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Review

A comprehensive review of approaches to detect fatigue using machine learning techniques

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Abstract

In the past decades, there have been numerous advancements in the field of technology. This has led to many scientific breakthroughs in the field of medical sciences. In this, rapidly transforming world we are having a difficult time and the problem of fatigue is becoming prevalent. So, this study aimed to understand what is fatigue, its repercussions, and techniques to detect it using machine learning (ML) approaches. This paper introduces, discusses methods and recent advancements in the field of fatigue detection. Further, we categorized the methods that can be used to detect fatigue into four diverse groups, i.e., Mathematical Models, Rule-Based Implementation, ML and Deep Learning. This study presents, compares and contrasts various algorithms to find the most promising approach that can be used for the detection of fatigue. Finally, the paper discusses the possible areas for improvement.

Keywords: Fatigue detection; Machine learning; Deep learning; Driver monitoring; Healthcare

Introduction

Artificial intelligence (AI) is a term which can be referred to any machine that exhibits traits that are associated with the human mind like problem-solving or learning. Machine learning (ML) is a subfield of AI that enables the machine to learn patterns using historical data without being explicitly programmed to do so.[1] The most common algorithms used in this field are Bayesian learning, Support Vector Machine (SVM), Clustering, Regression, Classification.[2] Another subfield of AI is deep learning (DL) that uses Artificial Neural Networks (ANN) which were inspired by the biological neurons in human brain. These neural networks progressively extract high level features from the input.[3] The most popular used DL algorithms are Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNNs), etc.

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Fatigue is associated with change in the psychobiological state of a person, caused by relentless periods of arduous activity.[4,5] It is one of the most common problems occurring amongst patients, in which an individual experiences resistance against an activity,[4,6] mood swings[4,7] and feeling lethargic. It is a symptom that is mainly linked with illness, stress, aging and depression. Also, it is reported that one of the major symptoms in multiple sclerosis and Parkinson's disease, post-stroke, and Poliomyelitis is fatigue.[8,9] Fatigue is mainly categorized as physical and mental fatigue. Physical fatigue is an ephemeral condition in which an individual is unable to maintain optimal physical performance, whereas mental fatigue is a psychobiological state induced by a prolonged period of demanding cognitive.[10,11] In mental fatigue, an individual can experience a temporary decrease in cognitive performance which can manifest sleepiness, lack of energy, attention[5] and sometimes an acute decline in cognitive performance might be observed as well.[10]

A recent study shows that 3.6 % of fatal road accidents are the consequences physical exhaustion or drowsiness.[12,13] According to some reports, about 20% of fatal accidents and 30% of crashes happened in Australia are because of some kind of driver error. Moreover, in the US about thousands of people die each year because of driver's somnolence.[12,14] A study has shown that fatigue severely affects the spontaneous response of an individual to a situation. A recent survey shows that 20% of fatal accidents occur due to various types of fatigue.[15] So, monitoring the attention of the driver is considered a very crucial parameter for safe driving.[16,17]

There are some novel methods in ML and DL which are promising for the detection of fatigue which is presented in the literature.[18−22] The areas where ML and DL can be helpful are: (1) Monitoring/analyzing electroencephalogram (EEG) signals[23]; (2) Yawing detection; (3) Facial muscle detection; (4) Drowsiness detection; (5) Pupil detection.

For example, EEG is majorly used and auspicious method for measuring the brain's electrical activity for detecting sleep patterns, and hence it has been observed as a crucial feature in detecting fatigue.[23]

Finally, to recapitulate ML and DL can be useful in fatigue detection as well as in the diagnosis of it which in turn can benefit the growth of the healthcare industry. This article reflects a thorough review of research findings related to fatigue detection.

Methodologies of review

Search methodology and article selection

The literature review presented has retrieved articles by querying the terms like [“physical” or “mental” or “driver”] + “fatigue” + [“effects or detection or monitoring”] + [“EEG” or “EOG” or “sleepiness detection” or “face tracking”] into few databases like: Google Scholar, PubMed, Science Direct, IEEE and Springer.

