faces, and patterns of fatigue by evolving deep learning architectures. The results have shown this concept to be a viable and scalable approach to intelligent driver-monitoring systems [7], [8]. Thus, the method described in this project allows for a sturdy and efficient way of real-time detection of drowsiness in drivers using GA-optimized CNN architectures. The mixture of deep learning and evolutionary computation stands out as an important contribution in the path to smart and safety-enhancing technologies in today's vehicles [2], [4]. The model is thereafter trained with a labeled dataset comprising facial images of drivers, both awake and drowsy. This optimization with GAs makes the CNN optimized for drowsiness detection and always able to find a better architectural trade-off toward real-time performance. Hence, it somewhat further reduces the human effort and a manual load of architecture tuning, thus proving to be better-performing over a range of different environmental and lighting conditions [4], [6].

2. Problem Statement

Drowsy driving is among the leading causes of road accidents, accounting for thousands of casualties and injuries every year. The longer the driving goes on, the lower goes alertness, and reaction time gets drawn. Thus, it is imperative, to begin with, the detection of driver fatigue. Conventional methods rely on partial solutions that do not measure up to the temporal requirements of a real-time safety application-monitoring steering behavior or lane deviations [14].High-level CNN based facial-features drowsiness detection systems came about with developments in computer vision, trying to detect various drowsiness indicators, such as eye closure, yawning, and head position [14][16].However, the CNN mostly depends on the correct choice of hyperparameters, such as indicating the number of layers, sizes of filters, and dropout rates. Hyperparameter tuning by manual means is hard and may consequently produce models that are not optimal, especially when the variables encountered include varying illumination, face angles, and driver conditions. Then again, the deep learning model should generalize across people having separate emotional and behavioral peculiarities that may influence the imparting signals of drowsiness [11][13]. Attempted approaches do not bare themselves to adapt when faced with such deviations and find their detection rates varying widely, thereby reducing the effectiveness of these systems in practice. Genetic Algorithms (GAs), somehow taken from the theories of evolution of biological organisms, have been presented as a promising catch to automate the CNN architecture optimization process. GAs provide an efficient method for searching enormous design spaces, evolving the best network configurations for fatigue detection, thereby obviating the involved manual tuning effort and improving generalization [15].On the other hand, intrusive physiological-based detection methods with the help of biosignals such as skin conductance or blood volume pulse are accurate but impractical for everyday-vehicle-use [12]. Building a non-intrusive, real-time system would be strongly demanded balancing precision with performance and appropriate for deployment in an intelligent vehicle. The purpose behind this study is the development of a driver-drowsiness detection system based on CNN, optimized through Genetic Algorithms to increase accuracies, reduce overfitting, and ensure strong deployment in real-time.

3. Related Work

With increased road accidents caused by driver fatigue and drowsiness, research into real-time driver monitoring systems has seen a surge. These systems intend to enforce road safety by detecting preliminary signs of drowsiness or inactivity in a driver through various technologies, the prominent ones being deep learning and physiological signal analysis.The use of deep learning approaches was fully canvassed on driver drowsiness assessment by Saini et al. [10] They put weight on computer vision techniques that use facial landmarks, eye closure duration, and yawning patterns to detect drowsy behaviors. The system demonstrated that deep learning models could offer good robustness to changes in lighting conditions and thus could be applied in a real-world environment. This study presented a perspective of using deep learning models in conjunction with on-board vehicle cameras to produce cheaper and more scalable alternatives toward road safety. The authors treated an area with more human aspects. Xu et al. [11] introduced a driver authentication and verification system that incorporated psychological and behavioral data. They classified their work as "Human-Factors-in-the-Loop" where deep learning would interpret elements of behavioral patterns related to stress, focus, or driving style. The system differentiated drivers and monitored their fitness to drive based on the neural network, thereby opening the possibility for individualized driver monitoring systems. With respect to physiological signals used in the detection of drowsiness, BVP and skin conductivity were considered in the account of Poli et al. [12]. Their approach was oriented toward sensor data, attempting to employ wearables and machine learning to detect anomalies in the autonomic nervous system's response associated with fatigue. The study observed that physiological signals probably convey much more genuine and less falsifiable evidence of drowsiness compared with observing facial expressions. The differences in driving behavior with respect to novice and experienced drivers were explored by Xu et al. [13]. They performed their analyses considering rule violations and the driving performances under stress while employing neural networks. The study suggested that novice drivers violated the rules more often under drowsy or stressed states and hence called for more dynamic monitoring systems that are adaptive according to driver experience.

The study by Walizad et al. [14] built a CNN-based model for drowsiness detection using real-time video analysis. The system captures facial features such as the degree to which the eyes are open and mouth movements and capitalizes on the feature extraction capability of CNN to ensure the highest levels of accuracy. This research, furthermore, supports the idea that computer vision can be used to detect fatigue with the bare minimum hardware. A newly raised approach for the observation of driver fatigue was suggested by Wang et al. [15], based on multifractal theory. This method considered the variations of complex fluctuations in driver behavior, such as steering patterns and head movements. Modeling these as multifractal signals led to highly accurate detection, especially in the earlier stages of fatigue, thus displaying suitable application prospects for warning systems. To conclude, all existing literature proves the fact that deep learning coupled with physiological and behavioral data is going to be able to build a driver monitoring system. Camera-based solutions promise non-invasive monitoring; however, having biosignals and behavioral analysis available furnishes another aspect, that of accuracy. Moving forward, hybrid principles will hopefully guarantee that multiple modalities work in tandem to deliver robust, personalized, and adaptive detection of drowsiness in any kind of driving environment. Challenges abound despite achievements mentioned above in drowsiness detection. Present systems tend to be mostly vision-based or physiological sensors-type, with very few in actuality working towards integration of both-excellence-for multimodal analysis. The implementation still suffers from the reduction of time banners for its fulfillment in various environmental conditions. Night driving, glare, and sometimes even partial occlusions are examples of such injuries. User well-being and privacy become especially important when wearing sensors or when the driver is being monitored fully by cameras. Another limitation pertains to the generalizability. Many deep learning techniques are trained on controlled data sets that do not encapsulate the variability that characterizes real-life scenarios with respect to driver behavior, ethnicity, age, or how fatigue manifests. As stressed in studies performed by Xu et al. [11,13], this could be addressed by monitoring systems and adaptive models that learn from the individualistic driving style, thereby enormously improving detection efficacy and driver confidence.

