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A DEEP LEARNING CNN MODEL FOR DRIVER FATIGUE DETECTION USING SINGLE EEG CHANNEL

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ABSTRACT

Driver fatigue and losing wariness during long driving hours is considered as one of the main road accidents causes. It affects road safety directly. Road safety is a major disquieting problem, since traffic accidents endanger divers, travelers, and everyone in their scope, in addition to the road and vehicle damages. The EEG signal becomes one of the most dependable biological signals utilized to estimate the drivers' drowsiness state, although a multichannel acquiring system must be used to transmit the EEG signal. Wearing a multi-channel headset is not readily accepted by drivers. Many attempts have been done by researchers to reduce number of EEG channels used to detect drivers' fatigue. The present study proposed utilizing only one of EEG channels signal to estimate driver fatigue state to raise the acceptance of the system and its flexibility. The system starts with receiving the EEG signals, then pre-processing them using filtering and transformed them to color image using spectrogram. After that, the EEGs spectrogram passed to the proposed CNN deep network model to identify them either fatigue or normal fatigue. The present study measured up many EEG channels to identify the most accurate and dependable one to classify driver fatigue. The results indicate that the FP1, T3, and Oz channels considered as the most efficient channels to identify the drive's state either fatigue or not. They achieved an accuracy of 94.33%, 92.57 and 93% respectively. Therefore, using a single one of these channels and the proposed CNN model will lead to a more robust driver drowsiness/fatigue detection system using EEG signals.

Keywords: *Adam Optimizer, Convolutional Neural Network, Driver Fatigue, Deep Learning, EEG Spectrogram, EEG Signal.*

1. INTRODUCTION

The problem of driver fatigue detection is essential as it affects roads safety directly. Fatigue can be described as a state reached when the brain is no longer capable of maintaining ongoing activity. Driver fatigue could happen as a result of many factors such as sleeping disorder, long work hours, driving hours or taking special medication. Staying awake for a long time could result in body crashing. Drivers' conscious during late time driving is also affected, as some researchers reported that the brain tells the body it should be asleep after midnight till the sunrise [1]. In general mental fatigue dropping attentiveness and delaying reaction while performing activity [2]. It also causes the presence of blurred and distorted vision, problems with remaining alert and recalling [3]. It is hinders drivers from making decisions in time while driving, thus raising the risk of traffic crashes. According to the National Sleep Foundation, almost half of U.S. adult drivers report that they felt drowsy during driving hours, considering 20% admit that they fall asleep during driving hours at any stage in their driving professions. [4]. As reported in [5],16.5% of disastrous crashes related to driver fatigue.

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Driver fatigue detection systems could be categorized as vehicle based, behavioural based or physiological characteristics based. The behavioural based techniques rely on the driver's visible indicators such as blinking eyes, facial characteristics, yawning, the changes of head position or gaze direction. Vehicle based approaches includes metrics related to the vehicle such as steering wheel grip or steering wheel angle [6], [7]. Both of behavioural and vehicle-based methods affected with drivers' culture and driving style.

The physiological approaches make use of the measurement of physical characteristics of a drivers' body. For example, these measures could be:

1. Body temperature.
2. Electroencephalogram (EEG) to indicate brain activity.
3. Electrocardiogram (ECG) to indicate heartbeat.
4. Breathing frequency.
5. Electrooculogram (EOG) to indicate eye movement.
6. Electromyography (EMG) to indicate muscles activity

Drive fatigue physiological based methods characterized by its efficiency as they have sufficient information to reflect the driver's physical state. The main limitation facing the usage of the physiological approaches is that almost all of the physiological features are obtained using physically attached sensors to the driver's body. The contact of the sensors with the driver's body has an impact on the driver's comfort and decreasing the system acceptance. Therefore, several researchers tried to overcome this limitation by creating physiological portable, smaller, or even contactless sensors [8] and [7]. Among driver's fatigue physiological based approaches, EEG is the most trustworthy one, but the EEG signal acquiring sensors makes it less flexible due to its nature and contact to the driver's body [9]. The brain electrical activity had been recorded for the first time in 1924, by the German psychiatrist Hans Berger. It had been recorded by using electroencephalography (EEG). Brain consists of different lobes of cerebral cortex as shown in Figure 1, these lopes are responsible for handling different types of activities so, the EEG related to these lobes reflects different activities performed by the brain. For example, the frontal lobe is engaged with personality, problem-solving, motor development, reasoning, planning, and movement. Visuall processing controlled by the occipital lobe . The temporal lobe is implicated in recognizing auditory stimuli, speech, perception, and memory [10].

EEG representing the brain electrical (voltage) activity along the scalp, these activities are resulting from the brain neurons ionic current flows [10]. Electroencephalographic (EEG) signal comprises a rich information related to the functional processes in the brain. It reflects the brain state, activities, and diseases. The study of spectral features in electrode space has significantly relation to the brain process and their analysis, which has certainly confirmed useful to study the human brain in different states [11]. It allows monitoring driver's brain waves and analyze them to detect drowsy, or fatigued state [7].

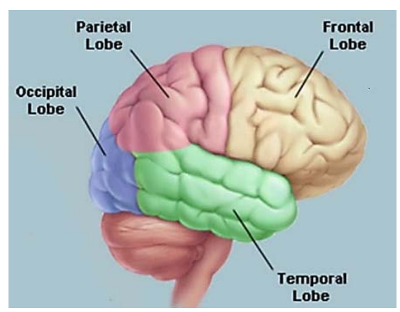

Figure 1. Anatomical areas of the brain [10].