All the applications where fatigue detection can be used have been discussed in this review. Prior Studies are considered to be less relevant as the techniques introduced had less accuracy, were costly and the scope of implementation was comparatively less.

Methodological and thematic analysis of articles

A total of 67 articles were retrieved using the above-mentioned method. On reviewing these articles, 17 articles were excluded using: their title, language, and having less relevance with the objective of this article.

The focus of this article is to understand causes, manifestations of fatigue followed by developing a method for its detection using advanced Machine Learning methods. The summary and analysis of the methods in these 50 articles is done by considering the following four questions: (1) What is the main objective of the article? (2) Which different features are used to detect fatigue? (3)What is the resulting outcome? (4) What type of data was considered during the process? Finally, a comparative analysis is presented between the methods to find out which method is more promising when compared to other methods.

Clinical manifestations of fatigue

Fatigue is mainly categorized as active fatigue and passive fatigue.[24] Active fatigue is a state caused by continual involvement in an arduous activity. Some characteristics like an increase in feeling of tiredness, an aversion towards a task or a decrease in mental and athletic performance can be observed. People who work long hours in grueling task experiences this kind of fatigue.

Passive fatigue is a consequence of any dull or repetitive task. For example, prolonged periods of road driving can cause the person to lose interest resulting in accidents. While driving, the relation between eye flickering and response time shows a positive correlation to this kind of fatigue.[25] A research[26] suggested that the driver's performance on non-curved roads when compared to the curved road is less because driving on a straight road is uninteresting and causes passive fatigue. A study[26,27] suggested that the driver's performance on straight roads as compared to the curved road is less because driving on a straight road is monotonous and causes passive fatigue. Philip[28] illustrated that the performance of the driver is dependent on the time of day and the number of hours he/she slept in the last 24 hours. Fig. 1 shows the effects of fatigue.

Comparative analysis of simple fatigue and fatigue induced by diseases

Tiredness is the most common problem occurring amongst patients in health care. According to a Dutch health care registry, fatigue is most commonly observed symptom in patients.[29,30] Another study from Canada shows that[30,31] 13.6 % of patients consulted a physician for treatment of fatigue. Fatigue is a state of feeling lethargic to carry out the daily chores. It is normal to feel tired after doing an intense physical exercise with which an individual is not acquainted. The most common daily routine activities that cause tiredness in an individual are: extended wakefulness,[32] long working hours,[33] sleep debt,[34] depression.[30]

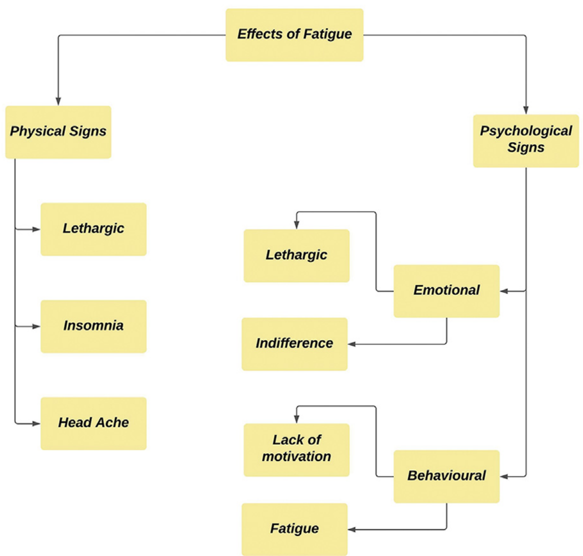

Fig. 1. Classification of effects of fatigue on the basis of clinical manifestations.

Every fifth patient consulted a general practitioner for tiredness suffered from a depressive disorder.[30] Taking an adequate amount of sleep, a healthy nutritional diet, vitamin supplements, and taking less stress can help cure tiredness. Although fatigue is the most common symptom in diseases like cancer or multiple sclerosis, it is also experienced by the general healthy population.

