

A Review of Face-based Fatigue and Drowsiness Detection Models

Nizar Ali Alhaj Abdellah*, Hussein Abdulateef Hussein*, Amin Babiker Abdalnabi†

*Electrical Engineering Department, College of Engineering and Technology, Nile Valley University, Sudan

†Electrical and Electronics Engineering Department, Faculty of Engineering, Alneelain University, Sudan
mawamutaz@gmail.com

Abstract

Fatigue and drowsiness are critical issues affecting safety in various domains, including driving and industrial sectors. The ongoing progress in computing technology and artificial intelligence over recent years has facilitated advancements in fatigue detection systems. A multitude of experimental investigations have amassed empirical data and implemented diverse artificial intelligence algorithms alongside various feature combinations, with the intention of substantially improving the efficacy of these systems in real-time applications. This paper aims to find effective models for fatigue and drowsiness detection based on face feature analysis. For this, comprehensively the latest models are examined, focusing on techniques, datasets, and performance metrics. The models are categorized into traditional machine learning, deep learning, and hybrid approaches, highlighting their strengths and limitations. This paper demonstrated that hybrid models emerged as the most effective and versatile solution for fatigue detection, offering superior accuracy, adaptability, and real-time performance across varied use cases.

Key words-*fatigue detection; drowsiness detection; traditional machine learning models; deep learning models; hybrid models.*

I. INTRODUCTION

Fatigue can result in detrimental effects on individuals as well as material assets in various domains, such as transportation, and may even culminate in fatal outcomes. In sectors such as machinery operation, healthcare, and vehicular operation, it is imperative for individuals to maintain vigilance and engagement throughout their working hours; otherwise, the likelihood of an incident occurring is significantly heightened. For a healthy body, an adequate amount of sleep plays an important role in staying active and healthy. When a person sleeps poorly or not at all, it can also lead to various kinds of illness, drowsiness, and fatigue. Sleep deprivation also indicates a person's activity level. Insomnia has many causes. Some of the causes are anxiety, arrhythmia, etc. One of the main causes is the lack of a balanced diet. If a person cannot sleep for two consecutive nights, it is called "sleep debt." Lack of sleep is directly proportional to a person's sleepiness and fatigue. Drowsiness can occur after sleep deprivation or regressive training. During exercise, our bodies are stressed and muscles are broken down. To recover from this condition, our body needs more energy, so less energy reaches the brain, causing drowsiness. Most importantly, early detection of drowsiness, followed by alerting the person, can prevent the risk of accidents, especially in driving applications. A number of signs can help in distinguishing drowsy drivers from others: they include frequent yawning, repeated eye closure, and moving out of road lanes[1]. Absolutely, Driver Drowsiness Detection techniques (DDD) have gained considerable momentum in research in contemporary years[2][3][4][5][6][7][8]. Scholars have developed various measures for the early detection of drowsiness signs to prevent accidents. These measures are classified into four broad categories: **image-based**, using cameras to analyze facial expressions and movements; **biological**, involving sensors to capture the driver's bio-signals; **vehicle-based**, which monitor behavioral and movement character-

istics; and **hybrid**, which combine two or more of these approaches. Researchers categorize DDD methods into three groups: behavioral, physiological, and vehicular parameter-based methods. They further reviewed the top-performing supervised learning models reported for detecting drowsiness. In the end, they discussed the advantages and disadvantages of the three DDD in a comparative study[4]. On the other hand, a very comprehensive review on the modern developments in driver fatigue detection demonstrates that, the methods of DDD are categorized into five categories, depending on the extracted fatigue features, including physical features, vehicular features, biological features, subjective reporting, and hybrid features. Moreover, the fatigue effect on driving performance was discussed, along with the existing commercial products in the market for fatigue detection[5]. Furthermore, a comprehensive review of driver inattention monitoring technologies reveals that inattention consists of two primary dimensions: distraction and fatigue[7]. Thus, similar to[5], the study synthesized five categories of the detection measure. The study introduced the concept of driver inattention and its effect on driving performance, besides covering some of the commercial products related to inattention detection, along with a detailed review of previous research done in inattention detection. This review contributes to the literature by examining the specific models used in modern fatigue and drowsiness detection systems. Our paper categorizes these approaches into three distinct frameworks: traditional machine learning, deep learning, and hybrid models. The literature indicates that DDD methods are categorized into three areas: behavioral, physiological, and vehicular parameter-based methods. This review enriches the literature by focusing on the underlying architectures of recently implemented detection systems. Specifically, our paper classifies these approaches into three frameworks: traditional machine learning, deep learning, and hybrid models. Furthermore, the review tabulates the param-

ters, extracted features, and quality metrics—such as accuracy, sensitivity, and precision—while discussing the datasets used to evaluate each system. Finally, the text addresses the recent challenges currently facing these models. The remainder of this paper is organized as follows: Section 1 provides the introduction, while Section 2 discusses drowsiness indicators and their various phases. Section 3 presents a comprehensive investigation of detection models developed in recent years. In Section 4, the challenges currently facing drowsiness and fatigue models are explored. Section 5 evaluates the practicality and reliability of the three model categories, synthesizing the methods introduced in Section 3. Finally, Section 6 offers concluding remarks and future perspectives.