EEG signal is mainly characterized by the richness of its frequency. This richness of frequency information facilitates the diagnostics of abnormalities in EEGs and for understanding its cognitive and functional behaviours. EEG has five main distinguished bands, as shown in figure 2, each of them associated to a specific human activity [10]. The EEG frequency bands, as described in [10] and [12] as follows:

1. Delta (0.5–4 Hz), it can be observed in all sleep stages, particularly in deep sleep stages it indicates also the waking state and serious brain disorders.

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2. Theta (4–8 Hz), it arises in deep relaxation and subconscious activities, emotional stress, creative inspiration, deep meditation, and unconscious material.
3. Alpha (8–13 Hz), it is the semi-conscious state indicator, it arises also in intense mental activity, tension and stress.
4. Beta (13–30 Hz), it indicates the fully involved with a mental activity, state of clear alertness, entirely focused, learning, active attentions and focusing on the outside world or solving concrete problems. It is identified easily during relaxed vigilance or early drowsiness.
5. Gamma (>30 Hz), it indicates the usage of multiple senses on the same time, associated with high energy activities such as cognitive or motor functions.

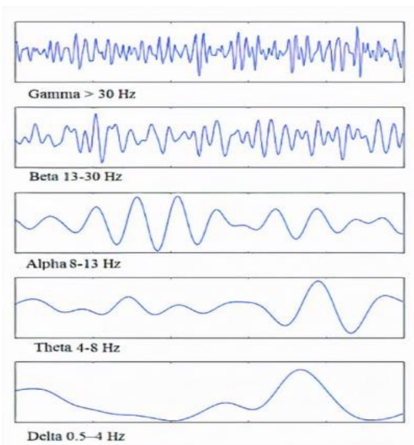

Figure 2. EEG different frequency bands.

The use of such a full 32 channel (10-20 EEG channel Montage system), as shown in Figure 3, tends to increase the complexity of the system. Prior training is required for the user to attach the electrodes to the head. Using a multi- channel system leads directly to a time-consuming and embarrassing feeling for drivers [13]. The amount of data that should be processed also increase as the number of used EEG channels increased. Complexity and time-consuming make EEG based driving fatigues system inapplicable in real life. Researchers are trying to minimize the number of used channels to detect driver drowsiness state, to reduce complexity and high cost when using the full EEG multichannel. They used machine learning techniques as in [13] [14], [15], [16], [17], [18] , [19] and [20]. Recently deep learning techniques arises on this field as a reliable technique such as in [3], [21], [22], [23], [24], [47],[48] and [49].

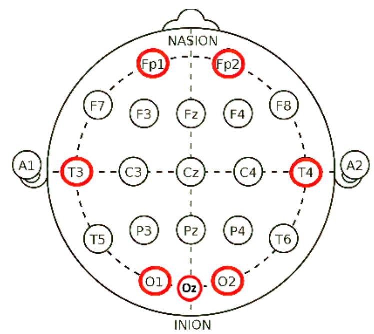

Figure 3. The standard EEG electrodes location on scullion, the tested electrodes *on the current work surrounded with red.*

1.1 Machine Learning Based Driver Fatigue classification systems:

In [16] they use the signal sample entropy as features with only one EEG channel which is F3. They reported results reach 95% correct classification. In [17] the authors tested different combinations to identify fatigue state by combining EEG , EOG, and ECG signals. For EEG they use only three channels which are Fz, T8, and Oz. they used fuzzy mutual information (MI)-based wavelet packet transform (FMIWPT) feature-extraction method for classifying the driver drowsiness state into one of pre-defined drowsiness levels and achieved the lowest error rate by combining the proposed three EEG channels.

Li et al. in [14] attempted to find the best channels to indicate the fatigue state. They used Grey Relation Analysis (GRA) to find the best power indicator parameter and used Independent Component Analysis ICA to find the most appropriate channel to identify fatigue state. They concluded that using the mean value of signal power spectrum and Channels FP1 and O1 give the best results.

In [25], Li et al. continued to work on EEG channels minimization to classify fatigue state. They used the signal mean power spectrum and concluded that the difference between using only two channels (FP1 and O1) and the whole 16 channels system is non-significant as using the only two channels gives 92.2% correct classification while the use of the whole 16 channels gives 94.6% of correct classification.

In [26] the authors used only the frontal head channel and proposed a wireless driver fatigue detection using U- Wake interfaced with a mobile device. To classify fatigue state, the system depends on calculating the frequency power of deferent EEG frequency bands to know their brain dynamic changes. They divided frequency power into the four main bands of the EEG signal which are, delta (l~3 Hz), theta (4~8 Hz), alpha (9~12 Hz) and beta (l3~30 Hz). They used the frequency power level indicates the fatigue state by increasing the delta band power. The system needs 2 seconds to determine the driver state. Their result reached 93.9% mean accuracy of correct classification. The limitation on the classification computation method related to the dependence on the mobile device platform in calculations. Table 1 summarize the machine the previous researches that tried to reduce EEG channels to detect driver fatigue state.

Table 1: Reduce Channels EEG based research groups to detect driver fatigue state.