Chronic Fatigue Syndrome (CFS) is a type of tiredness that is difficult to cure. CFS is a long-term condition in which an individual feels extremely sluggish. This syndrome depending upon the severity of it can affect an individual's life. In severe cases of CFS, an individual may find it difficult to perform basic daily tasks like taking a bath or brushing teeth. According to the NHS, CFS affects around 25,000 people in the United Kingdom (UK). It is more common amongst women compared to men. Some of the common symptoms experienced by an individual in CFS are as below: A loss of memory and lack of concentration; Severe headache; Sleeplessness; Muscular pain; Brain fog.

The exact cause of CFS is still unknown. Some theories point to problems with the immune system or hormone imbalance or emotional trauma or bacterial infection. Hence it is the responsibility of the general practitioner to take the history of individuals to decide up to what extent diagnostic measures should be taken.[30] Hence risk mitigation strategies for fatigue detection should be implemented, not only to reduce these short and long-term health risks in individuals but also to create more efficient and effective workplace.

Fatigue detection methods

The methods for fatigue detection can be implemented via mathematical models, DL models, ML models which is summarized in Fig. 2.

Fatigue detection using mathematical models

Mathematical models help us in understanding the correlation between sleep cycles and the performance of an individual. These models consider the features such as sleep duration, wakefulness duration, a circadian cycle, and history of sleep periods to predict the level of fatigue. One of the primary models for the detection of fatigue was known as Two Process model.[16,34]

The Two Process model is based on the activity between two processes which are homeostatic (S) and

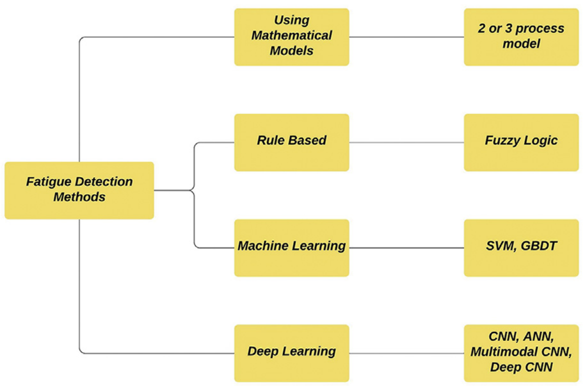

Fig. 2. Classification of fatigue detection methods.

circadian (C) processes. The mentioned process is used to predict the level of fatigue and performance of the driver. Later Two Process model was upgraded to Three Process Model of Alertness.[16,35] Three Process model takes the features such as sleep duration and wakefulness into consideration and predicts the level of fatigue and alertness of the driver. Another system known as Aircrew Fatigue Evaluation (SAFE) Model[36,37] was developed by taking pilots as the center focus. This model presents the alertness levels of the pilot during flight. Another model which is based on Activity, Fatigue, Task Effectiveness (SAFTE)[38,39] has also been created which is similar to SAFE. The only difference between these two algorithms (SAFE and SAFTE) is that SAFTE considers both real-time data and the data which is being generated by the sleep algorithm, whereas SAFE only takes in real-life data.

The models illustrated above are only for general purpose use. They can be used to supervise long working hours. Most mathematical models-based approaches are used in generic setup i.e., in factory, aviation, etc. But, due to the recent development in smarter systems, researchers are focusing towards other systems.

Fatigue detection based on certain defined rules

This approach is considered a less challenging approach for detecting fatigue. For complicated detection system a system/algorithm known as Fuzzy Inference Systems (FIS)[16,40] is preferred over rule-based approach. It uses fuzzy rules and membership functions to find an accurate outcome. It also offers inbuilt functions and maps input to output by using IF-THEN rules. An advantage of FIS is that it provides parallel processing of data. Another advantage of FIS is that it can learn the task from the knowledge base as well as from incorporating additional rules.

