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ORIGINAL PAPER

Fatigue Detection Using Artificial Intelligence Framework

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Abstract
Technological advances in healthcare have saved innumerable patients and are continuously improving our quality of life. Fatigue among health indicators of individuals has become significant due to its association with cognitive performance and health outcomes and, is one of the major factors contributing to the degradation of performance in daily life. This review serves as a source of studies which helped in better understanding of fatigue and also gave significant detection methods and systematic approaches to figure out the impacts and causes of fatigue. Artificial intelligence was turned out to be one of the essential tactics to detect or monitor fatigue. Artificial neural network, wavelet transform, data analysis of mouse interaction and keyboard patterns, image analysis, kernel learning algorithms, relation of fatigue and anxiety, and heart rate data examination studies were used in this paper to precisely assess the source, factors and features which influenced the recognition of fatigue.

Keywords Artificial intelligence · Fatigue · Healthcare · Detection techniques

Introduction

Artificial intelligence (AI) is the sign of human intellect procedures which include learning, reasoning and self-correction. It eases computer programs or a machine to think and learn. With the rise in growth and technology, computer systems are able to perform tasks such as visual insight, decision-making, adaptation, sensory understanding and communication [1].

AI technologies have grown to the point where its expertise is contributing aids in numerous applications. In the current global world situation, primary artificial intelligence fields are natural language processing, expert systems, speech understanding, robotics and sensory systems, scene recognition and neural computing. Also, expert system is a quickly rising technology and is having an enormous influence on various fields of life [2, 3].

There are different areas in artificial intelligence which are significant and helpful for humankind such as language understanding, learning and adaptive systems, problem solving, visual perception, robots, gaming, modeling and many more. Each of these is proved to be substantial in the growth of technologies. For example, we can translate from vocal language to a written or printed language and also form one language using several different languages using language understanding. Learning from previous experience can also be achieved using adaptive systems which use AI. Problem solving is very useful to do predictive analysis. For instance, robots can manipulate the objects by perceiving, picking and moving, and gaming also uses AI to generate adaptive and intelligent behavior similar to human.

AI can be used potentially in health and social care facilities. It has been claimed that ML can offer a crucial tool for biomedical difficulties relating complex heterogeneous data when conventional statistical tools fail [4–6]. Modern medicine is facing significant challenges of obtaining, examining and applying different types of machine learning algorithms to treat illnesses. AI systems with their data mining and pattern recognition capabilities can help with these problems. Prediction, diagnosis and treatment or management of diseases are major requirements in medical sector. AI also helps in decision-making

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for selection of an accurate treatment option [7]. Cancer prediction models are generated from microarray data using neural network [8]. Parkinson's disease, which is chronic, progressive and neuron-degenerative illness, can be identified using AI [9]. Using different AI algorithms and accurate dataset, useful prediction can be achieved [10]. Furthermore, breast cancer survivability can also be predicted using different data mining methods [11]. Machine learning, in general, requires large dataset to train itself and then predict the outcome. Recent studies have shown that it can also make predictive models using small dataset [12]. Hence, AI technologies have the potential to benefit important health challenges.

Fatigue is generally considered as lack of energy and motivation. It can be further classified into physical fatigue (driver fatigue) and mental fatigue, or both. Both of these dimensions can be addressed independently even if there exists a frequent inter-dependence between them [13, 14]. AI can detect many kinds of fatigues using different approaches. For example, we can detect drowsiness using AI which is a cause of mental fatigue. Also, we can monitor mental fatigue by analyzing the keyboard and mouse interaction patterns [13]. Chronic fatigue, which is a disease caused by mental fatigue, is also measured using AI. Many incidents have been reported of mental fatigue as the result of constant workload. Therefore, understanding the nature of mental fatigue and its specific effects on behavior is necessary in order to avert or deal with fatigue. In mental fatigue, there are various factors like alertness, drowsiness and reduction in driving capabilities. These factors can be measured and can give us vital information about mental and driver fatigue. For example, alertness and drowsiness are recognized from EEG by an artificial neural network. Autonomous systems are designed to examine driver fatigue and detect driver sleepiness which is an integral part of the future intelligent to prevent accidents occurred by sleep. Convolution neural network (CNN) is a feed-forward neural net which joins several features like distribution of weights, local receptive fields and temporal pooling [15]. By adjusting weights and providing input/output (labels) to CNN, weights are learnt which eventually are used on test data to derive an outcome. In conclusion, fatigue can be diagnosed as well as measured using AI which benefits successive growth of healthcare.

Impacts of Fatigue

Fatigue, or exhaustion, can cause physical, emotional and behavioral symptoms. The adverse effects of mental exhaustion can differ from person to person during prolonged periods of extreme stress. If stress continues to weigh on, it may reach a point where a person suffers from chronic diseases such as chronic fatigue syndrome (CFS). It is important to be familiar with the signs that could indicate that you are suffering from exhaustion or burnout.

Mental exhaustion can lead to higher rates of stress in workplace while the triggers of mental exhaustion are not the same for everyone; some are more shared than others such as financial stress and poverty, job dissatisfaction, poor work–life balance and lack of social support.

Burnout is a condition which results from prolonged stress at work and has a number of consequences to workers' well-being and health [16]. For example, one may portray feelings of detachment and rage in all phases of work and personal life.

Fatigue is a psychobiological state caused by long periods of demanding cognitive activity and is classified into specific subjective, behavioral and physiological manifestations [17]. It is termed as a phenomenon of deteriorated capability and efficiency of mental or physical tasks, which is caused by carrying out excessive mental or physical tasks and illness [18]. Effects of fatigue on physical performance have recently been suggested. Mental fatigue can also be visible behaviorally, subjectively and physiologically. Also, mental fatigue results in cognitive impairment. Thus, it is of utmost importance to comprehend the neural mechanisms of mental exhaustion associated with cognitive performance and to propose appropriate methods for estimating and overcoming fatigue [18] Lack of sleep is frequently associated with major workplace accidents [19–21]. Marcora et al. [22] postulated that greater subjective ratings of fatigue and/or a drop in cognitive performance signify the presence of mental and/or driver fatigue [17].