Research Group	Used EEG Channels	Accuracy
Khushaba et. al.[17]	Fz, T8, and Oz	92.8
Li [14]	Fp1 O1	91.5
Z. Xiaohua [16]	F3	95
C. Zhang [18]	O1 and O2	96.5
Li-Wei Ko [20]	FP1	93.9
R. Fu [15]	FP1 and O1	91.5
J. Hu [13]	CP4	96.6
J. M. Morales [19]	FP1 and A1	Using other metrics
The Present study	FP1	94.36%

2.1 Deep Learning Based Driver Fatigue classification systems:

The previously motioned machine learning based techniques required a lot of computation in preprocessing and feature extraction stages while CNN has the ability of self-feature extraction as it require no feature extraction stage. In general, neural networks are themselves bio-inspired, i.e., trying to follow the same biological brain system learning and classification and particularly deep learning techniques more tended to the brain working system [27]. It is designed to suit the task of exploiting computational structure in data. These facts recommend it to be more appropriate to work with biological signals such as EEG signal.

Generally, if we considered the signal representation to the system, the use of CNN deep networks will be characterized by two main approaches. The first approach, depending on the temporal characteristic of the EEG signal using more than one channel. On this approach, the 1-D EEG signal converted to a 2-D image representation showing the signal amplitude change with time during a certain time interval, using filtering techniques such as common spatial patterns (CSPs) algorithm as represented on [28] and [29]. The second approach, depending on converting the1-D EEG signal, converted to a 2-D image representation depending on frequency transformation such an FFT and WTP as described in[30] and [31].

Deep learning had been combined with spectrogram for to classify EEG signal in many problems of classification. In [31], they used a multi-channel EEG signal spectrogram as an input a deep learning classifier to classify sleep stages into five stages. The used deep neural classifier based on transfer learning using VGGNet. They achieved an average accuracy of 86%. In [32], the same technique of using EEG signal spectrogram as an input to a CNN classifier was applied. They used a multi-channel EEG signal to classify Rapid Eye Movement (REM) Behavior Disorder. They implement their own deep convolutional neural network, and it consisted of a five-layer architecture combining filtering and pooling. They reached a maximum accuracy of 81% with 87% AUC. In [30], they also use the same approach by combining the multi-channel EEG

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signal frequency spectrum with a CNN classification model to classify the brain status into either an ordinary or new task.

Cheng et al. in [23] used a new approach to classify drivers drowsiness using their own developed CNN model. The CNN model input was the multi-channel EEG 1-D spectral feature interpolated to a topological map using Clough-Tocher scheme. The pixel data points related to a corresponding channel from the used 32 channel, resulting in a 32 ×32 input image size. Their results reached 82.8401% of accuracy.

In [33], Zeng et. al. tested the performance of two deep network classifiers with multi-channel EEG signal input. The 1-D EEG signal of multi channels is converted to 2-D temporal representation, they proposed two models. The first one is called EEG-Conv, it consisted of 8 ordinary CNN layers. The second model is called EEG-Conv_R, it combined CNN with recent deep residual learning. The first mode reached average accuracy of 91.78% while the second model reached 92.68% average accuracy.

Ma et al. in [21], introduced an EEG based driving fatigue detection system. They used the standard EEG montage channels standard system in acquiring the 32 EEG channels and use them as the system input. They use principal component analysis (PCA) to reduce the 32 EEG channels dimensions then feed the output to PCANet classifier which was proposed in [34]. The PCANet classifier was used as feature extractor. The PCANet output fed to SVM and KNN classifiers to test both of them. The system reached 95% as the higest classification accuracy.

Guarda et al in [3], introduced a driver fatigue system based on their designed CNN classifier. They used the standard montage EEG 10-20 channels to capture Fz and Pz channels as an input to their proposed system. They started with converting the selected two channels signal to the spectrogram into a gray level representation. The proposed CNN model contained three convolutional layers, each followed by a pooling layer. The proposed CNN ended with two fully connected layers. They reached average classification accuracy equal to 86%.

In 2019 Budak et al. [22] introduced a complicated hybrid model to detect driver fatigue. The system was composed basically of three main blocks. The final decision made through a voting layer fused the three classification blocks. They used three combinations of the 32 EEG channels. These combinations are C3-O1, C4-A1 or O2-A1 channels. The first block used EEG signal to get its zero-crossing rate and energy and also EEG spectrogram to get its spectral energy and instant frequency, then all of these inputs fed to a long-short term memory (LSTM) network. The second block used EEG spectrogram with transfer learning using AlexNet and VGG16 deep nets as a feature extractor. The extracted features then fed to an LSTM network. Finally, in the third block a tunable Q-factor wavelet was applied on EEG signal to get its the mean and standard deviation of each sub-band separately and then feed it to a LSMT network. The final output output is the three blocks fusion result. The maximum accuracy for each block separately reached 88.47%, while the three block fused output got 94% present of correct classification.

W. Shalash, in [24] the researcher used transfer learning techniques depending on the well-known CNN structure AlexNet as a classifier. The EEG signals converted to spectrogram to be suitable as 2D input to AlexNet. The author tested many channels to select the most appropriate one to identify the driver fatigue state. She concluded that channels FP1 and T3 are the most effective channels; they achieved 90% and 91% average accuracy, respectively.