Devi and Bajaj[41] suggested a technique for detection of fatigue, where the mouth and eye states were used as an input for FIS and then FIS predicted state of driver as dangerous, fatigue, or normal. The eye states were divided into the following categories: blinking, closed, or sleepy. Whereas, the mouth states were categorized as normal or yawning. Another research[16,42] has taken the above-mentioned features into consideration and developed a technique to detect fatigue using a two-layered FIS.

Fatigue detection using machine learning

Fatigue detection using Yawning as parameter

Fan[43] suggested a method for tracking face movement with the help of a camera. During yawning, geometric features of the face changes so, yawning can be detected using these geometric features. In the method proposed by Fan[43] a Gravity-Centre template[43,44] was used to detect mouth corners by using grey projection. Then, Fan[43] extracted the features of mouth by using Gabor wavelets. This produced information about organs such as eyes, nose, mouth, lips which are important for the detection of facial features. Finally, a Two-Dimensional representation Gabor wavelet was used to analyze and process the texture of the image. Then Linear Discriminant Analysis (LDA) was used to classify feature vectors to detect yawing.

This proposed technique was evaluated on 400 images and 20 videos consisting of 4512 faces. This method not only detects faces in instantaneously but also provides high accuracy. Gabor features were able to detect yawning with an accuracy of 96% whereas, the Geometric features were able to detect yawning with an accuracy of 69.5%. Hence the results of this experiment illustrate that Gabor coefficients are more efficient than Geometric features.

Fatigue detection using skin conductance

Bundele and Banerjee[45] designed two classifiers for detection of fatigue with skin conductance. The main goal of the paper was to provide a comparative study between Multilayer Perceptron Neural Network (MLP NN) and SVM. The authors of this paper consider features like skin conductance, oximetry pulse, respiration, and SPO2 as main primary features[45,46] for the detection of fatigue. To collect these parameters drivers aged between 25 and 55 years were asked to drive trucks, cars, bus. Some measurements (like EEG, pulse rate, respiration rate) were taken after each subject has

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completed at least 100−600 km of the drive. The features for skin conductance signal were then extracted using MATLAB. Finally, a MLP NN and SVM were designed to detect fatigue levels with skin conductance.

The classifiers designed had 18 input features consisting of 2392 rows. The accuracy for fatigue detection using skin conductance method using SVM and MLP NN were 92.95% and 89.45% respectively. Hence, it is quite apparent that the conductance of skin can be used as a supporting parameter for fatigue detection.

Fatigue detection using eye state

Wang[47] proposed a method for the detection of state of eye. There are mainly two challenges that are faced while detecting an eye's state: eye's position and light illumination. The eye-detection system has two main tasks. The first is eye detection and the second is eye state detection. There are many methods developed in the past that were developed to detect eye with geometrical features. So, in this paper, the author's main was to detect eye state.

Viola−Jones method was used to detect eyes from the video frames captured by the webcam. AdaBoost algorithm was used to select the feature set and to train classifier. It ensembles weak classifiers and forms a strong classifier.[47−49] Finally, to find the state of an eye a traditional binary image classifier was used. The above suggested method used 1500 open eye (positive) and 700 closed eyes (negative) with different illuminations for training. Table 1 illustrates the detection results of ensemble method.

It can be observed from Table 1 that this technique is promising for detecting eye states using a webcam. This algorithm can distinguish eye states in instantaneously with a camera in somewhat harsh conditions. The accuracy of this approach is higher when compared to previously done work under the same experimental conditions.

Fatigue detection using Gradient Boosting Decision Tree (GBDT)

Hu and Min[50] tried to detect the characteristics of EEG signals, by calculating feature sets which included the entropies such as a sample, spectral, fuzzy & approximate. The authors used Gradient Boosting Decision Tree (GBDT) for the detection of fatigue which had the above-mentioned features as input. To assess the GBDT method, three widely known classifiers namely K-nearest neighbors (KNN), SVM, ANN were used for comparison.