II. DROWSINESS INDICATORS AND PHASES

The scholarly discourse on drowsiness detection systems employs varied terminology. Although 'drowsiness' and 'fatigue' are conceptually distinct, they are frequently used interchangeably. Fatigue is defined as a diminished willingness to persist in a task due to physical or cognitive exertion or prolonged activity. Conversely, sleepiness—or drowsiness—is characterized as the physiological compulsion to sleep. Fundamentally, drowsiness arises from an intrinsic biological imperative and can be triggered by factors such as pharmacological side effects, extended working hours, sleep disorders, and sleep deprivation. Consequently, a clear intersection exists between these states, as fatigue often serves as a direct precursor to drowsiness[9]. Drowsiness does not occur instantaneously; rather, it manifests through specific physiological and behavioral indicators. These markers include ptosis (difficulty maintaining eye closure), frequent yawning, increased blink rate, and cognitive lapses. From a vehicular perspective, drowsiness is characterized by lane departures, delayed reaction times to traffic stimuli, 'microsleep' episodes, and inconsistent speed control. As these indicators become more pronounced, they serve as quantifiable metrics for assessing the severity of driver impairment. A precise measurement scale is essential for systematically assessing drowsiness stages and developing automated early detection systems. Various methodologies have been proposed for this purpose, with the Karolinska Sleepiness Scale (KSS) being among the most widely recognized. The KSS is a subjective, nine-point scale designed to quantify instantaneous sleepiness levels throughout the day. The specific levels and their corresponding descriptors are summarized in Table(I). In[10] the KSS was used to collect self-reported sleepiness levels from drivers every five minutes, with these ratings serving as the target values for training the machine learning models. The deep learning CNN-LSTM models in study outperformed models using manually extracted features. The regression model achieved a mean absolute error (MAE) of 0.78. When this regression model was adapted for binary classification, it achieved an accuracy of 82.6%, which was slightly better than the 82.0% accuracy of the model trained specifically for binary classification. This suggests that preserving the KSS scale in a regression model provides important information for robust sleepiness detection. Wierwille and Ellsworth put

forth an alternative scale for the assessment of drowsiness[11]. The various stages of drowsiness are delineated on a five-tiered scale, as illustrated in Table(II). In accordance with the aforementioned study, at the first level, one can observe rapid eye movement accompanied by a consistent eye blinking interval. At the second level, there is a manifestation of slow eye movement. The individual experiencing drowsiness may touch their face at the third level, along with yawning and blinking at a diminished pace. Regarding the fourth level, extraneous movements of the individual are evident; they frequently yawn, exhibit increased blinking, and engage in deep breathing. Ultimately, at the fifth level, the eyes are nearly closed, and there is a noticeable nodding of the head.

TABLE I: Karolinska sleepiness scale (KSS)

Scale	Verbal Description
1	Extremely alert
2	Very alert
3	Alert
4	Fairly alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to keep alert
8	Sleepy, some effort to keep alert
9	Very sleepy, great effort to keep alert

TABLE II: Wierwille and Ellsworth drowsiness scale.

Levels	Verbal Description
1	Not drowsy
2	Slightly drowsy
3	Moderately drowsy
4	Significantly drowsy
5	Extremely drowsy

III. FATIGUE DETECTION MODELS

Different models that are used in fatigue detection are categorized into three sections: Traditional models, deep learning models, and hybrid models.

A. Traditional Machine Learning Models

Fatigue and drowsiness detection were efficiently performed using traditional machine learning models which usually depended heavily on certain important features such as the eye aspect ratio (EAR), mouth aspect ratio (MAR), and head pose angles. These models remain a primary focus of investigation due to their computational efficiency and inherent interpretability. Consequently, this section provides a comprehensive review of recent advancements in traditional machine learning frameworks for face-feature-based fatigue detection, with a particular emphasis on contributions from the last few years.

1) *Feature Extraction Techniques*: Feature extraction scheme is one of the critical stages in the center of fatigue detection systems; obtaining significant facial characteristics representative of fatigue is involved. In traditional machine learning systems, features are primarily handcrafted by domain experts, leveraging specialized knowledge and heuristic experience to extract relevant descriptors.

- 1) Facial Landmarks and Key Points : Many studies extracted features for the states of the eyes and mouth using facial landmarks and key points. A widely used library for facial landmarking is Dlib, which offers a 68-point facial landmark model, used in applications requiring the identification of facial positions and orientations of the eyes and mouth. These landmarks are then used to derive several parameters such as the eye aspect ratio (EAR) and mouth aspect ratio (MAR) to determine the states of eye closure and yawning[12][13].
 - 2) Eye and Mouth Metrics : Some parameters that are generally associated with the eyes such as percentage of eyelid closure over time (PERCLOS), blink frequency, and eye aspect ratio (EAR) are frequently used in the measurement of fatigue. In the same sense, mouth-related metrics like yawn frequency and mouth aspect ratio (MAR) are also used in cases like this. Thus, those metrics are mostly combined to improve the accuracy of mental fatigue detection[14][15].
 - 3) Head and Facial Movements : Head dynamics, characterized by nodding and Euler angles (roll, pitch, and yaw), are also utilized for fatigue estimation. These movements are typically integrated with ocular and oral parameters to facilitate a multi-modal and comprehensive assessment of driver impairment[16][17].
 - 4) Pupil Dynamics : Metrics related to the pupil, such as average pupil diameter, blink frequency, and pupil fluctuation, have been investigated as potential indicators of visual fatigue. These metrics are often extracted through image processing techniques and have demonstrated promising efficacy in the detection of visual fatigue[18]. Table(III) summarizes some of face-extracted features.
- 2) *Classification Techniques*: Once the pertinent features are extracted, conventional machine learning models are utilized to categorize the fatigue state. These models are generally trained on labeled datasets and subsequently validated utilizing various performance metrics.
- 1) Support Vector Machines (SVM) : Support Vector Machines have been extensively employed for the detection of fatigue owing to their capability to manage high-dimensional data and non-linear decision boundaries. For instance, SVMs have been utilized to classify fatigue based on pupil metrics, attaining an accuracy of 92.86%[18].
 - 2) Random Forest (RF) : Random Forest, an ensemble learning technique, has been utilized for its robustness and elevated accuracy. In a particular study, Random Forest achieved an accuracy of 93.3 in the identification of fatigue through the utilization of eye-related features[28].
 - 3) K-Nearest Neighbor (KNN) : Using K-Nearest Neighbor integrated with extraction techniques like FaceNet for fatigue detection yielded an accuracy of 94.68% in discerning discriminations between focused, unfocused, and fatigued[29].
 - 4) Decision Trees (DT) and Logistic Regression (LR) : Decision Trees and Logistic Different types of regression techniques have been used for fatigue detection. They are mostly preferred owing to their simplicity and interpretability, even though sometimes, they do not achieve better accuracy than other techniques[30].
- 5) Fuzzy Algorithms : It is the incorporation of fuzzy logic into traditional machine learning models that makes fatigue detection systems more robust. For example, fuzzy logic integrated into a modified AdaBoost algorithm makes detection of fatigue faster and more accurate[31].
- 3) *Multi-Feature Fusion*: Several studies have emphasized the importance of multi-feature integration for reliable fatigue detection. By merging features, such as eye, mouth, and head movements, fatigue detection systems may portray fatigue features more broadly.
- 1) Multi-Parameter Fusion: A certain research paper proposed a multi-parameter fusion methodology wherein it combined PERCLOS, yawning frequency, and eye closure duration, resulting in a blink detection accuracy of 91% and a yawn detection accuracy of 96.43% [12].
 - 2) Hybrid Parameters: Another research tries to discover tiredness using hybrid parameters which includes face landmarks, eye aspect ratio, and mouth aspect ratio. The method showed a very good accuracy in real-time fatigue detection at 98.16%[24].
 - 3) Feature Union Auto-Encoder : In terms of combining eye-tracking features for fatigue detection, a feature union auto-encoder algorithm has been proposed. From comparison with traditional machine-learning algorithms, accuracy was increased from 82.4% to 87.9% using this method[19].
- 4) *Real-Time Fatigue Detection Systems*: Real time fatigue detection systems are important in driver monitoring applications where fast notifications can help avoid a number of accidents. Most of the advance machine learning frameworks in use have been compatible for real-time use by reducing the computational complexity as well as improving the feature extraction capabilities.
- 1) Real-Time Fatigue Detection : According to[24], the real-time fatigue detection system based on facial landmarks and eyes metrics succeeded in processing 65 frames per second (fps) with an accuracy of 98.16%.
 - 2) Optimized Feature Extraction: An alternative investigation enhanced feature extraction via the Dlib library, resulting in a recognition success rate of approximately 95%, thereby rendering it appropriate for real-time utilization[13].
 - 3) Low-Cost Systems : An economical fatigue detection system has been synthesized applied to conventional machine learning paradigms, designed for fitting into the automobile as an ancillary feature at a nominal cost[24]. Table(IV) explores Traditional machine learning models based on their extracted features, classification methods, quality metric, and datasets. While figure(1) presents the accuracy of these models.