In [47] and [48], the authors proposed a system for drivers fatigue detection depending on EEG and EOG signals. They acquired data from channels O1 and O2 for EEG signals and Vu and Vd for EOG (above and under the left eye). The system based on the alpha wave change as the alpha band is highly reflecting the difference between the sleepiness and awake cases. They used continuous wavelet transformation for feature extraction. As the signals have a temporal characteristic, they used Long Short Term Memory (LSTM) neural network to classify it. To overcome the shortage in subjects number, they used a leave-one-subject-out cross-validation method and achieved an average accuracy of 98%. Using four electrodes with two of them attached up and down to the drivers' eye helps achieve high accuracy, but it might not be suitable or accepted for drivers in real life.

F. Rundo et al.[49] suggested a system acquired the signals from O1 and O2. They collected their data from 62 subject. The signals acquired while the subjects were totally relaxed while the awakens signal was acquired while the subjects were performing mental activities. Then extract features using the Discrete Cosine Transform (DCT) and finally used a deep learning neural stage consists of stacked autoencoders with softmax layers. The autoencoder layers characterized with their ability to learn with correlated input. Their results indicated 100% accuracy in drowsy/wakeful discrimination. The data acquisition stage perfumed in both relaxes and mental activities, which is not an exact simulation for the driving state.

In [51], they proposed a recurrence network-based convolutional neural network (RN-CNN) method to detect drivers’ fatigue. After acquiring the signal, they passed the 30 channels to a recurrent neural network, each channel individually. They then employed a mutual information matrix to form a multiplex recurrence network to reduce the original EEG signal's complexity, dimension. They mentioned they tried to overcome the low signal-to-noise ratio and the signal's nonstationary nature by using a recurrent mutual matrix. Reducing the signal dimension also helped in improving the training efficiency of CNN. In the last stage, the signal fed to their own shallow CNN model, they reached an average accuracy of 92.95% on their on data. This method combines both the classical and deep learning methods but still depends on the whole 30 channels.

In [52], Zhang et al. introduced a mental fatigue detection method using a graph convolution combined with brain function connection theory. They focus on studying the effect of the electrodes’ special location relation as the brain function itself is a collaborative activity among different areas of it, so they use the graph neural network, reflecting this idea. They used the whole 32 channels. They called the method the partial directed coherence graph convolutional neural network (PDC-GCNN), which can analyze the characteristics of single electrodes while automatically extracting the brain network's topological features. They used the PDC method to construct a matric representing the relationship between EEG channels, and the GCNN combines to identify the fatigue state. They perform two methods, once by using differential entropy and the other by using power spectral density as an input to their model; they reached a result of 84.32% for using DE and 83.84% for using PSD.

In [53], they tied to reduce the number of used electrodes and used only FPz-Cz channel. They proposed a model combining both CNN and LSTM characteristics as LSTM prediction depends not only on the current state but also on the previous state. They designed a one-dimensional convolution neural network and bidirectional LSTM to learn the EEG signals' alertness level. The used data was obtained from the sleep edf dataset and Neurosky sensor readings, but they mentioned that most of the used data were taken from the sleep edf dataset. The sleep edf dataset is a five-stage sleeping record, not a driver fatigue dataset. They focus on developing a real-time system, so they implemented it on an ARM-based single-board computer (SBC). The trained CNN-LSTM based Model gave an accuracy of 93.3%, and the test model gave an accuracy of 89.4% percentage when tested with real-time signals using the Neurosky mind wave electrode.

The current work proposed s system to detect driver fatigue using CNN based on EEG signal, the proposed system used only one EEG electrode to simplify the system and make it more applicable, cheap, and accepted by drivers. The author emphasizes introducing a simple real-time system that could be attached to drivers during lengthened driving and easily attached electrode location.

The suggested model could be abbreviated as follows; firstly, the raw EEG signal is passed through a bandpass filter (0.5 and 45 Hz), next each

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1 sec. (sampling rate 1000 sample / second) length of the signal is downsampled to 500 sample/second rate. Then the EEG signal is transformed into a 2D color image using spectrogram. In the final stage the signal spectrogram is classified by the suggested trained CNN model to distinguish it, either Normal or Fatigue state. The present study aims to examine the accuracy of seven channels from the whole 32channels of 10-20 EEG standard montage system. These channels (FP1, FP2, T3, T4, O1, O2, and Oz) are on the rim of the head to find the uppermost one. The author suggests using the uppermost accurate channel only or combined with the second-ranked accurate channel with the proposed CNN classification model to recognize the driving fatigue state. Using the uppermost accurate channel as a single channel to classify fatigue state will increase the system acceptance among drivers and make it easy to wear and adjust a bandage with one

This paper's content is illustrated as follows: Section two presented the suggested system high-level architecture; section three presents method and data. Section four shows results, section five is the discussion, and lastly, section six presents the conclusion.

2. MATERIALS AND METHODS

2.1 The Proposed System High-Level Architecture

In recent times, deep learning, especially CNN, has demonstrated outstanding success in image classification and recognition, outperforming the classical machine learning methods. In the present work CNN utilized it to identify the driver's EEG signal, whether as normal or as fatigue. CNN is dedicated mainly to work with image input or 2D input data. Therefore, the driver's EEG signal is transformed to a spectrogram representation, color image, to be suitable as an input to the proposed CNN model. The spectrogram of a signal is defined as a 2D representation to the usual 1D signal. We can consider it a frequency-time representation to the signal. It is a visual way for signal representation, and a standard method to display a signal's frequencies. The spectrogram's vertical axis represents frequency, with the lowest frequencies at the bottom and the highest frequencies at the top, while the horizontal axis represents time; it runs from left to right of the axis. The colors enrich the spectrogram representation as its third dimension; different colors represent different energy levels [35].