Impacts of mental fatigue, clearly illustrated by the flowchart, are categorized into four signs which are emotional, physical, behavioral and social (Fig. 1). Physical signs include insomnia, upset stomach, increased illness, such as colds and flu and many more. Working conditions portray a distinguished effect on employees' well-being [23]. Job burnout results from adverse working situations and is categorized into overwhelming fatigue, undesirable attitudes, absence of commitment with clients and discontent with job performance [24]. From a psychosocial viewpoint, totally three scopes of burnout have been defined: (a) emotional exhaustion; (b) depersonalization; and (c) reduced personal achievement or inefficacy, that is, a feeling of personal and professional dissatisfaction as well as decreased productivity and coping abilities [16, 25, 26].

Behavioral signs include sleep loss, poor work–life balance and living with chronic illness. Also, sleep loss is one of the foremost reasons, which is frequently involved with most of the workplace accidents [19–21].

Fatigue also plays a crucial role in the reduction in response inhibition. It refers to the ability to deter

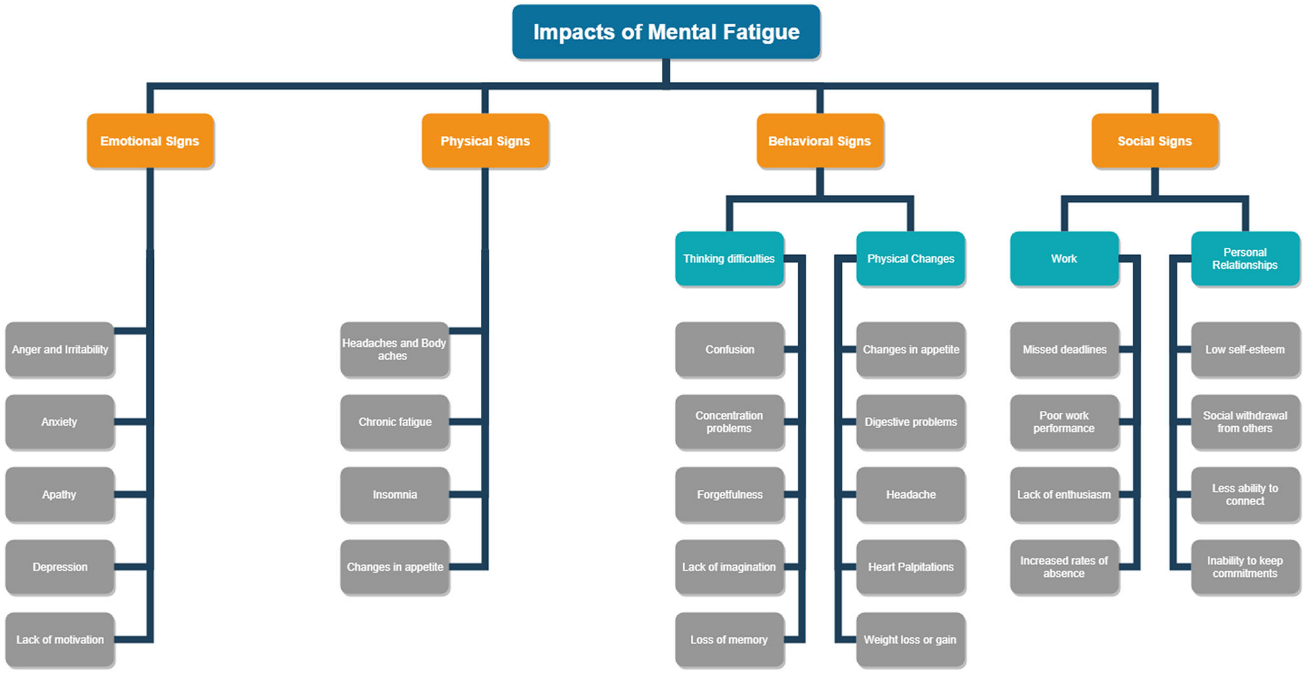

Fig. 1 Classification of impacts of mental fatigue

irrelevant or unfitting responses [27–29]. Response inhibition can be categorized into two different processes: conflict monitoring and the estimation of resource allocation [30]. Response inhibition is related to several day-to-day activities. For example, when a road incident takes place (e.g., vehicle driving ahead of us stops abruptly), the driver has to apply brakes suddenly, and if failed, it may lead to a disastrous accident [31, 32]. This job specifically requires deterring the practice of stepping on the gas and commencing the practice of smashing on the brakes.

However, high-level response inhibition cannot be maintained by an individual all the time as fatigue is one of the major reasons for the deterioration in response inhibition.

Related Work: Effects of Fatigue

Effects of Fatigue in a Processor Task: Rigidity and Reduction in Systematic Strategies

Van der Linden et al. [33] discussed the effects of mental exhaustion on exploration in a difficult computer task. People, in the existing world situation, generally must deal with progressively complex difficulties or, difficult tasks that need impromptu procedures rather than formal ones. So, exploration is required to achieve the goal and complete these types of notorious task as it provides some understanding of the task and finds out what kinds of actions are required to achieve task goals [34]. There are two ways of performing exploration, systematic and unsystematic way. [33, 35] explained systematic and non-systematic approach for exploring. Systematic exploration implies that people act in an objective-oriented way and reflect on their own behavior as well as on action feedback [36, 37], whereas, when exploring unsystematically, people generally act in an unstructured manner and thus do not follow a coherent way toward goal accomplishment [35]. As an alternative, actions are performed spontaneously or are directed by exterior provocations that tend to receive our attention [38]. An experimental study was performed in which 68 psychology students participated and were arbitrarily allocated to a fatigue group. Measures like fatigue, general computer experience, fatigue manipulation [39] on the computer and computer task (a task with Excel which is spreadsheet program and a task with ClarisDraw which is graphical program) were recorded. By using these measures, [33] accomplices were examined independently in sessions that took approximately 3 h. Exploration behavior was coded from the videos that included the participants' actions on verbalizations and computer screen. Behavioral groups were classified into systematic and unsystematic exploration, and three groups were used from this classification. Twenty videos were randomly selected and coded. Intraclass correlations (ICCs) were used, as described by Shrout and Fleiss [40], to evaluate interrater reliability. ICCs for decent interrater agreement ranged from 60 to 75, and ICCs > 75 were labeled as excellent interrater agreement [41]. In results, value of α was used as .10 for multivariate tests because of requirement of the comparatively strong statistical power to sense multivariate effects. Overall, α of .05 was used for all univariate tests. Eta squares (η^2) was stated as effect size.