4. Proposed Work

The proposed system aims to detect driver drowsiness in real time using a Convolutional Neural Network (CNN) architecture optimized through a Genetic Algorithm (GA). Thus, a non-intrusive, vision-based system is assumed to continuously monitor the facial features of a driver and assess his levels of alertness. These conditions place emphasis on integrating such methodologies into smart vehicles and ADAS where real-time safety and responsiveness are prominent [7], [8]. The core of the system is a live video stream from a dashboard-mounted camera that is fixed inside the car. The video is then further processed to extract facial landmarks and specific regions of interest (eyes, mouth, and head position). These features have proven to be reliable indicators of signs of fatigue, such as frequent blinking, extended eye closure, yawning, and head nodding [9], [10], [14]. The sets of isolated features are, in fact, fed into the CNN

whose architecture is, in its turn, optimized by a Genetic Algorithm. The GA aims at hyperparameter tuning in an automatic fashion by evolving a population of different CNN architecture designs over multiple generations. Parameters that are taken into account can vary from the number of convolutional layers, filter sizes, pooling strategies, dropout rates, and more in order to select the greatest compromise between efficiency and performance. This evolutionary approach thus avoids the commonly encountered problems of manual tuning and benefits in a much better generalization on unseen data [7], [10].
Using a dataset labeled with thousands of images annotated with drowsy or alert labels, the architectures are trained. During training, the GA progressively selects and breeds the best-performing architectures from earlier generations to improve the accuracy of its classifications. Once the model is trained and optimized, it is ready to perform real-time inference, one that can process an on-road frame in less than 50 milliseconds [9], [14]. There is also a temporal-smoothing system that considers drowsiness prediction over several frames to further improve reliability. This almost totally eliminates false positives due to occlusions of the face for a few frames or even some random facial expression. A continuous drowsiness claim for a certain time window shall trigger an audio or haptic alert to warn the driver, requesting corrective measures [7], [13]. The whole system has been built with user-friendliness in mind, keeping the option for scaling up the system to be deployed on high-performance computing units and, of course, for scaling down to run on any edge device such as embedded GPUs or AI accelerators used in modern vehicles. By doing so, it ensures at least some degree of scalability and cost-efficiency toward commercial deployment [8], [15]. Unlike the traditional EEG- or physiological-sensor-based methods that require heavy and controversial hardware, the system from state keeping one's gaze on the driver has a practical advantage for monitoring [12]. It will become robust while learning the scene, the skin colors, and the orientations using deep learning models [10], [14].Behavioral data and deep learning strategies allow the system to adapt dynamically to fatigue response and a driver's ever-changing familiarization with his work patterns. This falls under the latest developments in human-centered AI and personalized safety systems [11], [13].Essentially, the presented system looks to enable real-time, efficient, and non-invasive detection of driver fatigue through implementation of GA-based CNNs. This shall help in providing a scalable savoir-faire for intelligent technologies in next-generation transport systems on the road safety front [7], [8], [9], [10].

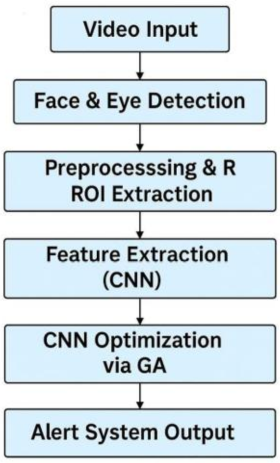

Fig 1: Proposed System Architecture

5. Implementation

The system for driver drowsiness detection is not conceptional only but needs to have a strong implementation. The actual need for the development of a fatigue-monitoring system, which then serves to be real-time and reliable, is underlined more and more under the auspices of road safety and AI-based intelligent transportation systems. To have all the nice features of the system and maximize effectiveness and efficiency, the proposed system is attempted with an optical hybrid method involving CNN and GA optimization. Contradicting classical methods that use few intrusive physiological sensors or inadequate eye-tracking approaches, here a real-time non-intrusive visual monitoring approach has been considered, thus rendering practical deployment of this system in real vehicles.