Further, the authors conducted experiments in 22 humans. They were asked to not consume alcohol or any kind of medications before the experiments and during the experiments. Initially, they were asked to practice driving for several minutes to get acquainted with the system. The duration of the experiments conducted was around 40−120 minutes. The output of GBDT is used to determine whether the driver was in a state of fatigue or not. The results of these experiments demonstrated that it is possible to achieve accuracy up to 95% for detecting fatigue using EEG. This shows that this method can be used for detecting fatigue in daily applications. Table 2 shows several methods for the fatigue detection:

Fatigue detection using facial behavior

Dey[12] suggested novel and economical method for real-time detection of eye state, yawning and head movement. The article suggested that a pre-trained model which consists of Histogram-Oriented Gradient method (HOG) and SVM. The model assessed Eye Aspect Ratio (EAR), Nose Length ratio and Mouth Opening ratio. To detect the features in real-time, a camera was designed to take the video frame and a total of 68 data points were extracted from every frame. Along with this, a simultaneous model was used to evaluate the eye aspect ratio to detect drowsiness, nose length ratio for detecting head bending, and mouth opening ratio to detect yawning. These values are then compared with the threshold values from the original model. If these values are not in the specified range, it would be considered as an outlier thereby detecting fatigue. The accuracy for the detection of facial behavior with Functional Linear Discriminant

Table 1
Accuracy of eye state detection in different lighting conditions.

Lighting Condition	Overall Accuracy	Accuracy to detect Open Eye	Accuracy to detect Closed Eye
Indoor Video	99.17%	97.34%	97.11%
Outdoor Video	89.51%	96.11%	98.50%
Driving Video	81.86%	93.30%	81.25%

Table 2
Comparative analysis of above mentioned[50] methods with several other methods.

References No.	Feature Method	Classifier	Average Accuracy
51	Multimodal Analysis	Neural Network	83.6%
52	Fast Fourier Transformation	Linear Regression	90%
50	Fuzzy Entropy	Gradient Boosting Decision Tree	95%

Analysis (FLDA) and SVM were 93.3% and 96.4% respectively.

It can be noted that the method is promising for detecting eye states using a webcam. This technique can detect eye states in real-time with a webcam in slightly harsh conditions. The accuracy of this approach is higher when compared to previously done work under the same experimental conditions.

Comparing and contrasting methods of fatigue detection using machine learning

Table 3 shows a comparison various Machine Learning (ML) method that are introduced and discussed in the above section. The better method for the detection of fatigue is by using features like EEG signals and Facial behavior, and yawning detection. Although fatigue detection using Yawning has higher accuracy, there are some disadvantages of the method.

Dey[12] suggested a novel approach to detect fatigue by combining head, eye, and mouth movement and calculating their ratios to get an accurate result. The method suggested by[12] is easy and less costly to implement. Hu and Min[50] introduced an approach to detect fatigue using EEG signals. They tried to detect the characteristics of EEG signals, by calculating feature sets which included the entropies such as a sample, spectral, fuzzy & approximate. They then used Gradient Boosting Decision Tree (GBDT) for the detection of fatigue which had the above-mentioned features as input.

The method of detecting fatigue using EEG signals has a slightly higher accuracy but, there are some disadvantages and limitations of this method. Firstly, capturing EEG signals requires more sensors, and attaching them to the human body is also not possible as they are prone to noise and movement. Secondly, implementing this method is costly as it requires costly sensors and equipment. Dey's[12] method for fatigue detection requires only a high-resolution camera even though it has slightly less accuracy. Also, his method can be implemented in real-time whereas, implementing Hu and Min's[50] method in real-time is not feasible.

Fatigue detection using deep learning

Fatigue detection with multimodal deep learning

Du[53] proposed a multi-modal approach by combining EEG and electro-oculogram (EOG) to detect fatigue. Physiological signals are used widely to detect the state of human beings, as they are more stable and accurate. The amplitude of EOG signals when compared to EEG signals is higher which is why EOG signals are more effective against noise. In this paper, the authors introduced a multimodal deep autoencoder model for fatigue detection. The model introduced uses EEG and EOG signals for fatigue detection. The experiment was performed on people which were asked to drive for at least 2 hours. Then, EOG and EEG signals were captured using a NeuroScan System and SVM along with Radial Basis Function (RBF) was used as a regression model.