The above data collected throughout this study are displayed which exhibited that changes in behavior of exploration could not be described by changes in the number of verbalizations (Table 1). The final results concluded that comparison of non-fatigued participants and fatigued participants showed lesser number of phases of systematic exploration in fatigued participants. This evaluation proposes that fatigued participants were less reflective as compared to non-fatigued participants in their exploration behavior [36]. Unsystematic behavior showed diverse results which presented that fatigue did not overlap with variations in unsystematic or random trial and error.

Effects of Fatigue on Task Control

Lorist et al. [42] conducted a "time on task" in which subjects had to switch task for 2 h and established the impacts of mental fatigue on preparation and planning. Subjects had to change in between tasks on every second trial. To inspect whether subjects equipped themselves for the task change, they manipulated the response (stimulus intervals). For evaluating the impacts of mental fatigue, different types of measures like behavioral, event-related potentials and mood-related surveys were used. Reaction times were quicker in which no modification in task set was essential. Preparation processes became less satisfactory, and also the number of errors seems to be increased as metal fatigue increased. Examination of the effects of mental fatigue introduces an observation that subjects can perform simple tasks, but efficiency of performing complex tasks declines [43]. These effects could be connected to the processing levels manipulated by mental fatigue. Performance in more complicated jobs relies largely on processes related to cognitive control. These processes are particularly susceptible to mental fatigue state. The task switching model was introduced [44] to verify the hypothesis that mental fatigue affects higher-level control mechanisms. Sixteen subjects participated in the study in whom four were males and 12 were females (age between 18 and 26 years). During the execution of task, subjects were settled in a room (dimly lit) and were then faced toward a VGA color monitor at a distance of 70 cm. After the demonstration, a white square divided into four squares (232 cm each) was presented uninterruptedly on the black screen (at the middle). Stimuli were presented in a clockwise fashion in the middle of one of these tiny squares. The stimuli were selected arbitrarily from the set which contains letters A, E, O, U, G, K, M and R. The colors of the stimuli were selected from the set, such as blue and red, and it was shown in capital (MEL: SWD-S30). On the screen, these letters stayed until either 2500 ms had passed or the subjects gave a reply by pushing any response buttons. After choosing RSI randomly, the next stimulus was shown on the screen. Subjects were also told to switch tasks every second trial.

They also discussed the switch task which resulted in decreased levels of stamina and increased levels of fatigue with time on task. Furthermore, dislike toward task performance increased as the experiment conducted. Emotional state of mental fatigue was conveyed by effects of undesirable moods, such as anger or depression, on the subjects as a result of which gained more score in the POMS fatigue subscale. The relationship between aversion and SPL was observed which indicated rises in mental fatigue levels which portrayed aversion against task performance. They detected increment in the levels of fatigue with time on task and concluded that this increment was a result of performance decline in performance. ERP data obtained from ERP showed that different procedures triggered some of these effects related to mental fatigue. Preparation processes which were engaged in the planning for future actions were largely affected by the incremented levels of mental fatigue. Additionally, there were signs that mental fatigue negatively affected the preservation of a prepared state [45].

Effects of Fatigue on Endurance Performance

Schiphof–Godart et al. [46] explained how endurance performance or athletes' drive to workout and exercise is deteriorated by mental fatigue as the performance in the endurance sports depends on athletes' drive. Subsequent reduction in performance in athletes was observed due to the deleterious effects of mental exhaustion on the brain of athletes or cyclists or any other sportsmen, which eventually leads to low performance. The biopsychological perspective tells that after mentally fatiguing work, alterations occur in brain. These alterations in brain activation decrease the drive to exercise. This has also been elucidated by the

Table 1 Standard deviations and mean of pre- and post-manipulation measures of fatigue

	Time × condition	Pre-manipulation			Post-manipulation		
		Control	Fatigue	t	Control	Fatigue	t
Mental fatigue	25.64	53.12	48.74	0.62	48.12	97.88	4.26
Physical fatigue	0.96	59.12	60.97	− 1.20	73.46	88.47	− 0.09

presence of two discrete structures of the brain engaged in the regulation of behavior, which are (1) mental facilitation system and (2) mental inhibition [47]. It is thus reasonable to deduce that motivation can be affected by mental fatigue, as willingness to exercise physical task in order to gain a reward is also negatively affected by it [48, 49]. From a biopsychological point of view, dopamine can trigger brain region and affect athletes' determination to exercise [50–54]. Increased concentration of dopamine in the brain pushes athletes in the direction of exerting efforts [55] and instigates a choice of "not giving up," especially under tough situations [56]. While level of mental fatigue rises adenosine concentration (which decreases dopamine level) in the brain, materials like caffeine can reverse the neurotransmitter balance and eventually invalidate the impacts of mental fatigue [57–59]. They have also mentioned that both the facilitative system and the mental inhibition were engaged in athletes' exercise pattern and drive [47, 60]. Thus, by manipulating athletes' intrinsic motivation, drive of athletes to exercise can be improved and subsequently mental fatigue can also be reduced. The cost of a reward or alteration in brain neurotransmitter concentrations is also proven to be significant factor for decreasing mental fatigue. They have concluded that the examination of impacts of mental fatigue should be inspected concerning athletes' perceived effort as well as modifications in their motivation toward a reward.

Fatigue Detection

Drowsiness or driver fatigue is a significant factor in the motoring of vehicle accidents. Driving performance depreciates with increased drowsiness which was established with resulting crashes comprising more than 25% of all automobile accidents [61]. Recently, driver fatigue which induces sleepiness and tiredness has been one of the most significant reasons of vehicle accidents and is further proven to be the cause of critical bodily injuries, demises and substantial financial losses [62]. In other types of fatigue, mental fatigue is also considered as a substantial factor contributing to deterioration of accuracy and inclination of spiritual exhaustion. Detection of mental fatigue is crucial because in recent years, workload has increased.

Fatigue Detection using Different Sensors

According to statistical data, more than 1.25 million people decease every year on the road and 21–50 million people suffered non-fatal injuries due to accidents that took place on road. These figures propose that driver sleepiness is one of the foremost reasons of vehicle accidents. Researchers have used four different measures for monitoring the state of sleepiness of the driver, in order to avoid these devastating events [62].