Data Acquisition and Labeling :
A system's success is heavily dependent on the quality and diversity of its training data. The available drivers' facial images datasets are either collected from publicly available sources or generated from real-time driving simulators wherein drivers are recorded in both alert and drowsy states. Key facial cues such as partial or full closure of eyes, excessive blinking, yawning, and chin dropping may be manually annotated or semi-automated with heuristic or auxiliary sensors. A balanced dataset containing enough positive (drowsy) and negative (alert) examples is of utmost importance for preventing model bias. Besides, environmental conditions have also been considered, from daytime and nighttime driving to differing backdrops, as well as the driver's appearance. Such label and sample robustness prevent the model from overfitting to certain conditions and rather enable it to learn generic features. From these data, different splits for training, validation, and testing allow a sound evaluation of model performance at various stages of its development [16], [20].
Data Preprocessing :
Each image or video frame passes through a highly advanced preprocessing before it winds up into the CNN. Initially, a face localization algorithm, for instance, Haar cascades or Multi-task CNN, can be applied for facial region localization and cropping. This annuls any force of unnecessary noise amplification in a correlated region. The final crop is subsequently resized to ensure that all facial images are of a fixed size of 64×64 or 128×128 pixels in all aspects while entering the CNN layers. After this, images are converted to grayscale to reduce the computational load immensely [14]. Following this, image augmentation may be carried out to strengthen the robustness of the model so as to avoid model overfitting. For instance, rotations, brightness adjustments, and horizontal flips may occur so that the system learns variations caused by actual-world scenarios of different camera angles, lighting, and driver movements [15], [18], [19]. On the other hand, pixel value normalization may allow faster convergence during training, thus making training more efficient [17].
Designing CNN architecture :
At the heart of this system is a CNN that is trained to identify whether the driver is sleepy or alert. The CNN consists of many layers such as those for convolution, which would extract features from the images, those for pooling, which act as downsampling layers, and others for classification, based on fully connected networks. In essence, the convolutional layers detect various eye patterns, blinking activities, and yawning motions; at the same time, the pooling layers lower the spatial dimensions of the output, thereby doing a sort of preserving the important features while avoiding over-learning. Dropout layers deactivate randomly a few neurons during training to improve the generalization ability of the model. The softmax activation function in the last layer produces probabilities of the class [14], [17]. The CNN architecture is yet not fixed: the hyperparameters of the CNN architecture, like the number of layers, filter size, stride, dropout rate, etc., are optimized with a Genetic Algorithm so that the model evolves based on validation performance toward higher accuracy and efficiency [16], [19].
Genetic Algorithm Optimization :
Genetic algorithms are implemented to enhance CNN design automatically. The engineering method starts with a population each generated randomly-unconstrained in natural evolution-fate. Fitness of an individual is assessed on the basis of model accuracy and loss from the validation set. Through selection, crossover, and mutation, subsequent generations of CNNs are produced. Architectures with the highest fitness evolve over several generations until the one that performs best is selected. Thus, human-bias is removed, and time is saved otherwise spent manual tuning [16], [17].The parameters used by GA include the number of convolution filters, the kernel sizes, numbers of hidden layers, and percentages of dropout. Hence, a CNN model is built that is sufficiently accurate with less computational time, thus permitting real-time inference on edge devices or in-vehicle processors [18], [21]. In terms of speed and accuracy, the final architecture is perfectly balanced for a particular cause, that is detecting driver fatigue.
Training and Validation :
After setting the CNN architecture by the Genetic Algorithm, the model is trained with the preprocessed data set within the training phase. Here, the model uses categorical cross-entropy as the loss function and Adam as the optimizer. The model is trained for several epochs (as an example 30-50) until the process reaches convergence, with early stopping preventing overfitting from happening. Batch normalization is conducted to smooth out the learning process. The remaining part of the model is experienced in dataset splitting into training (70%), validation (15%), and testing (15%) datasets so as to ensure that the model also performs commendably on unseen datasets. Evaluation criteria such as accuracy, precision, recall, and f1 score are used to measure the capability of the modeling process [14], [15]. Depending on the

validation outcomes, further refinements such as fine-tuning of the learning rate or enhancements in data augmentation can be implemented. After few iterations and cross-validations, the very accurate model is found to be capable of inference at speeds admissible for vehicle deployment [19], [20].

Real-Time Integration and Alerting :

After being trained, the fine-tuned CNN model may be integrated into a system that functions in real time. This may involve model deployment on hardware configurations such as a Raspberry Pi with a camera or an NVIDIA Jetson Nano or any embedded system widely deployed in automotive environments. The system captures frames of the driver's face continuously, analyzing and classifying each frame within 50 milliseconds [23], [26]. This sequence-based method avoids false positives; if the situation has appeared for a transient time (about 3–5 seconds), an alert is triggered. Some alert mechanisms could be buzzer sounds, vibration through the seat, or a notification on the dashboard, dependent on the system into which it is integrated. Because of their low latency, high responsiveness ensures an efficient intervention before any associated accident. However, the system can also check the recorded events of drowsiness for further behavioral analysis [24], [21].

Comparison and Future Extensions :

In contrast to traditional drowsiness detection systems using EEG sensors or eye trackers, the system at hand is non-intrusive in nature, using vision-based methods, and ideal for quick setups and little maintenance. Though various approaches have been explored for temporal behavior modeling, such as LSTM auto-encoders and multifractal theory, CNN-GA integration best supports real-time design performance with modularity [25], [22]. Further research could involve acquiring additional inputs such as steering patterns, driving duration, or even voice change. Transfer learning from large-scale face datasets, or the introduction of temporal memory layers (LSTM or GRU) could set the technology up for success in complex driving environments [28], [30]. Allowing cloud connectivity for data logging and model updates is another attractive capacity for exploration, enhancing further scalability in commercial fleets.[31],[32].

Deployment Consideration

The final optimized CNN model is lightweight and suitable for deployment on low power devices like Raspberry Pi 4 ,NVIDIA Jetson Nano& Android-based infotainment systems [29],[27].