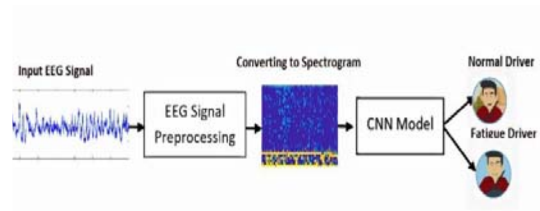

Figure 4: The high-level structure of the suggested driver fatigue detection system.

The suggested system consists of three stages. The first stage is the preprocessing stage, where the raw EEG signal rolled filtered to select the desired band. The second stage converts the 1-D signal representation into a 2D image representation using the spectrogram representation. The third stage is the classification stage, where the proposed CNN receives the driver's EEG spectrogram, to evaluate the driver's mantel status, whether it is Normal or Fatigue. Figure 4 shows the proposed system high-level structure (building blocks).

2.2 The Dataset

There is a shortage in the available public data set which measures the drivers fatigue status. Most of the mentioned work in the literature review used private data set. The author selected to use a dataset exported from [37] web site as described in [38]. This data set was easily used as both normal and fatigue state was separated by the authors [38] research group. A static driving simulator was used in recording the dataset in a controlled lab environment including both normal and fatigue drivers and saved in. cnt format. The dataset was recorded with the participation of twelve subjects. All of the twelve participants were fit, stable people, aged between 19 and 24 years, engaging in a highway-driving simulator project. The data was collected with a 32-electrode Neuroscan data acquisition system as described in [37], and the international 10–20 system was used for the EEG collection protocol. All channels data were referenced to two electrically linked mastoids at A1 and A2and

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digitized at 1000 Hz. The present work examined only a limited number of channels on the head rim. These channels were FP1, FP2, T3, T4, O1, O2, and Oz. The Checked channels have been chosen on the head rim to indicate that the usage of simple head banding requires just one channel (electrode) rather than a complicated 10-20 EEG 32 channels method. The author selected these channels as they are related to frontal, temporal and occipital lobes as these lobes related to personality, problem-solving, motor development, reasoning, planning, movement, visually processing perception and memory. While all of these activities expected to be affected by fatigue status. After the downsampling process for each channel, , the author took each sample size as 500 samples which resulted in a total number of 3440 sample for each class (Normal or Fatigue) per single channel. These samples converted to signal spectrogram images.

2.3 Signal Pre-processing

The preprocessing began with signal filtering. A bandpass filtering was applied to clean the input signal and limit signal frequency between 0.5 Hz and 45 Hz. Singles lower or higher than the band is not included in the current study Next, the signal is downsampled to 500 sample/sec. The first 10 seconds from the signal database are excepted to avoid unstable records.

2.4 EEG Signal 2D representation

The second stage started with calculating the spectrogram for each 500 sample. The present work used Short- time Fourier Transform (STFT) with Kaiser window type (β = 10) of size 64 samples (equation 1) , as illustrated in[36]. The current study applied the reassignment technique to increase the sharpening of the spectrogram (time- frequency) representation. If the signal has a well-localized temporal or spectral component, this will generate a sharper spectrogram to emphasize the temporal change [33],[50]. A sample from the EEG spectrogram is shown in Figure 5 and 6; It shows samples of EEG spectrogram for channels FP1 and T3 for both normal and fatigue state.

$$w[n] = w_0\left(\frac{L}{N}\left(n-\frac{N}{2}\right)\right) = \frac{I_0\left[\pi\alpha\sqrt{1-\left(\frac{2n}{N}-1\right)^2}\right]}{I_0[\pi\alpha]},\ 0 \le n \le N\ , (1)$$

Where: The length of the window is N+1, and N can be even or odd, I0 is the zeroth-order modified Bessel function of the first kind, L is the window duration, and, α is a non-negative real number that determines the shape of the window. In the frequency domain, it determines the trade-off between main-lobe width and side lobe level, which is a central decision in window design, and β = πα.

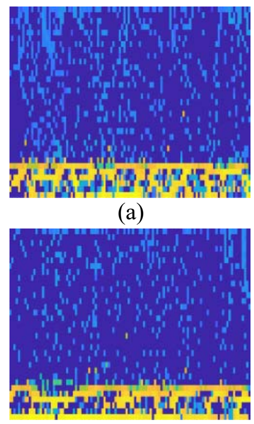
(a)
(b)

Figure 5 A sample of EEG signal spectrogram using reassignment technique for FP1channe (a) Normal state and (b) Fatigue state.

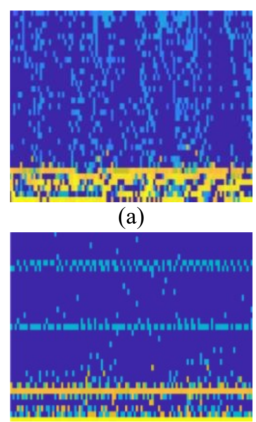
(a)
(b)

Figure 6 A sample of EEG signal spectrogram using reassignment technique for T3 channel, (a) Normal state and (b) Fatigue state.