- What causes driver fatigue?

The phases of sleep can be characterized as:

1. Alert or awake
2. Rapid eye movement sleep (REM)
3. Non-rapid eye movement sleep (NREM)

The NREM stage, can be sectioned into the following three phases [63]:

Phase 1	Conversion from wakeful to asleep
Phase 2	Light sleep
Phase 3	Heavy sleep

- Environment for driver fatigue manipulation

Researchers have made virtual arrangements to create an environment which can be used to perform their tests as it is not ethical and also harmful to let the lethargic driver drive on road. The simulators used in driving can be categorized as: (a) low-level simulators (Fig. 2(I)) containing computer, steering wheel, pedals, gear box and monitor; (b) mid-level simulators also known as fixed-base simulators; and (c) high-level simulators also known as motion-based simulators [64].

- Methods for measuring driver fatigue

  1. Subjective measures

Subjective measures estimate the level of fatigue and sleepiness which are dependent on the driver's own approximation. Karolinska sleepiness scale (KSS) is the most frequently used drowsiness and fatigue scale. It is a nine-point scale and has a different measure of fatigue for each point, as displayed in Fig. 2 [65]. Every 5 min, KSS ratings of drivers were measured by Hu and Zheng [66]. Portouli et al. [67] assessed EEG recording by approving driver fatigue through both a licensed medical expert and a questionnaire. Ingre et al. [68] established a correlation between KSS ratings and the respective eye blink duration which was also collected every 5 min throughout the driving task. Ratings were calculated subjectively a simulated environment as shown (Fig. 3).

2. Vehicle-based measures

The measurements generated by placing sensors on various vehicle components such as steering wheel and acceleration pedal in a simulated environment are known as vehicle-based measurements. The signals shown by the sensors are then examined to determine the phase of fatigue. There are two commonly used measures for determining fatigue.

Fig. 2 Simulated driving environments

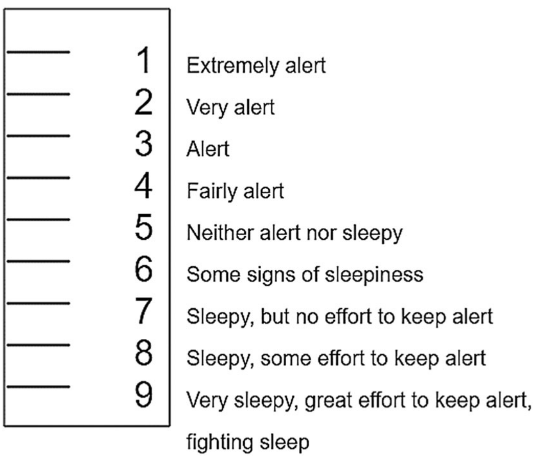

Fig. 3 Karolinska sleepiness scale (KSS)

Table 2 KSS ratings with its SDLP measurements

KSS ratings	SDLP measurements
1	0.19
5	0.26
8	0.36
9	0.47

Steering wheel movement (SWM) is a vehicle-based measure which is widely used for estimating driver fatigue. It is calculated using steering angle sensor [65, 69, 70]. It is likely to evaluate the drowsiness state of the driver based on small SWMs and, thus, provide an alert. Standard deviation of lane position (SDLP) is an alternative factor by which the amount of driver fatigue can be calculated. Measurement of SDLP is given by the software itself in a simulated setting. Ingre et al. [68] carried out an experimentation for gathering numerical data on SDLP and established that SDLP increases as KSS ratings increase (Table 2) [68].

3. Behavioral measures

A drowsy person or a person experiencing fatigue exhibits a number of distinctive facial actions, such as continuous blinking, vacillating the head or nodding, and yawning. PERCLOS is another consistent measure to predict fatigue and drowsiness. It is termed as the percentage of shutting of eyelid over the pupil over time, which portrays "droops," also defined as slow eyelid closures, rather than blinks and has been utilized in several commercial products [71]. Feature extraction techniques, for example, wavelet decomposition, discrete wavelet transform (DWT) or Gabor wavelets, are used to extract characteristics such as PERCLOS, rate of yawning and inclination angle of head which is further linked to artificial intelligence [72, 73].

4. Psychological measures

Psychological signals become apparent when the vehicle begins to stroll away from the middle of the lane. Hence, they are more suitable for detection of fatigue as it becomes likely to alert a tired driver in time and thus avert many vehicle accidents. This method uses psychological signals to detect fatigue. For example, electroencephalogram (EEG) has various frequency bands.

The computation of the raw physiological signals is vulnerable to the noise due to the movements related to driving. Hence, to remove unwanted noise, digital filtering technique can eradicate the noise in an optimum way [74]. By using various feature extraction methods, such as fast Fourier transform and discrete wavelet transform, a number of statistical features, are mined. Methods like support vector machine (SVM), artificial neural network (ANN) and linear discriminant analysis (LDA) are applied to classify extracted features (Table 3) [66, 75, 76].

This paper concludes that the results obtained from each measure give us an indication to merge physiological measures (ECG) with behavioral and vehicle-related measures for developing an effective and optimal system.

Table 3 Advantages and limitations of various measures

Measures	Subjective measures	Vehicle-based measures	Behavioral measures	Physiological measures
Parameters	Questionnaire	Deviation from the lane position, loss of control over steering Wheel movements	Yawning, eye closure, eye blink, head pose	Statistical and energy features derived from ECG, EoG and EEG
Advantages	Subjective	Non-intrusive	Non-intrusive, ease of use	Reliable, accurate
Disadvantages	Not possible in real time	Unreliable	Lightning condition background	Intrusive
Refs.	[68, 88]	[89, 90]		[91]

Fatigue Detection using Drowsiness Warning System

Sharma and Banga [77] propose several artificial detection methods for detecting driver fatigue or drowsiness. The first approach is based on the analysis of image using fuzzy logic. The basis of this system is facial images analysis using fuzzy logic models and ANN. In this system, facial images are taken using a CCD camera and based on those images, eyelid closure is calculated. Finally, a fuzzy logic model is used to distinguish the driver's alertness and drowsiness, which assesses the level of fatigue by estimating the duration and frequency of blindness of the driver. As a result, the driver is warned.