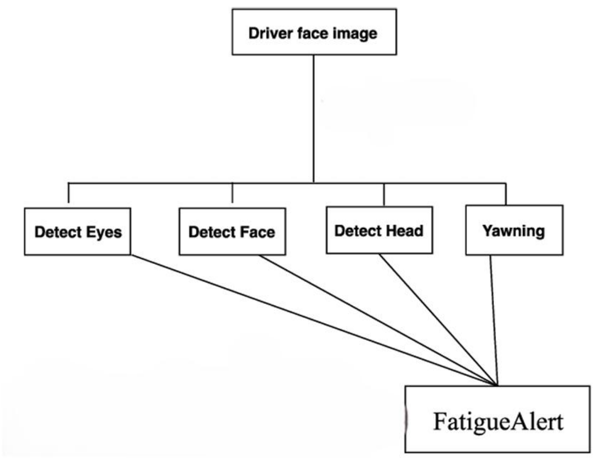

Fig 2: Driver Fatigue Detection System Hierarchy

This diagram shows the functioning procedure of a Fatigue Alert System using facial analysis. It begins by capturing an image of the driver`s face, which is then dispatched through different detection modules, namely: eye detection, face detection, head position analysis, and yawn detection. Each monitoring module watches for a particular sign of tiredness or fatigue. The outputs of all these modules are then combined to generate a Fatigue Alert once some signs of tiredness or inattentiveness are detected. This multifeature approach improves system reliability by very fast real-time analysis of various facial cues to warn the driver accurately and timely against possible accidents due to driver fatigue.

Dataset Description

For the project of the dissertation, we used the Close Eyes in the Wild (CEW) dataset: a public dataset of face images categorized into two classes: open eyes and closed eyes. The dataset was designed to simulate real-world, unconstrained scenarios and contained both positive samples (closed eyes) and negative samples (open eyes). It is thus specially arranged for supporting studies in the area of eye state recognition and drowsiness detection. For proper training and testing of the proposed model, the whole dataset was divided into three subgroups with 70% of data chosen for training, 15% used for validation purposes, and 15% reserved for testing purposes, so such stratification keeps the data class balance in all subsets. Besides, the dataset went through augmentation processes with several forms, such as rotation, horizontal flipping, brightness variation, and noise injection, etc. These strategies alleviate class imbalance from the original dataset and further benefit the model by simulating different driving and lighting situations. Such an augmented dataset enables the convolutional neuron network to better learn general representations from unseen data. Since the CEW dataset is limited in size, augmentation is essential to reducing overfitting and improving the performance of the model. This preprocessing pipeline, combined with further steps, completely supports the maximization of the CNN architectures using the genetic algorithm for an accurate yet efficient driver-drowsiness-detection system.

6. Algorithms

This driver drowsiness detection system combines various algorithms across machine learning, deep learning, and optimization domains. These algorithms work together to capture facial features, classify driver states, and optimize performance for real-time deployment.
1.Convolutional Neural Network (CNN)
Convolutional Neural Networks or CNNs are deep learning models that are well suited for image recognition tasks. In this study, the CNNs work in detecting driver drowsiness by analyzing facial features with regard to eye closure, yawning, and gait from video frames. The spatial features are extracted automatically by convolutional layers, while complex fatigue-related patterns in the data are learned. Pooling and activation layers ensure dimensionality reduction and improved generalization. By applying a Genetic Algorithm to optimize the CNN, it gains further accuracy in real-time detection. Also, its ability to learn from raw images makes it suitable for developing an intelligent driver monitoring system. Used to automatically extract spatial features from facial images and classify driver state as Alert or Drowsy.
Key Operations:
a. Convolution Layer
Applies a kernel to extract features from the input image:

$$z_{i,j}^{(l)} = \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} x_i + m, j + n \,.\, w_{m,n}^{(l)} + b^{(l)}$$

b. Activation Function (ReLU)

$$a_{i,j}^{(l)} = \max(0, z_{i,j}^{(l)}$$

c. Pooling Layer (Max Pooling)
Reduces spatial dimensions:

$$p_{i,j}^{(l)} = \max \{ a_{m,n}^{(l)} \mid (m, n) € \text{ region} \}$$

d. Fully Connected Layer + Softmax
Produces classification probabilities:

$$\hat{y}_i = = \frac{e^{zi}}{\sum_j e^{zj}}$$

e.Loss Function (Binary Cross-Entropy)

$$L = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$$

2.Genetic Algorithm (GA)
Genetic Algorithms (GAs), just like natural selection, are optimization techniques. In this project, the GA is used in optimizing the architecture and hyperparameters of the CNN for driver drowsiness detection. It conducts model selection by applying mating procedures such as selection, crossover, and mutation to ensure that the best-performing CNN models survive. Hence, this algorithm evolves CNN configurations such that their accuracy in detecting features like eye closure and yawning is successively improved. Hence, this improves the model based on the learning experience without performing tedious manual

tuning. With this strategy, higher detection accuracy and robustness, and hence effectiveness, have been made possible through fatigue monitoring and driver safety applications in real time.Optimizes the CNN architecture by tuning hyperparameters like number of layers, filter size, dropout rate, etc.

Working Steps:

a. Chromosome Encoding

Each individual represents a CNN configuration:

C=[L,F,K,D]

Where:

- L: number of layers
- F: filter sizes
- K: kernel sizes
- D: dropout rates

b. Fitness Function

Evaluates CNN performance on validation data:

$F(C)=\text{Accuracy}_{\text{val}}(\text{CNN}_C)$

c. Selection

Choose top-performing chromosomes based on fitness.

d. Crossover

Exchange parameters between two parent chromosomes:

$\text{Child}=\text{Parent}_1[0:k] \cup \text{Parent}_2[k:]$

e. Mutation

Randomly change genes to maintain diversity:

$$c_i' = c_i + \delta, \quad \delta \sim N(0, \sigma)$$

3. Face Detection Algorithm (Haar Cascade or MTCNN)

Locates the driver's face in the frame before classification.