TABLE III: Some of face extracted features.

Features	Description
Blink frequency [19] [20]	The number of times an eye closes over a specific period of time.
Maximum closure duration of the eyes[21]	The maximum time the eye was closed. However, it can be risky to delay detecting an extended eye closure that indicates a drowsy driver.
Percentage of eyelid closure (PERCLOS)[15][22][23]	The percentage of time (per minute) in which the eye is 80% closed or more.
Eye aspect ratio (EAR) [13][14][16][24]	EAR reflects the eye's openness degree. The EAR value drops down to zero when the eyes are closed. On the other hand, it remains approximately constant when the eye is open. Thus, the EAR detects the eye closure at that time.
Yawning frequency[12][25]	The number of times the mouth opens over a specific period of time.
Head pose[17][26][27][25]	Is a figure that describes the driver's head movements. It is determined by counting the video segments that show a large deviation of three Euler angles of head poses from their regular positions. These three angles are nodding, shaking, and tilting

TABLE IV: Traditional machine learning models

Ref	Extracted Features	Classification Method	Quality Metric	Dataset
[12]	PERCLOS, yawning frequency, and eye closure duration	A multi-parameter fusion	Blink detection accuracy: 91% Yawn detection accuracy: 96.43%	DliB library
[18]	pupil metrics	Support Vector Machines (SVM)	Accuracy: 92.86%	collected from seven volunteers who participated in a visual ergonomics experiment
[28]	Electrooculographic, electroencephalographic signals, facial images, wrist movements, and heart rate signals.	Random Forest (RF)	Accuracy: 93.3%	NA
[29]	Face features	K-Nearest Neighbor (KNN)	Accuracy: 94.68%	UTA-RLDD
[24]	facial landmarks, eye aspect ratio, and mouth aspect ratio	hybrid parameters	Accuracy: 98.16%	NA
[19]	eye-tracking features	A feature union auto-encoder	Accuracy: 87.9%	experimental data samples

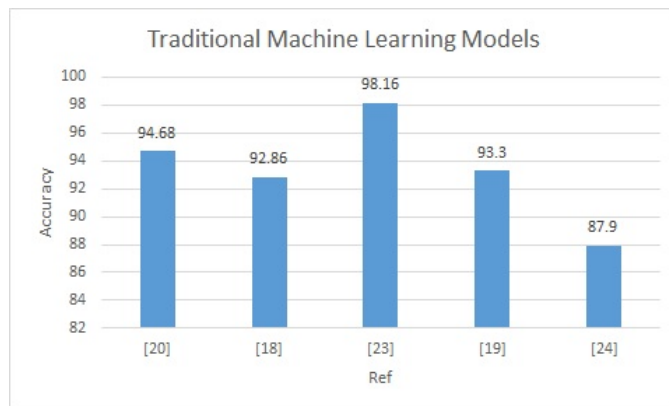


Fig. 1: Traditional machine learning models Accuracy

B. Deep Learning Models

In recent years, deep learning models, especially convolutional neural networks (CNNs), have gained considerable attention due to their automatic feature extraction from raw images. However, with advancements in deep learning, new applications have also set to develop highly sophisticated models capable of accurately detecting fatigue through facial analysis. The objective of this section is to summarize the latest deep learning models used for fatigue-detection systems based on facial characteristics, considering their main contributions, methodologies adopted, and performance evaluations.

1) *CNN-Based Models for Fatigue Detection*: Over the years, CNNs have been useful for detecting fatigue due to their ability to efficiently extract spatial features from facial images. A myriad of researches has presented various innovative methods based on CNNs for better accuracy and robustness of fatigue detection systems.

- 1) *Enhanced Facial Recognition with CNNs*: This work exposes a new and effective methodology in detecting driver fatigue using the most advanced facial recognition technology based on deep CNN architectures. The system also includes the emotional state analysis, which will give a more comprehensive representation of driver fatigue. It has reached 95.3% detection accuracy on the YawDDR dataset, thus presenting improvements over ordinary facial recognition methods[32].
- 2) *VGG16 and CNN for Eyeball Movement Analysis*: A method for assessing driver fatigue forms the foundation of this research using the analysis of eye movements with the use of CNN and VGG16 models. The model gives four classes from face sleepiness, which comprises open, closed, yawn and no yawn and gives an accuracy percentage of 97 percent for the CNN model while it has 74 percent for the VGG16 model[33].
- 3) *Real-Time Fatigue Detection with CNN*: This paper introduces a CNN-based fatigue detection framework that observes facial features in real-time. This model achieved an astounding accuracy of 97.34% in the 64th

epoch while maintaining appreciable validation accuracy with a peak of 96.02% in the 67th epoch[34]

2) *CNN-LSTM Models for Temporal Fatigue Detection:*

The synthesis of CNN and LSTM architectures gave rise to sophisticated models that could examine temporal sequences of facial characteristics for a more holistic evaluation of operator fatigue.