The second technique discusses driver fatigue detection using an algorithm based on artificial neural network (ANN). An experiment was performed in a simulated environment where licensed drivers were subjected to fatigue conditions using an algorithm based on neural network. Correlations between steering angles and various stages of drowsiness were established. The input pattern of ANN is the statistical data of steering angle in a summarized form, and the output pattern is the current driver state, that is, the output vector, $D(n)$. $D(n)$ is denoted by a categorizing vector value of [1,0] for alert or awake, and [0,1] for sleep is fed to the network. Hence, correct and optimal selection of architecture for several training factors is a prerequisite for the training of ANN.

Hybrid system for the detection of driver fatigue was proposed in the next method which incorporates piezo-film sensors into the seating area of the car and steering wheel. These sensors record various statistics such as movement of the driver, heart rate and breathing frequency for the identification of driver fatigue. Sensors display significant reduction when they encounter drowsiness conditions. The first step is to select appropriate components of algorithm such as processing methods and signals. The second step comprises drowsiness measures related to several states of risky drowsiness conditions. The fourth method measured drowsiness intensity by focusing on certain parts of the face. The state of drowsiness was initially measured using frequency of eyelid closure time per unit period. Driver fatigue is surveyed using a CCD camera system which concentrates on the opening of eyelid which then captures face and eye part using a neural network model. This method is well applicable to detect drowsiness because it predicts if the eyelid closure time is directly proportional to drowsiness intensity [78].

This paper concludes various approaches to detect driver fatigue using artificial intelligence techniques such as ANN, fuzzy logic and several bodily movements.

Fatigue Detection using EEG and Artificial Neural Network

Vuckovic et al. [79] presented a technique for categorizing alert and drowsy states using ANN in which the input was intrahemispheric and interhemispheric cross-spectral densities depicted using time series of full-spectrum EEG. The two discrete outputs were drowsy and alert. There were mainly two goals for the study: first, creating a technique which processes the input data from EEG recordings of full range, and second, choosing a neural network which can differentiate between drowsy and alert conditions by using processed signals of EEG. Eight females and nine males (age 25–35 year) of usual intellect and without mental illnesses were comprised in the study. In this study, the subjects were said to lie in a room with complete darkness and with their eyes closed. In an electromagnetically protected room, an EEG was used during 30-min recording sessions. After data preparation and parameterization, data preprocessing was done. In data preprocessing, network was trained using Widrow–Hoff rule. Feed-forward network was trained with the Levenberg–Marquardt learning rule which included 8 neurons and 75 training epochs in the hidden layer. The representations were

- Linear: Linear ANN

- LM: ANN trained using the Levenberg–Marquardt rule
- LVQ: ANN trained using learning vector quantization rule

To find results, five experiments were performed in which ANN with the worst results in the earlier experiment was removed from the subsequent experiment. To categorize the alertness and drowsiness, three types of neural networks were trained. Mean values of three subjects' data are shown in Table 4.

In the next experiment, data were gathered from three subjects to examine the characteristics of classification which then were used to train the LM and LVQ networks. Information of subjects 1–3 was involved in the training set, and information of subjects 4–10 was involved in the validation set (Table 5).

The results of experiment 2 are shown in Table 6.

Since the LVQ network presented improved results related to the mean values of correctly classified EEGs, in third experiment LVQ was used. The outcomes of those experiments are revealed in Table 7.

In addition, two subjects' data were integrated in the training set and then LVQ3 was applied. The outcomes of experiment 4 are given in Table 8.

Through the network LVQ3, the EEG data set 2 was passed. The outcomes of experiment 5 are shown in Table 9.

After five experiments, the results specified that the nonlinear network with a distinct output performs well, for the aim of categorizing drowsy and alert states, associated with the ANN of continuous output.

Table 4 Matches found (%) between artificial neural network and skilled neurologist for alert and drowsy state

	Training		Validation	
	Alert	Drowsy	Alert	Drowsy
Linear (%)	75	75	65	65
LM (%)	100	100	100	100
LVQ (%)	100	100	100	100

Table 5 Abbreviations and representations of drowsy validation

Abbreviations	Representation
A_t	Alert for training set
A_v	Alert for validation set
D_v	Drowsy for validation set
D_t	Drowsy for training set

Fatigue Detection using Wavelet Transform and Artificial Neural Network

Kiymik et al. [80] proposed a method to automatically recognize alertness level by analyzing the recordings of

Table 6 Matches found (%) between artificial neural network and skilled neurologist which are based on mixed data of three subjects, that is, results for nonlinear ANN for alertness and drowsiness

No.	1	2	3	4	5	6	7	8	9	10
LM (%)										
A_t	100	100	100							
A_v	74	89	38	70	46	3	3	20	10	10
D_t	100	100	100							
D_v	74	40	98	100	100	90	85	85	70	90
LVQ (%)										
A_t	100	96	90							
A_v	100	96	86	94	87	97	86	70	69	63
D_t	100	93	100							
D_v	87	93	100	100	100	98	98	100	100	100

Table 7 Matches found (%) for alert and drowsy state between learning vector quantization and skilled neurologist

No.	1	2	3	4	5	6	7	8	9	10
LVQ1 (%)										
Alert										
A_t	100	90	95							
A_v	100	78	87	90	27	10	9	35	29	25
Drowsy										
D_t	95	95	100							
D_v	97	92	97	100	100	100	100	100	97	100
LVQ2 (%)										
Alert										
A_t	95	85	95							
A_v	82	82	89	87	57	65	63	10	10	10
Drowsy										
D_t	95	95	100							
D_v	95	95	100	99	100	95	98	100	100	100
LVQ3 (%)										
Alert										
A_t	100	96	90							
A_v	100	96	86	94	87	97	86	70	69	63
Drowsy										
D_t	100	93	100							
D_v	87	93	100	100	100	98	98	100	100	100

Table 8 Matches found (%) between artificial neural network trained by learning vector quantization (LVQ3) and skilled neurologist

No.	Training		Validation	
	Alert	Drowsy	Alert	Drowsy
1	100	100	100	90
2	100	80	100	75
3	100	100	100	100
4	75	100	75	100
5	85	85	88	100
6	–	–	98	98
7	–	–	97	89
8	–	–	97	88
9	–	–	100	94
10	–	–	96	100

full-spectrum electroencephalogram (also called EEG). The aim was to create a technique which processes input data from an EEG using ANN. This ANN would further be used to differentiate drowsy and alert states in random subjects. Power spectral density (PSD) of discrete wavelet transform (DWT) was used as the input of ANN. Three discrete outputs were used which were sleep, alert and drowsy. In the study, 30 healthy subjects were used (14 females and 16 males). Data acquisition system gathered records which were analyzed by two experts for detecting various levels of alertness. The wavelet transformation specifically allows discrimination of non-stationary signals with different frequency features.