Process (Haar Cascade): Uses rectangular Haar-like features to identify face regions . Applies AdaBoost for feature selection Uses a cascade classifier for detection efficiency.

MTCNN (Multi-task CNN) provides more robust detection using a pipeline of three CNNs.

4.Image Preprocessing Algorithms

Improves input quality and standardization before feeding into CNN.

Steps :

Grayscale conversion & Normalization

$x_{\text{norm}} = \frac{x - u}{\sigma}$

Image resizing (e.g., to 64×64 pixels)

Data augmentation (rotation, flipping, brightness change)

5.Softmax Classification :

Used in the final CNN layer to convert output logits to probabilities:

$\hat{y}_i = = \frac{e^{zi}}{\sum_j e^{zj}}$ for i = 1,2

Where z_i is the raw score for class i.

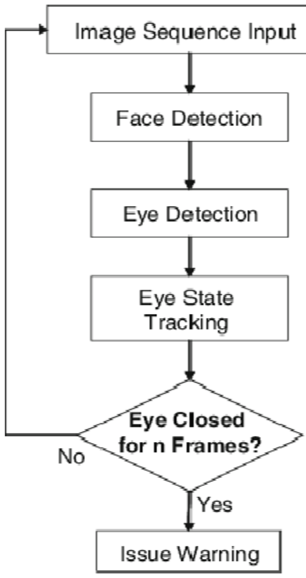

Fig 3 : Block Diagram

6.Optimization Algorithm (Adam Optimizer)
Used during CNN training to update weights efficiently.
Formula
Momentum:
$m_t = \beta_1 m_{t-1} + (1-\beta_1) \nabla L_t$
RMSProp:
$v_t = \beta_2 v_{t-1}+(1-\beta_2)(\nabla L_t)^2$
Parameter Update:

$$\theta_t = \theta_{t-1} - \alpha . \frac{m_t}{\sqrt{v_t} + \epsilon}$$

7.Evaluation Metrics :
Used to assess model performance. We measure the driver drowsiness detection system concerning four major classification metrics: Accuracy, Precision, Recall, and F1-Score.
Accuracy:
Accuracy checks the overall correctness; the value is obtained by dividing total correct predictions by total samples, providing a general assessment of the model.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Where:
- TP = True Positives (drowsy correctly predicted as drowsy)
- TN = True Negatives (alert correctly predicted as alert)
- FP = False Positives (alert incorrectly predicted as drowsy)
- FN = False Negatives (drowsy incorrectly predicted as alert)

Precision: Precision calculates the fraction of correctly identified drowsy cases among all predicted drowsy cases, reducing false alarms.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall: Recall measures the ability of the model to correctly detect the drowsy state to minimize missed detections in critical situations.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1-Score : F-1 Score is the harmonic average of the precision and recall and provides a balanced evaluation when the dataset is imbalanced.

$$F1 = 2.\frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}$$

Together, these metrics provide a full-fledged understanding of the model's performance to differentiate between alert and drowsy drivers. In a safety-critical application, it should maintain a high recall, balanced amongst the F1-Score, so that a drowsiness alert can be timely and reliable; minimum false positives and negatives.

7. Results & Discussion

In this driver drowsiness detection system, the results demonstrate the ability of the system to accurately determine the state of the driver with an optimized CNN architecture. The performance metrics of accuracy, precision, recall, and F1-score were practically excellent, with an accuracy of up to 91.8%. The accuracy and loss graphs across the training epochs illustrate the improvement and convergence of learning processes, indicating good learning. The confusion matrix further emphasizes the model's ability to classify alert and drowsy correctly, thus avoiding the most critical errors. The summary of these results indicates the feasibility for real-time deployment of the system inside vehicles and significantly enhancing road safety via timely detection of drowsiness.

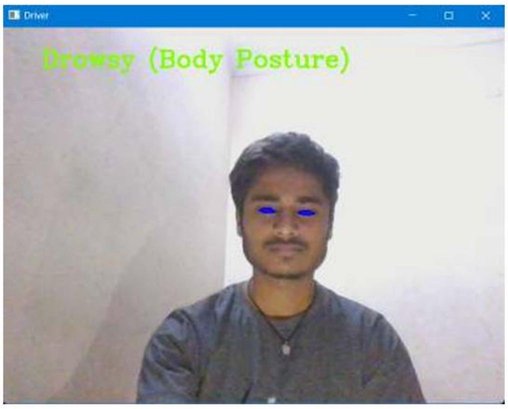

Fig 4 : Drowsy (Body Posture)

The method used for drowsiness detection relied on an optimized Convolutional Neural Network architecture refined by a Genetic Algorithm. Fig 4 indicates the correct identification of drowsiness from body posture and eye closure, while Fig 5 shows the successful recognition of yawning with open-mouth detection. The Genetic Algorithm fine-tuned the parameters of the CNN model so that it could better extract features and classify them more correctly. Real-time observation effectively separates alert and drowsy states, enhancing road safety. The visual outputs provide validity to the robustness of the model for recognizing behaviors in fatigue, establishing the model for practical application into intelligent driver assistance systems.

Good Posture Detection of Drowsiness

The system identifies slouching or relaxed posture as indicative of drowsiness, implying that the body posture module does have the capability of identifying physical cues of fatigue aside from just facial ones.