To measure efficiency of the fusion technique, the authors trained two unimodal models with EEG and EOG signals only. The outcome of this was compared to another model trained with fusion strategies. The experiment outcome suggested that the feature fusion model performs better than the model trained on individual features. The authors of this paper finally presented a multimodal Deep Auto-encoder model which gave an accuracy of 85%.

Drowsiness detection using deep learning

Rundo[23] presented a method for the detection of drowsiness using Machine Learning. The overall aim of the research was to develop state-of-the-art techniques for detecting drowsiness stages in EEG (the best

Table 3
Overview of all the machine learning methodologies for fatigue detection discussed in this article.

Features for detection	Types of features	Authors [Ref]	Year	Data Extraction	Model	Accuracy
Yawning Detection	Physical	[43]	2007	400 images	Gabor Coefficients	95%
Skin conductance	Biological	[45]	2009	Driving footage of people 25−55 year age group	Support Vector Machine	92.95%
Eye state	Physical	[47]	2010	2100 images	AdaBoost	90.18% approximately
EEG signals	Biological	[50]	2018	22 features comprising 6600 rows data	Gradient Boosting Decision Tree	95%
Facial Behavior	Physical	[12]	2019	68 facial points extracted from 30 min of driving	Support Vector Machine	94.8%

ECG: electrocardiogram.

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physiological measurement). A Discrete Cosine Transform (DCT) block is used to perform frequency domain transformation of EEG samples. The results are then resized by bicubic remapping constituted of 256 samples. The outcome transformed is converted into a single-dimensional matrix consisting of 256 frequency samples. The inputs for the autoencoder layers were optimized frequency signals of EEG generated from DCT. An Autoencoder is used to discover unsupervised data patterns along with dimensionality reduction. In order to increase the efficiency of the system, a greedy layer-wise approach is considered (Fig. 3).

In the above architecture each autoencoder has 256 neurons as input and a 10-neuron hidden layer. The output of the first encoder is discarded and correlated features are considered as an input to next autoencoder. Then a Softmax function is used for classification of k-dimensional normalized vector into two classes. If the output falls in the range of 0−0.5 (class 0) then the person is classified as a drowsy person or if it falls in the range 0.51−1.00 (class 1) then the person is classified as wakeful.

The results obtained from the above method were 100% accurate when tested on 62 individuals dominating all the previous methodologies and promising usefulness in the future generations of medical devices. This approach is the most promising one when compared with several other methods like[54] SVM + Bayes which had an accuracy of 90.6%, whereas SVM was 98% accurate, ANN had an accuracy of 99.5% whereas the current method proposed had an accuracy of 100%.

Comparing various parameters for detection of driver fatigue

In the above sections, there are numerous methods and features discussed which can be used for fatigue detection. But, at the time of development of a system that can detect fatigue, some features are more important than the other features. Few things that should be kept in mind while designing such a system. Firstly, the sensor that is used for detecting fatigue should not hinder the driver. Secondly, the detection process should be autonomous and must process data in real-time.

The detection of fatigue using biological features provides the most accurate results as they show the internal state of the body. For generating biological features (like EEG, EOG, electrocardiogram (ECG) signals) many electrodes and sensors are connected to the body which makes the driver feel uncomfortable and thereby making the system not advisable to detect fatigue in real-time.[16,55] There is another problem with this approach. During the retrieval of EEG, signal noise might be induced into signals due to external factors.[56] ECG can be measured easily when compared to all the other biological features. But ECG differs from person to person so we can use them for the identification of a person.[57,58] The sensors required for the detection of biological features are complex and expensive. Also, signals generated from these sensors require pre-processing to remove noise. So, detection of fatigue in real-time using biological features is difficult and expensive.