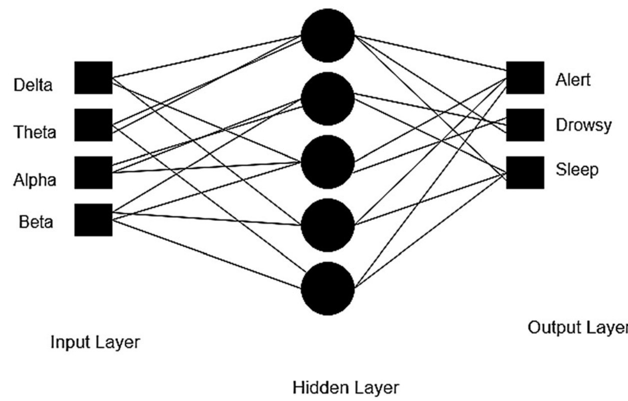

Fig. 4 Multilayered neural network model

Three-layer feed-forward ANN with one hidden layer and one output layer was trained using standard back-propagation algorithm (Fig. 4).

Each neuron in hidden layer aggregates inputs and creates a value which is then converted using an asymmetric sigmoid function. Multiplication of the output vector of hidden layer and weights of final layer generates the output for the final layer. There are mainly two ways to measure the error: (1) SSE and (2) MSE. SSE, which is the mean value of the squares of the difference between output and the anticipated output [81], was applied in this study to evaluate the performance of neural network. Limited hidden nodes of a network would be unable to differentiate between intricate or, complex patterns which may lead to only a linear approximation of the real trend. If the ANN comprises numerous hidden nodes, then it will track the sound in the data. Selection of network parameters uses

Table 9 Matches found (%) between skilled neurologists and LVQ3 for raw and previously unclassified EEG data (no artifacts present)

Subject no.	Percent	Drowsy	Alert	Percentage of drowsiness in whole EEG
1	92	5	3	60
2	86	6	8	45
3	100	0	0	42
4	92	4	4	45
5	94	4	2	47
6	96	2	4	60
7	96	2	4	48
8	92	3	5	57
9	90	5	5	52
10	98	2	0	45
11	95	1	4	47
12	92	6	2	53
13	95	2	3	47
14	97	3	0	62
15	95	2	3	60
16	98	1	1	55
17	94	4	2	45

classification which aims to allocate the patterns used to provide input to one of numerous classes which thus represents the likelihood of class membership.

The outputs were signified by unit basis vectors:

[010] = drowsy
[001] = sleep
[100] = awake

After training, testing phase of the ANN was conducted. The unseen or novel data were provided to the network for testing the network performance. The selectivity, accuracy and sensitivity of the neural network are given in Table 10.

In conclusion, this study gave a way for classifying states of alertness, drowsiness or sleepiness based on EEG. Wavelet analysis was recognized to be significant equipment for classifying various sleep stages and additionally detecting the conversions from an alert to a drowsy state due to mental fatigue.

Fatigue Detection through the Analysis of Keyboard and Mouse Interaction Patterns

Pimenta et al. [82] have proposed a detailed monitoring system for the detection of different mental fatigue states. First, the system developed was used to analyze the interactions of the individuals (without having fatigue) with computer or a processor. After getting trained by these data, system classifies stages of mental fatigue by measuring deviations in the subject's behavior. In this work, it has been indicated that the occurrence of cognitive or mental fatigue can be from multiple sources which may include characteristics of a person (for example, age, gender, consumption of alcohol, mood and memory) or from performance indicators (mouse or keyboard click movement). The study focused on each factor and explained the effectiveness and relevance of the same.

Table 10 Classification and performance of ANN for alert, drowsy and sleep states

	Alert	Drowsy	Sleep
Accuracy (%)	96 ± 3	95 ± 4	94 ± 5
Sensitivity (%)	94	96	93
Selectivity (%)	93	91	89

1. Profile-related factors
   - *Stress* Stress is a supplementary attempt made by the brain for prolonged period of time which will eventually result in mental fatigue.
   - *Precision and accuracy* Precision and accuracy can be a factor of quality and performance for a given subject. It also signifies unexpected errors. Both of these factors can be used to detect fatigue.
   - *Reaction time* It is a time span between movement and response of body or mind to that movement. Slow reaction time can be judged as symptom of mental fatigue.
   - *Concentration* Concentration is a significant factor to determine mental fatigue. Concentration is generally related to focus which decreases as mental fatigue increases.
2. Mental fatigue indicators

The first method of detecting fatigue has certain disadvantages like

1. People may be lying or hiding truths in surveys;
2. People may feel afraid to answer correctly;
3. People may have incorrect and subjective perceptions of their symptoms; the second approach is more suited and accurate than the former method.

The recognition and classification of fatigue are related to biometrics behaviors like mouse and keystroke dynamics. By using a logger application's data, certain features (shown in Table 11) can be considered to acquire data.

Mental Fatigue Layered Framework

Fatigue detection and monitoring require creation of a layered architecture (Table 12) where data gathered by system are analyzed and used for accurate detection [82].