- 1) **CNN-LSTM Framework for Drowsiness Detection:** This study presents the CNN-LSTM framework of facial landmark analysis with action-on time series of several aspect ratios, mainly trained on YawDD, NITYMD, and FL3D datasets, reaching to excellent values of accuracy of 98%, precision of 95%, and F1 score of 94%[35].
- 2) **CNN-LSTM for Facial Movement Analysis:** This paper employs a CNN-LSTM architecture to ascertain driver sleepiness through the examination of video recordings of facial movements. The model effectively differentiates sleepiness by analyzing the sequence of motor actions exhibited by the driver, achieving enhanced accuracy relative to alternative deep learning methodologies[36].
- 3) **Advanced CNN-LSTM Approach:** This paper proposes a resilient CNN-LSTM methodology for the detection of facial characteristics and ocular movements. The model is meticulously crafted to assess driver drowsiness through the identification of yawning, detection of eye movements, and observation of head movements, thereby offering a thorough solution for real-time fatigue monitoring[37].

3) *Lightweight Models for Real-Time Detection:* In light of the computational limitations inherent to vehicle-mounted devices, numerous investigations have been dedicated to the advancement of lightweight deep learning architectures aimed at facilitating real-time fatigue detection.

- 1) **Lightweight Yolov8 Model:** This paper proposes a streamlined network architecture predicated on Yolov8, wherein the C2F module has been supplanted by MobileNetv3, thereby effectuating a reduction in both parameters and computational expenditures. This model attains a remarkable detection velocity of 109.81 frames per second alongside an average accuracy exceeding 95%[26].
- 2) **SRNet-FR for Facial ROI Analysis:** This paper introduces a lightweight approach for fatigue detection predicated on facial analysis. This model incorporates a Ghost module to minimize parameters while employing a 3D non-parametric attention mechanism to enhance accuracy. It achieves an impressive 99.03% accuracy in the recognition of eye and mouth states, utilizing a mere 0.61M parameters and 16.45MFLOPs of computational effort[27].
- 3) **Optimized CNN for Eye Region Extraction:** This paper delineates a real-time strategy for driver fatigue detection, which utilizes an optimized CNN specifically for the extraction of the eye region. This model demonstrates an accuracy of 94.84% on public face

dataset, thereby underscoring its efficacy within low-cost embedded systems[38].

4) *Attention Mechanisms for Enhanced Fatigue Detection:*

Attention mechanisms have increasingly been integrated into deep learning frameworks to emphasize pivotal facial attributes, including the eyes and mouth, which are essential for detecting fatigue.

- 1) **Global Attention Mechanism (GAM):** This paper introduces an advanced YOLOv5 architecture augmented with GAM to assign weights to significant regions within the image, thereby enhancing the model's capacity to discern subtle facial expressions associated with fatigue. This model exhibits superior accuracy and reliability in comparison to the conventional YOLOv5 algorithm[39].
- 2) **Attention Mechanism for Iris Recognition:** This paper delineates an improved fatigue detection approach that amalgamates iris recognition with facial feature analysis. The model employs an attention mechanism to concentrate on critical fatigue indicators, resulting in a 5% enhancement in accuracy[40].
- 3) **Dynamic Distributed Attention (DDA):** This paper presents an innovative framework that synthesizes facial fatigue characteristics with upper body postures through the utilization of a video vision transformer featuring DDA. The model attains an accuracy rate of 96.24%, along with a substantial enhancement in inference speed[41].
- 5) *Multi-Feature Fusion for Comprehensive Fatigue Assessment:* The earliest studies attempting to combine multiple facial and physiological markers into an integrative assessment of driver fatigue have been published in numerous works.
 - 1) **Facial Multi-Feature Fusion:** A driver fatigue warning system that collects ocular movement, facial expression, head position, and other facial features data. Real-time alerts are provided to help drivers take early corrective actions to avert accidents[42].
 - 2) **Facial and Physiological Features:** A fatigue detection model that integrates facial features, head posture dynamics, and PPG signals. The model achieves accuracy, precision, and recall with percentages of 97.36, 97.4, and 97.4, respectively, thereby showing the effectiveness of multi-feature fusion[43].
 - 3) **Facial and Upper Body Posture Analysis:** This paper consolidates facial fatigue characteristics with variations in drivers' upper body postures, resulting in an accuracy enhancement of 3.4% and 11.9% relative to single-feature models[41].
- 6) *IoT and Edge Computing for Real-Time Monitoring:* The amalgamation of Internet of Things (IoT) technology with edge computing has facilitated the emergence of real-time fatigue detection systems that can be seamlessly incorporated into vehicular environments.
 - 1) **IoT-Assisted CNN-LSTM Framework:** This paper delineates a CNN-LSTM framework executed on NVIDIA's Jetson Nano GPU platform. This system identifies eye closure and yawning as indicators of driver fatigue,

subsequently issuing alerts through tactile vibrations and auditory messages[35].

- 2) IoT-Assisted Automatic Detection: This paper introduces a deep learning model that harnesses IoT technology for the real-time analysis of facial movements. This model is meticulously designed to notify drivers expeditiously prior to the occurrence of any disastrous incidents[36].
- 3) Edge Computing for Fatigue Detection: This paper unveils an advanced driver monitoring system employing deep learning models such as YOLOv8. The system is specifically structured for integration within automobiles, thereby enhancing accessibility and promoting road safety[44].

7) *Novel Architectures and Techniques*: The innovation of novel architectures and methodologies has propelled advancements within the domain of fatigue detection, culminating in the development of more precise and efficient models.