2.5 CNN Model Architecture

The third stage of the suggested system is the classification stage. The author developed a convolutional neural network (CNN) and trained it from scratch to adequate the EEG signal nature. Figure 7 shows the proposed CNN model architecture used to classify the driver EEG signals while, Table I shows each layer details. The model consists of input layer and ordinary CNN 18 layers. The input layer receiving the colored spectrogram image representation and resize it to 128×128×128×3, followed by a convolutional layer with 20 filters, 3×3 kernel sizes, and batch normalization layer to speed the learning process. A dropout layer was introduced, followed by a ReLU activation were used, and a max-pooling layer with kernel size (3, 3). This same structure is repeated on layers from 6 to 13 with different settings, as shown in figure 7 and table 2. The repeated structure consisted of a convolutional layer followed by batched normalization, ReLU activation layer followed by a pooling layer. Finally, 2 layers of a fully connected neural net introduced with ReLU activation. The model ended with SoftMax and classification layers to classify the input either normal or fatigue state.

Table 2: The Proposed CNN Model Architecture.

Input Layer	Input Layer 128×128×3
Layer 1:	2D Convolution layer - Layers size= 20 – Kernel size 3 × 3
Layer 2:	Batch Normalization Layer
Layer 3:	Dropout Layer with 25% probability
Layer 4:	ReLu Layer
Layer 5:	2D Max. Pooling pooling Size 3 × 3
Layer 6:	2D Convolution layer - Layers size =30– Kernel size 3 × 3
Layer 7:	Batch Normalization Layer
Layer 8:	Dropout Layer with 20% probability
Layer 9:	ReLu Layer
Layer 10:	2D Max. Pooling pooling Size 3 × 3
Layer 11:	2D Convolution layer -Layers size=45– Kernel size 3 × 3
Layer 12:	Batch Normalization Layer
Layer 13:	ReLu Layer
Layer 14:	Fully connected layer (Size = 12)
Layer 15:	ReLu Layer
Layer 15:	Fully connected layer (Size = 2)
Layer 17:	Softmax Layer
Layer 18:	Classification Layer

2.6 CNN Model Training

When training complex neural networks as the proposed CNN model, adaptive optimizers techniques are the right choice for faster converging. The present study used Adam (Adaptive Moment estimation) [39] as optimizer during the training process. Recently, when working with deep learning, Adam considered as the best optimizer for most cases. It also performs better than other adaptive techniques (adadelta, adagrad, etc.), but it is computationally costly [40].

Adam optimizer combines the pros of two common efficient optimizers in one optimizer; these optimizers are Momentum and RMSProp. Adam uses an exponential weighted average of past derivatives as Momentum optimizer, and it also uses the exponentially weighted averages of past squared derivatives as RMSProp. During training, Adam is too oscillating around the minimum, but it reaches it in most cases. Generally, it is faster and better than other optimizers till now [41].

The present study faced the problem of model overfitting during the training process. Overfitting prevents the CNN model from generalization to new data. Overfitting problem was recognized as the model achieved higheraccuracy and minim loss with the training data while it reached relatively lower accuracy and higher loss with the validation data. In other words, the model acts as it learned noise associated with data as well as data itself. To overcome this problem the researcher needed to apply a regularization technique to the proposed model. Regularization techniques were defined by Kukaka et al. in [42] , “Regularization is any supplementary technique that aims at making the model generalize better, i.e., produce better results on the test set.” Many techniques proposed by researchers to overcome this problem, such as L1, L2 regularization, dropout, and early stop [40],[41] and [43].

The present study used both L2 Regularization and dropout techniques. L2 Regularization is considered as one of the most common regularization techniques, and it aims to reduce model complexity by achieving weight decay. L2 Regularization technique adding a

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regularization term to the cost function. Adding the regularization term aims to reduce the network capacity in an effective way to adapt to complex datasets [40] and [43].

Dropout is applied simply by removing nodes randomly from the network during the training phase. The author achieved it by adding two dropout layers in the model architecture as layers 3 and 8, as shown in figure 7, setting the probability of removing nodes to 25% and 20% respectively. When a node selected to drop it out this resulting in dropping all of its incoming and outgoing connections from that node [43].

The model building and training process had been implemented using MATLAB 2019a [44]. The training process requires to tune many hyperparameters to reach the desired goal of the model. Adam optimizer was used during model training process. Table 3 shows the model tuned hyperparameters. As mentioned in Table II, the initial learning rate was started with 0.0001, batch size of 45 and L2 Regularization of 0.99.

Table 3: The proposed CNN model hyperparameters tuning values.

Parameter	Value
InitialLearnRate'	0.0001
LearnRateSchedule	'piecewise'
'LearnRateDropFactor'	0.5
'GradientDecayFactor'	0.6
'SquaredGradientDecayFactor'	0.6
'MiniBatchs'	45
'L2Regularization'	0.099
'Shuffle'	'every-epoch'
'ValidationFrequency'	20

3. RESULTS

The present study has been evaluated using performance indicators. These indicators are accuracy (***Acc***), sensitivity (***Sn***), specificity (***Sp***) and also receiver operating characteristics(ROC) curve and also the area under curve (AUC) [45]and [46].

The selected performance indicators to evaluate the current study, defined in the following:

$$Sn = \frac{TP}{TP+FN} \quad (2)$$

$$Sp = \frac{TN}{TN+FP} \quad (3)$$

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

- ***TP*** (true positive) : is the number of the data inputs that refer to fatigue state correctly classified as fatigue.
- ***FP*** (false positive): is the number of data inputs that refer to normal state classified as fatigue state.
- ***TN*** (true negative) is number of the data inputs that refer to normal state correctly classified as normal state.
- ***FN*** (false negative) is the data inputs that refer to fatigue state classified as normal state.