Table 11 Some significant indicators and features used to measure fatigue

Double click speed	Speed of the double click
Errors per key pressed	Number of times the backspace key is pushed versus the keys pushed
Mouse velocity	Speed at which the cursor travels
Number of double clicks	Total number of double clicks in a given time frame
Key time	Time consumed between two keys pushed
Total additional distance	Additional distance covered by the pointer between two successive clicks

Table 12 Layers of architecture and its significance

Layer	Significance of layer
Data acquisition	Data are collected from the use of the keyboard and the mouse.
Data processing	To transform data for evaluating it according to the metrics presented
Classification layer	Use machine learning algorithms to support decision-making
Data access layer	To give access to the lower layer
Presentation layer	To make interactive and visual illustrations of the mental conditions of the subject

Classification of Fatigue

Classification of fatigue was achieved in this experiment by applying K-NN (k-nearest neighbor) algorithm. The experiment was conducted by only considering statistically significant features which were mouse velocity, click speed, key time, total number of double clicks and error per key. Each feature was classified independently in order to consider stages of time where each feature was assigned a binary value describing it as fatigue or not fatigued. Subsequently, the weights' sum was computed to get accurate values of weights which justify their significance, i.e., more important feature will have larger contribution to the experiment. The presentation layer was made in an intuitive way.

This paper determines that experimental data were collected at two different parts of the day. To determine the influence of features, the first phase data were compared with the second phase data. Furthermore, for measuring two trials of independent data to prove that one has larger values than the other, Mann–Whitney test was used. In conclusion, this section explains possible factors or measures to detect mental fatigue using keyboard interactions and mouse movements. The loss of performance in subjects was measured using noninvasive tools. The results acquired from this study not only proved the effects of fatigue on the user's performance but also during the day which can be classified in real time.

Fatigue Detection based on multipsychophysiological parameters and kernel learning algorithms

Chong et al. examined multipsychophysiological parameters to measure mental fatigue using kernel learning algorithm. In this study, 16 males (21–26-year-old and right-dominated) were selected. A simple VDT task was conducted in which three random numbers were displayed at the same time on screen and modified once every second (Fig. 5).

Subjects were instructed to choose "click" using right mouse button and then push it upon recognition of the three unequal odd numbers. They were required to perform the task until they resigned from exhaustion or until they exceeded specified time limit of 1.5 h. Consequently, recorded measurements of response time and error trials were noted. Initially, the subjects were instructed to rest, and later, EEG and ECG were recorded for five minutes in the state of eye closure. These statistics were noted at two epochs, that is, before and after the task. Features were extracted at a later stage as an input of neural network based on wavelet packet decomposition. These 88-dimension features were condensed using kernel principal component analysis (KPCA). The output of the ANN was then classified using support vector machine (SVM). Linear decision function is expected to perform well due to the high-dimensional feature which directly contradicts the Cover's theorem. Integration of KPCA and SVM provides an optimal tool to evaluate the state of mental fatigue (Fig. 6).

This paper concludes that subjects were more or moderately fatigued after the task than before the task. Hence, combination of KPCA and SVM turned out to be a significant tool for estimating mental fatigue.

Future Scope and Challenges

Although the number of researches examining the fatigue on AI-specific outcomes is growing, numerous challenges remain. There is a significant scope to improve methodologies which are used to diagnose and measure fatigue.

There may be multiple factors which are collectively inducing the state of mental fatigue. So, identifying all those factors is important to accurately detect the fatigue. For example, consider an artificial intelligence algorithm which measures the alertness of a driver to detect fatigue. Now, if driver is not alert or vigilance due to reasons such as talkativeness, then it will not be detected by artificial intelligence [83]. Thus, in the future we can develop ways to measure chattiness during driving using several artificial intelligence algorithms. If the detected measurement is greater than some standard dataset, then the person will be labeled as "sleepy." Henceforth, there can be possible ways to find and detect fatigue considering all factors.

In the future, individual vigilance measuring models can be expanded to measure vigilance of mass audience. Using experiments, training data can be gathered to calculate