- 1) Temporal Adaptive Fuzzy Neural Network (TAFNN): This paper introduces an innovative model termed TAFNN for the assessment of fatigue. This model capitalizes on causal and dilated convolutions for the extraction of time series data, thereby achieving enhanced stability and runtime performance.
- 2) FER to FFR Approach: This paper presents a fatigue detection model that acquires facial expression features through a deep learning-based facial expression recognition paradigm. This methodology realizes both qualitative and quantitative enhancements in the accuracy of fatigue detection[44].
- 3) DA-ViT Framework: This paper articulates a groundbreaking framework that amalgamates facial fatigue characteristics with upper body postures through the utilization of a video vision transformer endowed with dynamic distributed attention. The model achieves exceptional accuracy and inference velocity, rendering it suitable for embedded applications[41].

Combining machine learning and deep learning techniques in fatigue detection offers significant advantages, primarily by leveraging the strengths of different models to achieve enhanced accuracy, robustness, and real-time applicability. For instance, the synthesis of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) architectures allows for the examination of temporal sequences of facial characteristics, providing a more holistic evaluation of operator fatigue than either model could achieve alone[29][30][31]. Furthermore, integrating attention mechanisms with deep learning frameworks helps emphasize pivotal facial attributes like eyes and mouth, which are crucial for detecting fatigue, leading to improved discernment of subtle expressions and enhanced accuracy[33][34][35]. The amalgamation of IoT technology with edge computing, facilitated by deep learning models, also enables seamless, real-time fatigue detection systems suitable for vehicular environments[26]. These combined approaches result in more precise, efficient, and robust fatigue detection systems adaptable to various operational constraints. Table(V) explores Deep learning models based on

their extracted features, classification methods, quality metric, and datasets. While figure(2) presents the accuracy of these models.

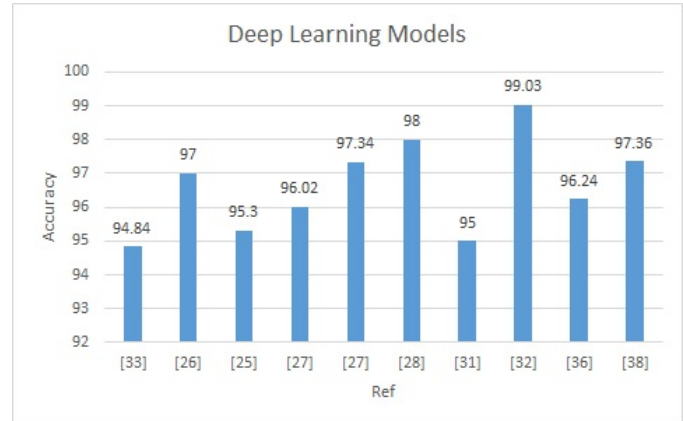


Fig. 2: Deep learning models Accuracy

C. Hybrid Models

Hybrid models combine traditional machine learning and deep learning techniques to leverage the strengths of both approaches. The most relevant research papers from the recent years, highlighting the key innovations, methodologies, and performance metrics of these hybrid models.

1) *Temporal Adaptive Fuzzy Neural Network(TAFNN)*: The TAFNN framework synthesizes an adaptive fuzzy neural network alongside causal and dilated convolutional techniques to analyze temporal data derived from facial video recordings. This methodology adeptly captures the cumulative and ambiguous characteristics inherent in the progression of fatigue. The TAFNN demonstrates superior efficacy compared to conventional methodologies regarding both evaluative accuracy and operational efficiency. The enhanced calculation technique for rule antecedents mitigates instabilities by 81.58% across 1000 iterative trials[45].

2) *AlexNet-Based Models with Transfer Learning*: This methodology employs transfer learning utilizing the AlexNet architecture to identify driver fatigue predicated on head positioning and oral movements. The model undergoes fine-tuning specifically for the prediction of driver drowsiness. The transfer learning approach attains an accuracy of 95.7%, whereas the feature extraction model based on Support Vector Machines (SVM) achieves an accuracy of 99.65% on the NTHU Driver Drowsiness Detection dataset[46].

3) *Multi-Source Fusion Approach*: This technique amalgamates physiological signals and facial image attributes through the application of neural networks designed for automatic feature extraction. It systematically records physiological signals and facial video footage from a cohort of 21 participants. The model realizes a detection accuracy of 93.15% within a temporal window of 3 seconds, exhibiting a specificity of 94.04% and a sensitivity of 91.71%[46].

4) *CNN-GTN Model for Multimodal Fusion*: This model employs Convolutional Neural Networks (CNN) for the extraction of facial features and integrates these with Electrocardiogram (ECG) and vehicle state variables through the utilization

TABLE V: Deep learning models.

Ref	Extracted Features	Classification Method	Quality Metric	Dataset
[32]	eyes, mouth, and overall facial expressions	Enhanced Facial Recognition with CNNs	Accuracy: 95.3%	YawDDR dataset
[33]	eyeball movement	VGG16 and CNN for Eyeball Movement Analysis	CNN accuracy rate: 97% VGG16 accuracy rate: 74%	a dataset of 2900 images of eye conditions
[34]	facial features	Real-Time Fatigue Detection with CNN	Accuracy: 97.34% during the 64th epoch, validation accuracy: 96.02% in the 67th epoch	NA
[35]	facial landmark analysis across multiple aspect ratios	CNN-LSTM	Accuracy: 98% precision rate: 95% F1 score: 94%	YawDD, NITYMD, and FL3D
[26]	Facial Features, Posture and Head Movement	Lightweight Yolov8 & MobileNetv3	Velocity: 109.81 frames per second. accuracy exceeding: 95%	NA
[27]	eye and mouth regions of interest (ROI)	SRNet-FR	Accuracy: 99.03%	NA
[38]	eye region	optimized CNN (MTCNN)	Accuracy: 94.84%	public face
[39]	facial features	Global Attention Mechanism (GAM) & YOLOv5	Accuracy higher than traditional yolov5	NA
[41]	facial characteristics	Dynamic Distributed Attention (DDA)	Accuracy: 96.24%,	DMD
[43]	facial features, head posture dynamics, and PPG signals	Multi-Feature Fusion	Accuracy: 97.36% Precision: 97.4% Recall: 97.4%	composed of data collected from real-road driving experiments involving 30 drivers

of a Gated Transformer Network (GTN). The GTN incorporates self-attention and masking techniques to effectively capture interdependencies. The trimodal architecture achieves an average predictive accuracy of 90% across four distinct levels of fatigue[25].