To resolve this problem we can use either physical or vehicular features which seem more desirable and are also not that difficult to generate. The vehicular features can be used to determine drowsiness because during drowsiness a driver might not be able to control the vehicle or there will be some deviation in the direction of the vehicle. But as illustrated in[59] the effect of fatigue might not be the same for each individual. Also, these features are influenced by weather or traffic conditions. So due to these difficulties in fatigue detection using physical features can be considered as an effective strategy for fatigue detection.

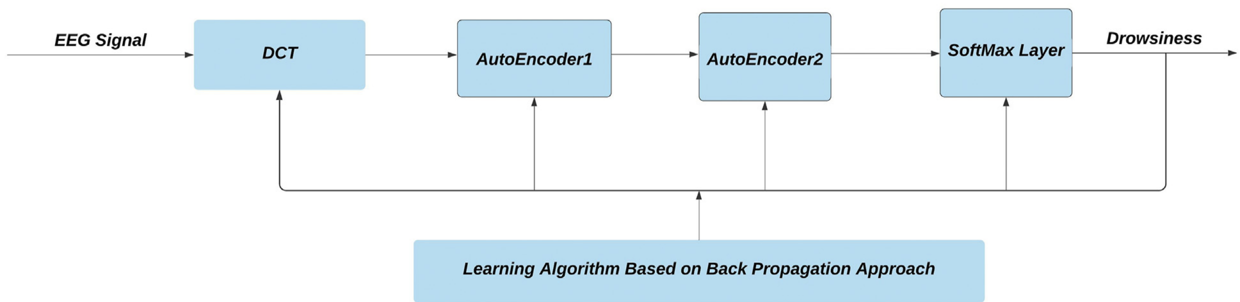

Fig. 3. Architecture of the proposed method. Discrete Cosine Transform (DCT) performs frequency transformation of electroencephalogram (EEG) signals. Then Autoencoders were used to extract the features and finally SoftMax layer is used for classification.

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There are several methods can be used to detect fatigue in real-time using these features. Barr[60] conducted an experiment and noted that lighting has a significant effect on the measurement and reliability of physical features. The methods that use physical features are highly dependent on Image Processing. So, these methods need to be robust and should be able to detect the features under any lighting conditions. To detect these features and achieve nice accuracy researchers have tried to used InfraRed (IR) cameras. Using this type of camera, the pupils can be detected under any light condition.

A comparative analysis of all detecting fatigue using these features, i.e., vehicular, physical, and biological was done by Naurois.[61] Many features like position of head, steering wheel, deviation of lane, etc. were detected using ANN which was trained by biological, vehicular, physical features, or using all of these features. ANN trained also incorporated some additional parameters such as driving time, participant information. It was observed that ANN trained with the physical features, driving time, and participant information achieved the best result. A study conducted by Horne[16,62] illustrated that the age of the driver and driving time played a crucial role in sleep-related accidents. So, external signs like this should also be considered while detecting fatigue. There were several other factors like speed limit, surrounding environment, weather conditions which should be taken care of while detecting fatigue and for driver safety.[16,63]

Finally, after comparing and contrasting all the methods and features that can be used for fatigue detection, we came to a conclusion that there is no single feature that can reliably detect fatigue. So, using a method that combines multiple features for detection would give accurate result. For real-time implementation of fatigue detection system biological features (EEG, EOG) are less feasible and hence should not be used for detecting fatigue. Vehicular features can be used to detect fatigue where the duration of the drive is longer. These features depend on other factors like weather, driving style, etc. So, they should not be used for the detection of fatigue in an urban environment. The detection of driver fatigue is an arduous task. The feasibility of a method for fatigue detection lies in the processing of data as fast as possible and also providing accurate results. Table 4 shows a comparison of techniques that can be used to detect fatigue. Most suitable feature for the detection of fatigue is physical feature. The accuracy can further be improved fusion between different features can be done.