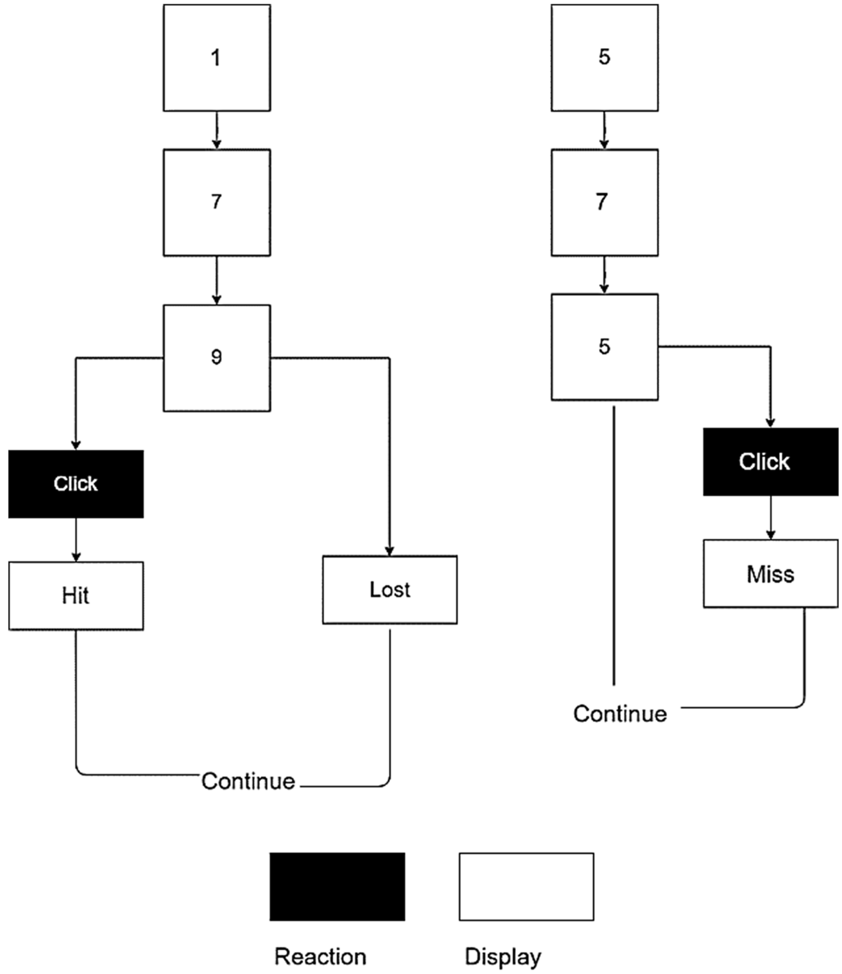

Fig. 5 Simple VDT task events—schematic

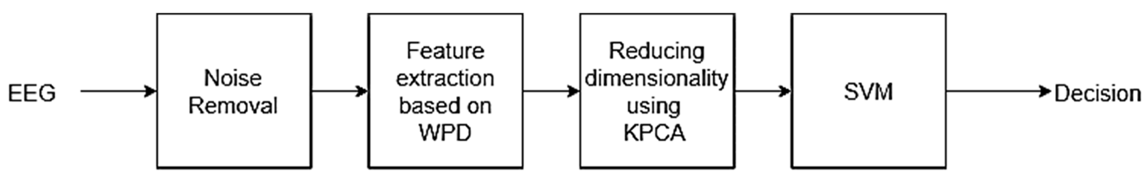

Fig. 6 Decision-making by integrating KPCA and SVM

visual measures using different machine learning algorithms. Using actual feedback and founded measures, we can establish a co-relation between them. This generated model then can be used to find overall interestingness measure. A model from these observations of mass audience can be created like whether vigilance level of particular people can also be related to vigilance level of their neighbors. Therefore, monitoring mass audience can be a useful study for the future [83, 84].

There have been many attempts to detect mental fatigue which are based on sensing eyes, gestures and face status. The eye-tracking data gathered can be improved for distinguishing eyes with wavering light conditions or when person is wearing spectacles [85]. Automation techniques like periodic beeps using artificial intelligence and machine learning algorithms can also be used to reduce mental fatigue.

In the process of detecting fatigue, researchers find several challenging conditions which may lead to distract them in data gathering and analyzing. For example, some fatigues are sensed by face detection. Therefore, any object that covers the face is undesirable. Dealing with several lightning conditions or face accessories can also alter the actual result of an artificial intelligence algorithm, so it becomes challenging to feed relevant data in neural network to achieve accurate results. Another challenge is to distinguish different faces and build model accordingly, for instance, round eyes or slanted eyes, long or short eye lace, and also expressive or non-expressive person [86].

In the near future, fatigue detection and prediction technologies will undoubtedly be useful to help guarantee workplace and road safety. The detection technologies can become more useful and relevant if it has portability or wireless capabilities combined with artificial intelligence algorithms. Portable devices are proven to be effective for monitoring, storing and bringing data and feedback to operators. Moreover, the wireless capability of many of devices may deliver a mechanism to detect mental fatigue in the near future (Table 13).

Table 13 Summary table of various AI algorithms used to detect fatigue

Ref no.	Device	Fatigue measure	Algorithms and techniques	Feature extraction	Classification algorithm	Accuracy
	EEG (electroencephalography)	Electrical brain activities	Back-propagation algorithm	Discrete wavelet transform (DWT)	Neural classifier	95 ± 4%
	Neuroscan 32 channel system	Visual display terminal (VDT)	Kernel learning algorithm	Wavelet packet decomposition (WPD)	Kernel principal component analysis (KPCA), support vector machine (SVM)	87%
[85]	Camera and infrared illuminator	PERCLOS, eye closure duration, blink frequency	Two Kalman filters for people detection	Modification of the algebraic distance algorithm for conics approximation and finite state machine	Fuzzy classifier	Close to 100%
	HRV (heart rate variability)	Variation in heart rate	Butterworth's filter	Fast Fourier transforms	Neural classifier	90%
[87]	CCD camera	Yawning	Gravity center template and gray projection	Gabor wavelets	LDA	91.97%
[72]	Digital video camera	Facial action	Gabor filter	Wavelet decomposition	Support vector machine (SVM)	96%
	Logger application	Analysis of user interaction patterns	Mann–Whitney test	Mouse acceleration, mouse velocity, keydown time, time between keys, and error per key	K-NN (k-nearest neighbor)	95 ± 3%
[73]	Fire wire camera and webcam	Eye closure duration and frequency of eye closure	Hough transform	Discrete wavelet transform	Neural classifier	95%
	CCD Camera, piezo-film sensors	Image analysis	Fuzzy logic model	Blink measurement, eyelid closure time	Neural classifier	96 ± 2.5%
[92]	Simple camera	Eye blink	Cascade classifier algorithm detects face and diamond searching algorithm to trace the face	Duration of eyelid closure, number of continuous blinks, frequency of eye blink	Region mark algorithm	98%
	EEG (electroencephalography)	Electrical brain activities	Widrow–Hoff rule and Levenberg–Marquardt learning rule	Wavelet preprocessing	Neural classifier	97.6 ± 4.3%
[93]	Camera with IR illuminator	PERCLOS	Haar algorithm to detect face	Unscented Kalman filter algorithm	Support vector machine (SVM)	99%

Conclusion

Fatigue can be destructive physically, mentally or psychologically. Detection of fatigue has more importance than curing it because after detection, treatment gets easier. In addition, diagnosing fatigue is not an easy task; we may have to apply indirect methods or learning pattern algorithms for sensing it. As discussed throughout this review, we have explained several studies which have accomplished incredible results for either monitoring or detecting fatigue. Numerous studies focused on root cause of the problem while other fixated their attention toward using artificial intelligence to predict the states of alertness or drowsiness which was subsequently used to detect the fatigue. The study on analysis of keyboard and mouse interaction patterns concluded that by gathering data from movements of mouse and keyboard, patterns can be generated which is then used to detect the level of mental fatigue of the subject. Also, study on complex computer task has proven that fatigued subjects possess less insight into their exploration behavior and thus exhibit loss of systematic strategies. Factors such as alertness and drowsiness are measured using wavelet transform, and the state of alert and drowsy can be automatically recognized from EEG using artificial neural network. In addition, we have also discussed the application of image analysis using artificial neural networks and its role in detecting and monitoring fatigue. Various EEG recordings were manipulated using kernel learning algorithms such as incorporation of KPCA in SVM, and the figures extracted were used to classify alert and drowsy states. This paper also reviews various measures for detecting and developing an efficient system to cure physical fatigue using artificial intelligence algorithms (for example, fuzzy classifier, SVM, DWT). Moreover, the outcomes of mental fatigue in endurance performance are the increased motivation in athletes which resulted from reduction in fatigue, manipulation of motivation and direct alteration of neurotransmitter concentrations. However, some issues are still open and require supplementary work which may, therefore, increase the efficiency of former technologies or extend the approaches to a more significant level. This work unlocks a door to the expansion of working and driving environments, which will improve the quality of life.

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