The (ROC) graph is defined in [46] as " a technique for visualizing, organizing and selecting classifiers based on their performance. " The AUC demonstrates the accuracy of binary classifiers with the change of its threshold value and how it will change. The ROC is developed by plotting the fraction of true positives out of the positives (TPR= true positive rate) versus the fraction of false positives out of the negatives (FPR = false positive rate), at different threshold settings. TPR is also known as Sn (equation 2), and FPR is one minus the Sp (equation 3). The AUC value of a classier is equivalent to the probability that the classier will rank a randomly chosen positive instance higher than a randomly chosen negative instance. The ROCs graphs are usually used to show the tradeoff between hit rates and false alarm rates of classifiers.[46], [45].

Table 4: The system average accuracy and AUC of each tested EEG Channel with the suggested CNN architecture.

Channel	Accuracy	AUC
FP1	94.36%	0.9798
FP2	81.83%	0.899

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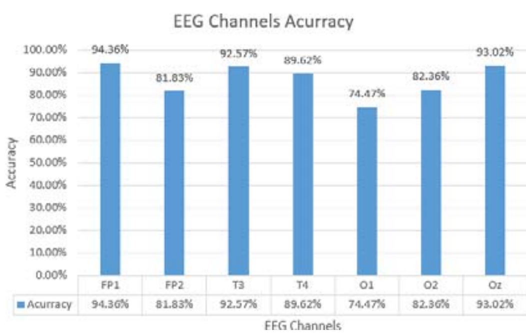
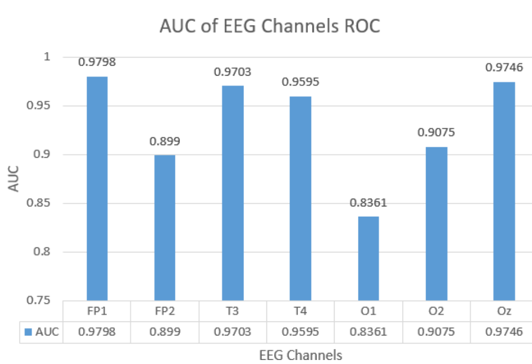
T3	92.57%	0.97
T4	89.62%	0.9595
O1	74.47%	0.8361
O2	82.36%	0.9075
Oz	93.02%	0.9746

The selected channels have been tested with the proposed CNN classifier. The data have been split into three groups, with the percentage of (70%, 10%, and 20%) for training, validation, and testing. The obtained average accuracy and AUC are listed in Table 4. The proposed CNN classifier model accuracy and AUC are illustrated in figures Figure 8 and 9 with each of the selected individual channel EEG channels (FP1, FP2, T3, T4, O1, O2, and Oz). As shown in figures 8 and 9 and Table 4, channel FP1, T3, and Oz achieved the highest accuracy and



AUC among all of the selected channels. The ROC curves for the proposed classifier is shown in figure 10 for each of the individual EEG channels (FP1, FP2, T3, T4, O1, O2, and Oz). The ROC graph



indicates that channel FP1, T3, and Oz achieved the highest AUC.

Figure 8: The accuracy for the proposed CNN classifier for the selected EEG channels.

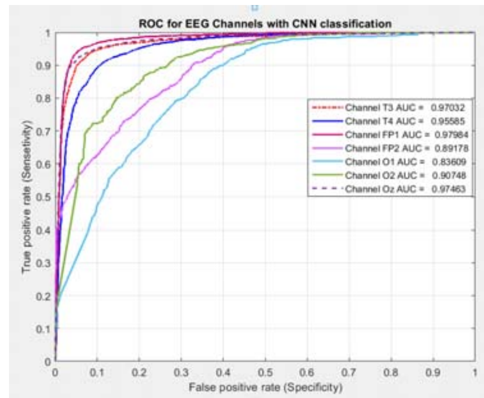


Figure 9: The resulted AUC for the proposed CNN classifier for each the selected EEG channels.

Figure 10. The ROC for the proposed CNN model for the selected EEG Channels.

4. DISCUSSION

The present study mainly aims to introduce a CNN neural network model to classify the driver's drowsiness state using driver's EEG signal acquired from only one channel (electrode). The presented study suggested a CNN based model combine with a driver fatigue detection system. The system stated with the input signal preprocessing, including limiting its frequency band to (0.5 Hz to 45 Hz) and downsampling it to 500 sample/sec. The second stage transforms the 1D signal representation to a 2D representation using spectrogram technique to be ready as an input for the classification stage. In the final stage, the author suggested a CNN model suitable to classify the EEG signal spectrogram into fatigue or normal state. The author tested a selected seven channels, these channels located on the head's rim according to the 10-20 EEG channel Montage system. These channels were tested to determine which one of them is capable of categorizing the driver fatigue state more accurately than the others. The findings demonstrate that the FP1, T3, or Oz channels

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obtained the highest average accuracy and the highest AUC among the seven tested channels, as shown in Table 4 and Figures 7, 8, and 9. The researcher recommended that the combining of only one of these EEG channels (FP1, T3, or Oz) with the suggested CNN classifier to identify driver drowsiness would achieve sufficient accuracy. Using only one electrode to detect driver fatigue state will increase the system reliability, solving the problem of driver comfortless and system acceptance, reducing cost, reducing the amount of processed data, and needing less train to wear it.