Future work and challenges

As the detection of fatigue needs to be in real-time, so the main goal of this section is to study the current problems and suggest some future areas of development for this technology. The future work can be based on 2 aspects: technology used for the detection and implementation of it. The methods that are currently used for the detection of fatigue rely on a single kind of parameter for the detection of fatigue. But fatigue is a complex phenomenon, it cannot be represented or detected accurately with a single feature. So, these methods need some improvement both in terms of accuracy and robustness. The methods which can use a combination multiple features are more credible.[65] So, how to develop these methods is a problem that needs to be addressed.

After studying many reviews, we have concluded that EEG is the most promising approach for the detection of fatigue.[23,66] Although, it is very promising there are some difficulties which need to be addressed as well. The physiological measurements like brain waves, muscle's

Table 4
Comparative analysis between various parameters that can be used for fatigue detection.

Category	Parameters	Cost	Limitations	Scope of Real-time Implementation
Biological Features	EEG[50]	High	Prone to noise and human movement	No
	ECG	High		No
	EOG[53]	High		No
Vehicular Features	Lane Deviation	Low	Dependency of environment and driver	Yes
	Pressure sensor	Low		Yes
Physical Features	Yawning[43] Slow	Low	Lighting and Background Dependency	Yes
	Eye Movement[64]	Moderate		Yes
	Drowsiness[23]	Low		Yes

EEG: electroencephalogram; ECG: electrocardiogram; EOG: electro-oculogram.

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electric signal's intensity, heart rate frequency, etc. are challenging to generate, as the user needs to wear or apply the components or tools to his or her body, which is very unwelcoming and also might affect his performance. There are two ways in which we can improve the sensors: Non-contact sensors and wearable sensors.[65] The Non-contact sensors can be attached to the vehicle and these sensors can collect different physiological parameters. But we need to keep in mind the cost of manufacturing such sensors, which can be costly and in turn making this method useless. In the recent decade, wearable sensors are becoming popular and have also been streamlined by major companies like Apple, Google, etc. Hence wearable sensors are a better choice when compared to non-contact sensors.

Another approach illustrated in this paper for the detection of fatigue involves monitoring the behavior of the vehicle which can include sudden changes in the position of the steering wheel, immediate deceleration, lane crossing, etc.[67] But this approach is not promising in some conditions. Another method that can be used for fatigue detection is based on the detection of facial features. This method seems the best when compared with other methods illustrated in this paper. But these methods rely on only a single feature. So, a method can be developed by the data fusion of driver and vehicle-related features for developing a more robust and accurate system for the detection of fatigue.

We think that the use of fatigue detection systems will prevalent soon and will be useful in maintaining a balanced life and safer roads. The widespread use of this system will only be possible if the underlying methods for the detection of fatigue are accurate and can detect it in real-time. In the upcoming future wireless capability might provide a boost for the detection of fatigue.

Conclusion

This review presents an in-depth analysis, advancements, and state-of-the-art methods for fatigue detection. Fatigue has physical, mental, or psychological effects on an individual. In this paper, we have discussed, compared, and analyzed various techniques for the detection of fatigue. Some methods address the cause of fatigue while, others use state-of-the-art methods to detect yawning, monitoring the state of the eye, or drowsiness of an individual. The features used for detection might be only physical features or biological features or a combination of both, i.e., hybrid features while, the methods that can be used for the detection of fatigue are classified mainly into four categories: Mathematical model, Rule-Based, ML, and DL. A system built for the detection of fatigue needs to detect fatigue in real-time and accurately, so in this review we compared and contrasted some methods and features that can detect fatigue. This comparison not only shows that biological features (such as EEG, EOG, heart rate) alone should not be used to detect fatigue in real-time but also, illustrates that to achieve higher accuracy for detection of fatigue a combination of both physical (such as eye, face, mouth) and biological features should be used. There are some ML and DL (like GBDT, SVM, ANN) methods that can optimize this process. Finally, we have discussed some challenges and future work that is left to be done, which might increase the accuracy of the existing work, thereby unlocking the door to expand the possibilities of advancements in the domain of fatigue detection.

Availability of data and material

All relevant data and material are presented in the main paper.

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Not Applicable.

Conflicts of interest

None.

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