5) *Hybrid System Utilizing Computer Vision and Deep Learning*: This system employs computer vision techniques for the preprocessing phase and implements deep learning architectures, specifically Convolutional Neural Networks (CNN) and MobileNet, to predict driver drowsiness by analyzing eye closure and yawning behaviors. The CNN architecture attains an accuracy rate of 92.4%, whereas the MobileNet architecture achieves a notable accuracy rate of 99.52%[47].

6) *Machine Learning for Detection of Fatigue and Distraction*: This methodology utilizes facial alignment networks to identify facial feature points and a MobileNet-based Convolutional Neural Network to analyze distracted driving behaviors. The proposed model exhibits superior accuracy and reduced computation time in comparison to preceding methodologies[48].

7) *RPPMT-CNN-BiLSTM Framework for Non-Invasive Fatigue Detection*: This technique integrates remote photoplethysmography alongside motion tracking within a CNN-BiLSTM framework, enhancing feature extraction through the advanced Pan-Tompkins algorithm and one-dimensional Multi-task Cascaded Convolutional Neural Network (1D-MTCNN). The model registers an impressive accuracy of 98.2% on the MDAD dataset[49].

8) *FPIRST Method Employing Residual Swin Transformer*: This approach leverages feature parameter images in conjunction with a residual Swin Transformer to facilitate fatigue

recognition, calculating eye and mouth aspect ratios derived from facial landmarks. The model accomplishes an accuracy of 96.512% on the HNUFD dataset[50].

9) *FEY-YOLOv7 Algorithm for Dynamic Tracking*: This algorithm employs YOLOv7 integrated with a Coordinate Attention module and a targeted detection head for the dynamic tracking of facial features. The model achieves a mean Average Precision (mAP) of 0.983 and a frame rate per second (FPS) of 101[22].

10) *Facial Feature Fusion Convolutional Neural Network (FFF-CNN)*: This multi-stream architecture comprises global facial and localized ocular streams, employing feature fusion techniques for the classification of eye states, utilizing feature attention mechanisms and stream interaction modules. The model attains an accuracy of 98.35% on the CEW dataset, surpassing the performance of single-stream architectures[51].

11) *Lightweight YOLOv5-Fatigue Model*: This model incorporates YOLOv5 architecture with bilateral convolution and deep convolution modules aimed at minimizing parameters and computational requirements, while integrating a Non-local Attention Mechanism (NAM) to enhance accuracy. The model achieves an (AP50) of 92.6% and an inference time of 2.1 ms[52].

12) *Multi-Facial Feature Integration Utilizing LSTM*: This technique improves the quality of low-light imagery through Gamma Correction and implements a modified Multi-Task Cascaded CNN for the extraction of salient features. It processes ocular and oral features into an LSTM for the purpose of fatigue classification. The model attains an F1 score of 0.98 and a Recall of 0.99 when evaluated on the YawDD dataset[20].

13) *MobileNet-AFF for Multi-Scale Feature Integration*: This framework synergizes MobileNet V3 with Attention Feature Fusion (AFF) to amalgamate global, facial, and critical region image features. The model accomplishes rapid inference rates alongside proficient fatigue characterization[23].

14) *DCNN-SVM for Facial Expression Analysis*: This system combines Deep Convolutional Neural Networks (DCNN) with Support Vector Machines (SVM) for the detection of fatigue expressions. The DCNN-SVM architecture exhibits superior performance in recognition rates over the single DCNN and SVM models[53].

15) *Face Mesh Features Integrated with LSTM*: Media Pipe Face Mesh Framework is used to extract the facial key points, while fatigue is detected dynamically using LSTM modeling. In comparison to other random forest models, the LSTM model has better accuracy[54].

16) *Lightweight YOLOv5s with Three-Dimensional Key points*: The model is built on a light YOLOv5s architecture with attention mechanisms and three-dimensional facial keypoint extraction to enable real-time detection. The model minimizes parameter usage and computational expense while maintaining a fatigue recognition rate of 96.3%[55].

17) *Two-Stream Network with Integrated Multi-Facial Features*: This system employs a two-stream approach to combine both static and dynamic facial characteristics, augmented with gamma correction in order to assist performance when lighting is low. The model achieves an accuracy rate of 97.06% on the NTHU-DDD dataset[56]. Table(VI) explores Hybrid models based on their extracted features, classification methods, quality metric, and datasets. While figure(3) presents the accuracy of these models.

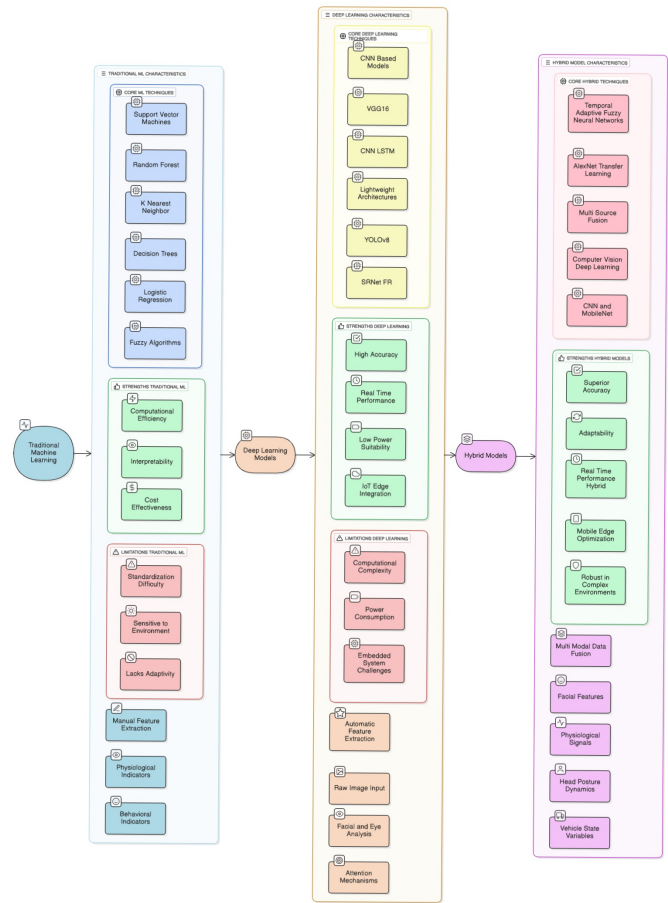


Fig. 4: Evolution of the Three Categories.