When comparing the proposed system with the previous state-of-art systems mentioned in the literature review, it would be evident that it achieves better performance with less complexity (fewer electrodes). Table 5 lists a comparison between the proposed system and the other systems in terms of the system's input representation, classifier type, number of used EEG electrodes, and average accuracy. Regarding to the input, it is noticed from the table 5 that the two main approaches for EEG driver fatigue detection with deep learning is either using spectrogram as [23], [3] and [24], temporal representation [33] and [21], combing spectrogram and temporal representation as in [22],or just using the original EEG signal in time domain representation as in [51],[52] and [53]. On the other hand, the classification approach is either building CNN model as [3] [23] and [33], using transfer learning as in [21], [22] and [24], or combining CNN with other classifier as in [51],[52] and [53].

Although the current work concluded that only one of the highest accuracy three channels is enough to detect drives fatigue state, but one of proposed system limitations that it needs more investigation to decide which one of these channels would be more accepted by drivers and easy to adjust without affecting the signals value, FP1 which will be attached to the front head, Oz which will be attached to the back head or T3 to the head side.

The usage of deep learning with the problem of driver fatigue detection faced many problems such as the lack of public dataset with sufficient amount of data as deep learning required huge amount of data for training. Most of the previous racehorses used their own developed EEG dataset, although table five provides a comparison among different works, this comparison will not be totally fair, or at least there is an error margin on it because most of the mentioned methods did not use the same dataset. As in [52], when they perform a comparison by repeating the same work introduced in [51] and compare it with their method, the results seem very different.

Most of the EEG datasets recorded for young, healthy drivers so, what would be the system on older drivers or the effect of taking medication, or coffee during driving. The problem of driver fatigue detection needs more efforts in building EEG with big number of subjects including all drivers' categories not only young healthy drivers.

The second limitation the computational power needed to train the deep neural model. Due to the limitation of used CPU and GPU, I limit the spectrogram size to 128 by 128, while this issue needs to be more addressed and the effect to study the effect of increasing the spectrogram image size on the efficiency of the system.

In future the author aims to test which one of the three highest accurate channels (FP1, T3, or Oz) would be comfort for drivers, and also to test the best fusion among the three channels would give high accuracy. As CWT and DWT are less in computation than STFT so, the author aims use it in future to generate signal spectrogram representation. The author aims also to study the effect of changing the input image size to the CNN on the performance.

5. CONCLUSION

Using multi-electrodes to detect the drivers' fatigue state increases the cost and the complexity and inconvenient use for the drivers. Many attempts have been exerted to reduce the number of EEG channels used to identify normal and fatigue states. The present study proposed a fully connected convolutional neural network model to classify driver fatigue state using single EEG signals channel with only one EEG electrode. Using only one electrode in a suitable location on

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the head rim will facilitate attaching it to the driver's head. The proposed work compares the proposed CNN's performance to build an EEG classification system using different EEG channels and proves that the CNN classifier can rely only on a single channel with excellent performance. Using a single EEG channel to classify driver fatigue makes the fatigue detection system simple and increases the driver's acceptance of the system use, making its usage possible to diverse of people. The proposed work supports the possibility of combining a simple headband with only one EEG electrode with low power consumption devices using edge AI technology to provide a full monitoring system for drivers of highways.

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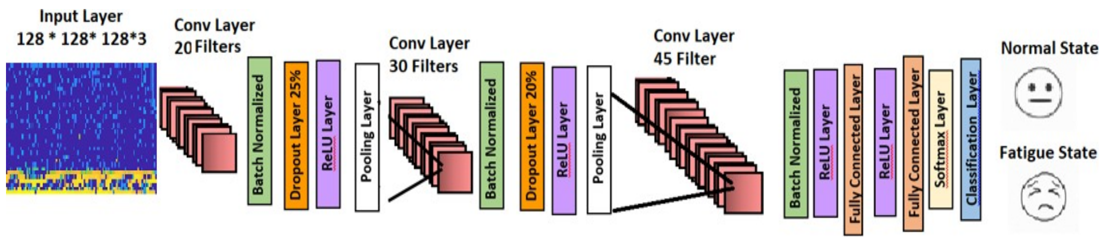

Figure 7. The proposed CNN layer model architecture.

Table 5. A comparison between the proposed system and the other systems in term of input representation, classifier type, number of used EEG electrodes, and average accuracy.

Research Group	Input Representation	Type of classifier	EEG Channels	Highest Accuracy
Cheng et al. in [23]	Spectrogram Image	CNN model	Multi-Channels	82.8401
[33], Zeng et. al.	Temporal Representation image	CNN model	Multi-Channels	92.68%
In [21], Ma et al	Temporal Representation image	CNN with transfer learning	Multi-Channels	95%.
In [3], Guarda et al.	Spectrogram Image	CNN model	Fz and Pz	86%
Budak et al.[22]	Both temporal representation and Spectrogram Image	(LSTM) networkand transfer learning with AlexNet and VGG16	C3-O1, C4-A1	94%
W. Shalash [24]	Spectrogram Image	CNN with transfer learning	FP1 and T3	90% - 91%
Gao et al.[51]	Time domain	RNN- CNN	Multi-Channels	92.95%
Zhang et al. [52]	Time domain	PDC-GCNN	Multi-Channels	84.32% for using DE 83.84% for using PSD.
Nissimagoudar et al. [53]	Time domain	LSTM -CNN	FPz-Cz channel	89.4%
Present study	Spectrogram Image	CNN model	FP1, T3 and Oz	94.36% 92.75% and 93%