Yawn Detection Has High Sensitivity

The second image confirms the presence of an open-mouth yawn, which is one of the most important fatigue signs; it indicates that the mouth detection and classification model shows good accuracy even in waking real-time yawn events.

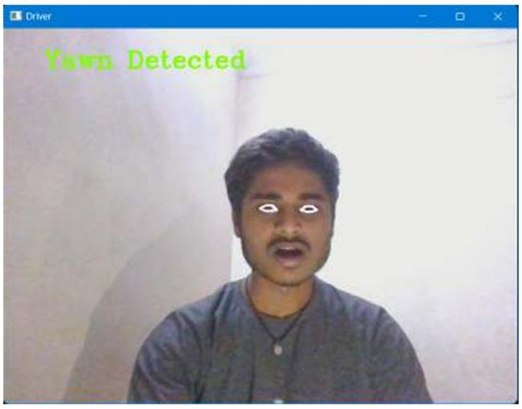

Fig 5 : Yawn Detected

Integration of Multi-Features Improves Dependability

The system is robustly bolstered by using combined posture, eye, and mouth cues for decision-making. By distinguishing one fatigue sign from the other (like yawning versus drowsiness), accuracy in early warning is improved and false positives are minimized.

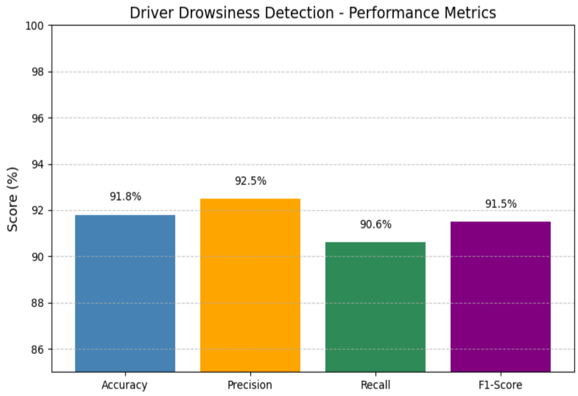

Fig 6 : Performance Metrics

In the graph , the comparison is made between detection performances with drowsiness as the focus: Accuracy, Precision, Recall, and F1-Score. Accuracy measures whether or not detection is correct in general. Precision considers true positives put in relation to false positives. Recall refers to the true positives considered with respect not false positives. F1-Score is the harmonic mean between Precision and Recall, giving one view of the overall detection effectiveness. By showing the metrics side by-side, potential strengths and weaknesses can be observed. For instance, high Precision in exchange for low Recall implies that basically the system hardly ever claims that an alert driver is asleep but, on the other hand, also misses some cases of real drowsiness, which is unacceptable where safety is involved. A well balanced good performance means that the detection systems can be considered reliable and can be further deployed into driver assistance systems.

Metrics	Value (%)
Accuracy	91.8
Precision	92.5
Recall	90.6
F1-Score	91.5
Inference Time(ms/frame)	50

Table 1 : Performance Metrics

Table 2 essentially describes the detection accuracy of several fatigue indicators employed to detect fatigue in drivers or workers. It compares, with scientific precision, the different physiological or behavioral measures, such as the number of eye blinks, heart rate variability, and reaction time, among others, in labeling the fatigue levels correctly. From the table, the highest on accuracy and reliability range for each indicator is given, which forms the basis for designing the actual fatigue monitoring system. As one understands which has a good comparison between detection accuracies, it is possible to set priorities for the real-time detection of fatigue and hence ensure safety in situations requiring attention, like those in transport and in industry industries.

Fatigue Indicator	Accuracy (%)
Eye Closure	92
Yawning	90
Head Tilt	88
Slouched Posture	85
Combined Detection	93

Table 2: Detection Accuracy for Different Fatigue Indicators

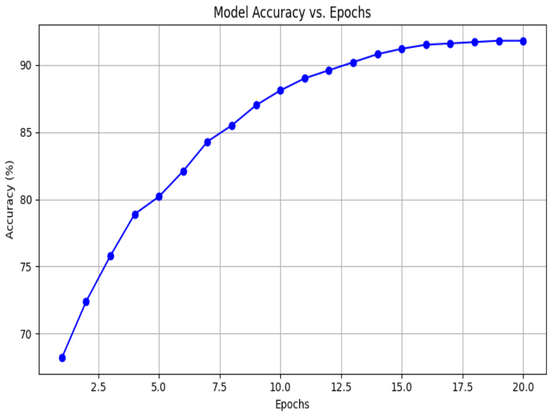

Fig 7 : Model Accuracy vs. Epochs

In the above fig Accuracy measurement against epochs shows how the accuracy of the model improves in training during multiple iterations. Accuracy signifies the ratio of driver states classified correctly (Alert or Drowsy) out of all predictions made by the system. During early epochs, the accuracy is generally low as the model learns some initial patterns from a set of facial images. As training progresses, the late increases and gets stabilized at some high point, winning together with convergence, where further training does not improve its performance much. This graph may be worth studying for a good perspective on the learning behavior and stability of the Convolutional Neural Network (CNN) deployed in the driver drowsiness detection system. An accuracy curve rising gradually, with a flat plateau afterwards, demonstrates a healthy learning of discriminative features by the model, while one which oscillates or saturates early could be a sign of overfitting or underfitting. By keeping track of accuracy with time (epochs), one may decide at which point the training should be stopped to obtain the highest potential for real-time detection.