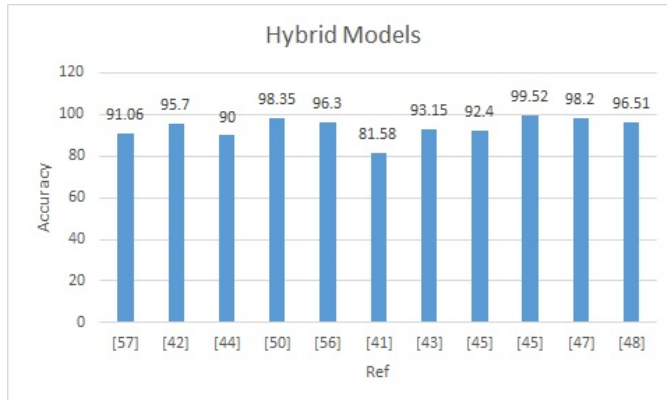


Fig. 3: Hybrid models Accuracy.

IV. CHALLENGES

Data-Related Challenges:

- **Individual Variations**: A major challenge is the wide range of facial expressions, shapes, and characteristics among different individuals. This makes it difficult to standardize feature extraction algorithms[31][34][43].
- **Environmental Factors**: Varying conditions such as lighting, angles, and background noise add complexity and can negatively affect model performance[45][48][22][20].

- **Data Quality and Generalizability**: A limited number of study subjects can weaken a model's robustness and its ability to generalize[18]. Input data may also not fully represent the entire spectrum of real-world driving situations[57][46].
- **Feature Identification**: Discovering the most dominant features for fatigue detection is a significant problem, as it requires evaluating numerous signals to understand their effectiveness[28].

Model-Related Challenges:

- **Feature Extraction**: Traditional models struggle with detecting facial features effectively[31]. Automating the extraction of eye and mouth areas under different head poses without manual tuning is also a challenge for deep learning models[27].
- **Distinguishing States**: There are difficulties in accurately distinguishing between normal and fatigue states due to individual variations in fatigue responses and potential misinterpretation of facial expressions[57][47].
- **Accuracy vs. Efficiency Trade-off**: Many models prioritize accuracy over speed and size, making them unsuitable for real-time applications[26]. Designing lightweight models that boost efficiency without degrading performance is a key challenge, requiring a balance between accuracy and computational load[48][22][20].

TABLE VI: Hybrid models

Ref	Extracted Features	Model	Quality Metric	Dataset
[45]	Facial features	Temporal Adaptive Fuzzy Neural Network (TAFNN)	reduces instability by 81.58%	NA
[57]	head position and mouth movements	AlexNet-Based Models with Transfer Learning	Accuracy: 95.7%	NTHU Driver Drowsiness Detection
[46]	physiological signals and facial image features	Multi-Source Fusion Approach	Accuracy: 93.15%	NA
			Specificity: 94.04%	
			Sensitivity: 91.71%	
[25]	facial feature, ECG, and vehicle state features	CNN-GTN Model for Multimodal Fusion	Accuracy: 90%	NA
[47]	eye closure and yawning	Computer Vision and Deep Learning	CNN Accuracy: 92.4%	NA
			MobileNet Accuracy: 99.52%	
[49]	Multi-Modal Fusion : (eyelid movement, heart rate, and PERCLOS)	RPPMT-CNN-BiLSTM	Accuracy: 98.2%	MDAD
[50]	Facial Landmark, Aspect Ratios	FPIRST Method with Residual Swin Transformer	Accuracy: 96.51%	HNUFD
[22]	facial features	FEY-YOLOv7	mean Average Precision (mAP): 0.983	NA
			frame rate per second (FPS): 101	
[51]	eye state classification	Facial Feature Fusion CNN (FFF-CNN)	Accuracy: 98.35%	CEW
[52]	proportion of eyes closed (PERCLOS), proportion of mouth closed (POM)	Lightweight YOLOv5	Average Precision at IoU 0.50 (AP50): 92.6%	VIGP
			inference time: 2.1 ms	
[20]	Multi-Facial Features	Integration Utilizing LSTM	F1 score: 0.98	YawDD
			Recall: 0.99	
[55]	Facial features	Lightweight YOLOv5s with 3D Keypoints	Accuracy: 96.3%	NA
[56]	Facial features	Two-Stream Network	Accuracy: 97.06%	NTHU-DDD

TABLE VII: Datasets

Ref	Dataset	Number of Subjects	Data Type	Environment	Availability
[28]	UTA-RLDD	60	Video	real-world	Public
[11]	Dlib Face	7,198	Image	Mixed	Public
[19][34]	YawDDR	100+	Video clips / image sequences.	Lab	Public
[27]	public face	5,749	Image	real-world	Public
[40]	DMD	37	Video	Hybrid	Public
[49]	MDAD	50	video	real-world	Public
[50]	HNUFD	10	Video and Image frames	Lab	Public
[51]	CEW	2,423	Image	real-world	Public
[23]	VIGP	37	Video	Hybrid	Public
[57][56]	NTHU-DDD	36	Video	lab	Public

TABLE VIII: Accuracy Trends Across Model Categories

Model Category	Feature Extraction	Average Accuracy	Accuracy Details
Traditional Machine Learning	Manual feature extraction based on domain knowledge.	90 – 95 %	98.16% (Multi-parameter fusion, real-time); 94.68% (KNN with FaceNet); 93.3% (Random Forest); 92.86% (SVM with pupil metrics); 91% (Blink detection); 96.43% (Yawn detection)
Deep Learning	Automatic feature extraction from raw data (e.g., images, video) using CNNs, RNNs, LSTMs, etc.	95 - 99.03 %	99.03% (SRNet-FR); 98% (CNN-LSTM); 97.34% (Real-Time CNN); 96.24% (DA-ViViT framework). 95.3% (Enhanced Facial Recognition with CNNs)
Hybrid Models	Combines traditional ML and DL techniques, often integrating pre-extracted features with deep learning for enhanced robustness.	95 - 99.65 %	99.65% (AlexNet + SVM); 99.52% (MobileNet architecture); 98.2% (RPPMT-CNN-BiLSTM); 97.36% (Multi-feature fusion); 97.06% (Two-Stream Network)

- Adaptive Capabilities: Traditional machine learning models often lack adaptive thresholding and online processing capabilities, which are crucial for effective fatigue

detection[31].

Implementation-Related Challenges:

- Real-Time Processing: Achieving the computational ef-

iciency required for real-time processing is complex, especially with algorithms that can be slow with video data[29]. Structuring a system for real-time processing while maintaining high prediction accuracy remains a fundamental barrier for practical implementation, particularly in autonomous vehicles[46][49].

- Real-World Application: Training models for unconstrained environments with varying conditions is a challenge that affects detection accuracy in real-world applications[57]. For on-road assessments, custom training with diverse background noises is essential but adds complexity[17][21].

V. DISCUSSION

In terms of scalability, speed, and trade-offs, traditional machine learning, deep learning, and hybrid models for fatigue detection are compared. Table(VII)explores some of the datasets are used in the deferent models, while Table 8 views the accuracy trends across model categories. Finally, Figure(4) shows the evolution of the three categories.

A. Traditional Machine Learning Models

1) *Performance and Speed*: Traditional models like Support Vector Machines (SVM), Random Forest, and K-Nearest Neighbor (KNN) achieve high accuracy, with KNN reaching up to 94.68% when combined with FaceNet for feature extraction. Some implementations can process data in real-time at 65 frames per second with an accuracy of 98.16%. This demonstrates their feasibility for real-world, time-sensitive applications.

2) *Trade-offs*: While models like Decision Trees and Logistic Regression may offer lower accuracy, their primary advantage is interpretability, making them suitable for scenarios where model transparency is a priority. They are also noted for being cost-effective, allowing for integration into commercial vehicles without significant financial overhead.

B. Deep Learning Models

1) *Performance and Speed*: Deep learning models show high performance in both accuracy and real-time deployment. Lightweight architectures, such as a modified Yolov8 with MobileNetv3, achieve very high processing speeds of 109.81 frames per second while maintaining over 95% accuracy. Another model, SRNet-FR, reached 99.03% accuracy with greatly reduced computational complexity.

2) *Scalability and Deployment*: These models are suitable for deployment on low-power hardware, such as embedded systems. The integration with IoT and edge computing platforms like Jetson Nano enables their operational use in vehicular settings for real-time alerts. Attention mechanisms are used to improve efficacy, with a vision transformer framework achieving 96.24% accuracy while accelerating inference speeds, underlining its potential for real-time monitoring. The DA-ViViT framework, using video-based attention, shows high accuracy with fast inference, making it suitable for embedded applications in dynamic environments.

3) *Trade-offs*: The main challenge addressed by lightweight architectures is the need to reduce computational complexity and power consumption for deployment on embedded and edge devices without significantly compromising accuracy.

C. Hybrid Models

1) *Performance and Speed*: Hybrid models, which integrate traditional machine learning with deep learning, often outperform single-modality approaches and are presented as the most efficient and versatile solution . For example, combining a Swin Transformer with feature parameter images yielded 96.51% accuracy, while a FEY-YOLOv7 model achieved a mean Average Precision of 0.983 at 101 frames per second. A lightweight YOLOv5 variant with attention balanced accuracy (92.6% AP50) with low inference time. Another model combining computer vision preprocessing with deep learning classifiers reached up to 99.52% accuracy.

2) *Scalability and Deployment*: Hybrid models are effective in both complex and constrained environments. Models are optimized for mobile and edge deployments, such as MobileNet-AFF, which yields fast inference for reliable fatigue characterization. The Temporal Adaptive Fuzzy Neural Network (TAFNN) is noted for its computational efficiency.

3) *Trade-offs*: By combining different methods, hybrid models achieve a superior balance of accuracy, adaptability, and real-time performance. For instance, a hybrid model of AlexNet and SVM achieved high accuracies of 95.7% and 99.65% on the NTHU dataset. The DCNN-SVM combination scores higher than standalone methods and a multi-feature LSTM framework achieved an F1 score of 0.98, reinforcing the efficacy of the hybrid approach. This suggests they overcome some of the limitations of using either traditional or deep learning models alone.

VI. CONCLUSION

During recent years, the field of drowsiness detection significantly advanced, and such improvement is a direct outcome of advancement in artificial intelligence technology. This study offers a detailed analysis of drowsiness detection models, categorizing them into traditional, deep learning, and hybrid approaches. It concludes that hybrid models are the most effective, demonstrating superior accuracy and real-time performance. For future scope, we suggests focusing on two main areas: developing lightweight models suitable for embedded systems, and expanding fatigue parameter features by incorporating data like facial expressions in varied environments to improve system robustness.

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Amin Babiker Abdalnabi Mustafa is a professor in electrical and electronics engineering Department, Faculty of engineering, Alneelain University, Sudan. He received his B. Sc. degree in Electrical and Electronic Engineering from Faculty of Engineering, University of Khartoum, Sudan. His PhD. from faculty of Engineering, Alneelain University, Sudan. He has the title of Professor in Electrical and Electronic Engineering since 2016. Prof Amin published over 200 articles in international Journals, his research interest covers Networking, Computing, Biomedical Engineering and Engineering Education Issues.



learning.

Nizar Ali Alhaj Abdellah is a lecturer of electrical engineering in electrical Engineering Department, College of Engineering, Elsheikh Abdallah Elbadri University, Berber, Sudan. He received his B.Sc. degrees in electrical engineering from Elsheikh Abdallah Elbadri University and M.Sc. degrees in embedded systems technologies from Jain University, Bangalore, India. He is pursuing Ph.D. degree in electrical engineering at Nile Valley University, Atbara, Sudan. His current research interest covers embedded systems, machine learning, and deep



Hussein Abdulatif Hussein is an Assistant Professor at Nile Valley University – Faculty of Engineering – Department of Electrical and Electronics Engineering, Sudan. He received his PhD in Electronics Engineering from Sudan Academy of Sciences (SAS) in 2018. Currently His research interests include Intelligent Control applications, Cloud Computing, Computer Networks, AI, and soft computing.