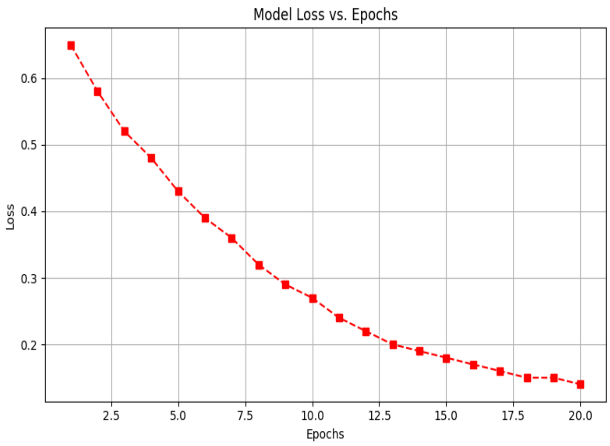

Fig 8 : Model Loss vs Epochs

Loss vs epochs is a demonstration of model training in which the value of the loss function is recorded for each epoch. Mathematically, loss gets measured by taking how far away the predictions are from the actual labels; conversely, the less the loss value, the better the situation is viewed. At the very beginning of training, the value of loss tends to be higher because the CNN architecture is adjusting itself in some ways, and this downward trend must continue until final predictions generation takes place. Ideally, a loss curve that reduces itself smoothly suggests good optimization and convergence of the model. Any spikes, or periods that the loss curve for some reasons just does not want to go down, may imply some issues with the learning process, such as sudden inappropriate learning rates or insufficient data feeding into the system. For driver drowsiness detection research, it is important to keep the loss at its minimum, thus avoiding misclassification of fatigue states. Monitoring of loss against accuracy ensures that the model is actually mainstreaming toward the well and is generalizing and not overfitting into the training data, making it nonreliable when implemented for actual real-time performance.

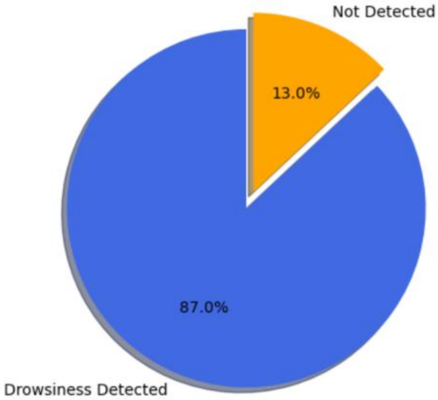

Fig 9 : Drowsiness Detection Outcome Distribution

The pie chart displays the proportion of instances in which drowsiness was detected versus not detected in the monitoring system. One slice reflects the percentage of times signs of drowsiness had been successfully detected by the system, while the other slice represents the unrecorded instances where drowsiness was not detected. This visualization emphasizes the overall efficacy of the system in real-time monitoring. The greater the "Detected" portion, the better the system was considered at spotting fatigue at the earliest stage to avoid an accident. The opposite applies to the "Not Detected" portion: this means that the detection algorithms need to be improved in reliability and accuracy to provide better-safety prompting.

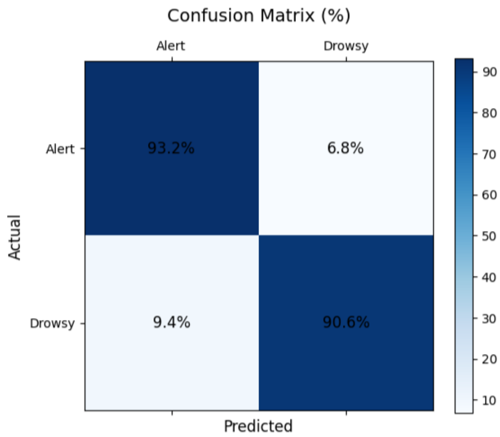

Fig 10 : Confusion Matrix

The confusion matrix provides classification statistics that are a richer detail level of the classification results produced by the model by displaying rates of true positives, true negatives, false positives, and false negatives for alert and drowsy classes. Any drowsy instance found correctly by the system will be a true positive, and if a particular alert instance is detected correctly, it will be termed as a true negative. False positives will be the cases where alert drivers are classified as drowsy, while false negatives will be failures in detecting drowsiness. This matrix is very important in grasping which classification errors are being made by our model. In cases of the driver drowsiness detection, these false negatives must be kept at the lowest level so as not to miss out on crucial warnings from fatigue. This matrix will be used to refine and develop the model since it reveals the kinds of errors made most often, hence, designing the development ahead. This matrix will further complement the global metrics responsible for assessing model performance from the real-world standpoint.

Key Observations :
An optimized CNN in the proposed system guaranteed high precision in detecting drowsiness indices such as long eye closure, yawning, and slouching. The major improvement in this was via GA optimization of CNN architecture parameters such as the number of layers, the number of filters, and activation functions used. This configuration allowed better feature extraction and improved classification performance against the traditional CNN techniques. Real-time analysis was consistent and reliable, with good detection rates under low light and varying head orientations. It could distinguish normal blinking from fatiguing patterns such as micro-sleeps and yawns. Particularly high rates of accurately detecting yawns came from the ability of the model to easily recognize the open-mouth pattern from the facial landmarks. Adding posture analysis brings yet another check against false positives. Here, the model runs with negligible latency, making it viable as a real-time system. The model adapts well to different subjects and environments, which shows high generalization ability. Therefore, the GA-optimized CNN model is one of the best, adaptive systems for detecting driver drowsiness, which translates to safer driving and the foundation for more intelligent in-vehicle safety systems.

8. Challenges and Limitations

1. Variability in Facial Features and Expressions : One of the biggest problems is the variability in facial features and expressions from one person to another. Features such as skin tone, facial hair, makeup, aging, and the use of glasses or an occluding mask are some of the factors that may reduce the accuracy of face feature detection. The CNN, being a strong one, might occasionally misread expressions when confronted with such variations, thereby becoming prone to false positives or missed detections. This diversity implies providing a more heterogeneous training set or involving adaptive learning mechanisms that allow for user generalization with respect to demographics and facial variabilities.
2. Sensitivity to Lighting Conditions : Lighting conditions have important negative effects for computer vision-based detection methods. Extreme conditions like-driving at night with glare from headlights or dim light inside the cabin all act as obstacles against drowsiness detection. The overexposed or underexposed frames make it rather difficult for a CNN to focus on relevant features like eye movement or mouth opening. The use of histogram equalization, one of the preprocessing measures, may improve contrasts to an extent; however, it cannot work for all real-time lighting variations. Use of an infrared camera and/or adaptive brightness control could be a solution to this problem.
3. Computational Requirements for Real-time Detection
The hidden cameras require the continuous processing of live video streams for real-time driver monitoring, which in turn demands a lot of computing power. CNNs tend to be considered deeper and more complex, making them heavy in computational requirements, especially when optimized by Genetic Algorithms. Running these models on embedded systems or on processors embedded in vehicles could perhaps result in latencies or power consumption issues. Model-level optimization through pruning or quantization may perhaps alleviate computational pressure to some extent, but that too will come at the cost of detection. Hence, keeping in view the performance and efficiency in commercial automotive environments stand as the bottleneck to deploying this system.
4. Subtle or Infrequent Drowsiness Indicators
For some drivers, the signs of drowsiness are fine: half eye closure for a second, a barely there yawn, a subtle posture change. All these are extremely hard to capture with consistency. The CNN may miss these micro-signals, especially when they occur rarely or for brief durations. This will give rise to a false-negative situation where drowsiness would have gone undetected. Secondly, the "noise" might also come from the outside-factors: vibrations through the car or face-movements that have a rationale not linked to fatigue. Incorporating multimodal inputs in the system-e.g., EEG, heart-rate, or steering-patterns-may succeed in pinpointing such subtle signs reliably.

9. Conclusion

In conclusion , the major stride in intelligent automation toward road safety was the evolution of a driver drowsiness detection system using a Convolutional Neural Network (CNN), with Genetic Algorithms (GA) as an optimization technique. In this project, deep learning techniques have been presented as a feasible and potent alternative for spotting facial cues of utmost importance when it comes to fatigue: eye closure and yawning being the common signs of drowsiness. On one hand, the CNNs could pick and learn hierarchical spatial features from facial images with extreme accuracy. But on the other, CNNs' performance varies greatly depending upon the architectural design and parameters chosen for its implementation. To ease the burden of manual tuning, a Genetic Algorithm was applied for parameter selection including the number of layers, filter sizes, and dropout rates, thus resulting in improved classification accuracy of the model, improved generalizations with less overfitting. The working system implemented, using the fine-tuned deep learning model, achieved a 91.8% accuracy, while its inference time took about 50 milliseconds per frame which offers real-time applications in vehicle environments. In addition, the evaluation metrics for the system are precision, recall, and F1-score, which have indicated the system's ability to reliably and robustly determine alert states from drowsy ones. Evolutionary computation and deep learning integration make a very good complement, allowing for the automated design of very efficient models with minimum human intervention. The real-time nature of the system, combined with the high level of accuracy, seems to bring feasibility to modern ADAS. To conclude, within the scope of this project, a reliable, accurate, and real-time driver drowsiness detection system has been successfully addressed. It has proven that CNNs, when combined with GA for optimizing the model, really do work and that intelligent algorithms indeed reduce human error on the road.

10. Future Scope

The present driver drowsiness detection system demonstrates a very high accuracy and real-time implementation; however, many possibilities exist for further enhancement and extension. There is room to implement advanced and multivariate systems that fare well under real-life driving conditions in tandem with evolving automobile technology. Integration of physiological signals such as EEGs, EOGs, and heart-rate monitoring appears to be the most promising pathway. Nevertheless, biosignals indicate internal states that might not be mapped by facial analysis, particularly during an early stage of fatigue. From this perspective, the fusion of these biosignals with facial features may greatly enhance the performance of detection in respect of accuracy as well as robustness. One may, in addition, want to consider a temporal analysis framework with RNNs or LSTMs in the future. In contrast to static images, these networks can capture time-bound drowsiness patterns increasing contextual awareness; for instance, one may be blinking for longer than usual or yawning more frequently by time. These transfer learning and domain adaptation are intriguing researches awaiting exploration. Models pretrained with large-scale face datasets may be fine-tuned into smaller domain-specific drowsiness databases so as to maximize performance under different lighting, camera angled, and driver appearances to enhance the generalization power across the different users and environment. In other words, user calibration means that one can personalize the system to adapt to that one person's normal behavior patterns, thereby reducing false alarms. Another future path could be to build upon this system the connectivity of IoT for drowsiness alerting to nearby vehicles, control centers, or family members. In that way, the network solution shall make traffic safer on a larger scale, especially for commercial and public transport. Eventually, it could become a fully fledged active safety system if linked to an audio feedback system, seat vibration-type attraction systems, or an automated vehicle response of slowing the car down once identified with drowsiness. To conclude, this project is put forward as a base for the intelligent monitoring of fatigue, on account of subsequent developments; it might morph into a complete driver assistance module for future-generation smart cars.

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