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Driver Fatigue Detection with Single EEG Channel Using Transfer Learning

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***Abstract*— Decreasing road accidents rate and increasing road safety have been the major concerns for a long time as traffic accidents expose the divers, passengers, properties to danger. Driver fatigue and drowsiness are one of the most critical factors affecting road safety, especially on highways. EEG signal is one of the reliable physiological signals used to perceive driver fatigue state but wearing a multi-channel headset to acquire the EEG signal limits the EEG based systems among drivers. The current work suggested using a driver fatigue detection system using transfer learning, depending only on one EEG channel to increase system usability. The system firstly acquires the signal and passing it through preprocessing filtering then, converts it to a 2D spectrogram. Finally, the 2D spectrogram is classified with AlexNet using transfer learning to classify it either normal or fatigue state. The current study compares the accuracy of seven EEG channel to select one of them as the most accurate channel to depend on it for classification. The results show that the channels FP1 and T3 are the most effective channels to indicate the drive fatigue state. They achieved an accuracy of 90% and 91% respectively. Therefore, using only one of these channels with the modified AlexNet CNN model can result in an efficient driver fatigue detection system.**

Keywords*— *AlexNet, Convolutional neural network, CNN, Deep learning, Driver fatigue, EEG signal, spectrogram, Transfer learning.

I. INTRODUCTION

Mental fatigue is affecting both individual psychological and physical state, decreasing attentiveness in the performed activity; it also causes a lacking in an individual reaction as proven in [1]. Many other symptoms are associated with mental fatigue such as appearance of blurred and double vision, difficulties on staying alert and remembering [2]. It is impairing drivers from taking timely mannered decisions while driving, higher the risk to be involved in traffic crashes. Driving fatigue is one of the most important problems facing the road safety. The rate of fatigue-related accidents is unexpectedly high. It is one of the main reasons for road fatalities. Most of traffic safety organization admit that driver fatigue is an often-overlooked area. With the increase of road accidents caused by driver fatigue, the global interest in this problem increased. They emphasized the importance of solving this problem and introduced some effective solutions [3], [4].

Driving fatigue is considered as one of the most critical problems facing the road safety. The authors of [4] believed that "fatigue not only decreases the effectiveness of essential processes to drive accurately, such as attention and vigilance, work memory and decision-making but predicts, in the short term, a higher risk to be involved in traffic crashes", The rate of fatigue-related accidents is unexpectedly high. The National Sleep Foundation in U.S reported that, about half of U.S. adult drivers admit to consistently getting feeling drowsy during driving hours, while 20% declare that they have fallen asleep during driving hours at some point in the past year, while more than 40% confess this has occurred at least once in their driving careers [5]. The National Highway Traffic Safety Administration reports that 16.5% of fatal crashes involved fatigued driving, It resulted in 5,000 death cases due to drowsy driving crashes in 2015 alone [6] beside injuries and properties damage.

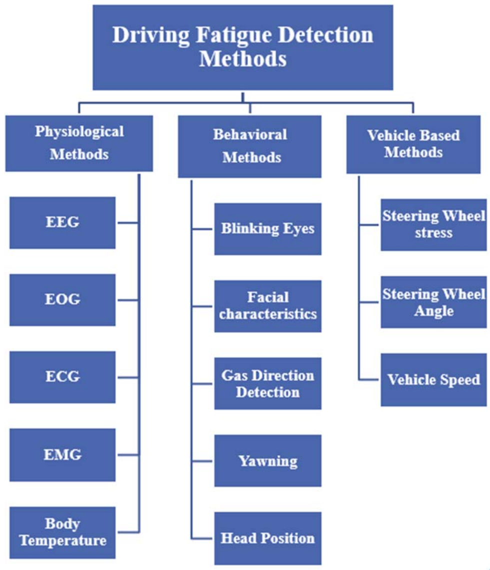

Fig. 1 Drivers' fatigue detection methods.

With the increase of road accidents caused by driver fatigue, the global interest in this problem increased. It has been found that "providing a driver with valid and real-time feedback about their alertness is the most effective means to motivate a driver to initiate self-alerting strategies, which then improves vehicle handling" [7]. The existing solution for drivers' drowsiness detection could be categorized into three main categories. These categories are vehicle-based, behavioral-based, or physiological characteristics based (Fig.1). Some of the existing systems combine two or more of the three categories to increase system accuracy.

The vehicle-based systems depending on integrating sensors inside the vehicle structure to mainly measure

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parameter related to vehicle such as steering wheel stress or steering wheel angle to detect the drivers' fatigue. It may also be combined with a heart beats sensors or temperature detector. This method main limitation is that the driving style is varying from driver to driver and it does not work in all situations also it requires multiple sensors to operate, this method has been indicated in [8] and [9].

The behavioral methods are based on the driver's visible indicators such as facial characteristics, head position, gaze direction, or yawning. In most cases, these techniques depending on image processing algorithms to detect driver fatigue by recognizing driver face and eye blinking rate duration. Many applications apply this technique because it is simple and easy to use and only requires a camera to operate. This method main limitations are that the algorithm used to detect driver fatigue may fail to detect eye blink in some situations such as when: the rotation of the driver's head is changed over certain degrees or if the illumination of the face has changed in large quantity and so on, this method has been mentioned in[10] and [9].

The physiological methods depend on the physical characteristics of a human body such as brain activity detected by Electroencephalogram (EEG), heartbeat measured by Electrocardiogram (ECG), eye signals identified by Electrooculogram (EOG), breathing frequency, electrical muscles signals Electromyography (EMG). These physiological methods tend to have high accuracy due to their information richness. However, most of the physiological parameters are acquired through physically attached sensors which have a negative impact on the driver comfort and the system acceptance. Recently, researchers have addressed this concern by creating a physiological portable, smaller or even contactless sensors [11] and [12].

When comparing the three main categories of drivers' fatigue detection methods, it would be concluded that EEG and ECG signals based methods are the most accurate and reliable ways to detect drivers state but they are also the less flexible among other methods due to the nature of the required sensors to acquire the signals and how it would contact to drivers' body[13]. Using EEG is considered as being the gold method to identify the driver fatigue since it is highly sensitive to analyze brain activities and often used in the diagnosis and very helpful to evaluate the brain state and function. It allows to monitor driver brain waves and analyze them to detect fatigued, or drowsy, state [7]. The usual way of capturing EEG signal is by using the full 32channel of 10 -20 EEG channel Montage system (figure 2) which increases the system complexity and needs training to adjust electrodes on the head, this leads to consuming time and awkward feeling for drivers[14]. These factors make EEG based driving fatigues system not practical to apply in real life. To avoid the complexity of use and the high cost when using the full multichannel many researchers [14], [15], [16], [17], [18] and [19] tried to minimize the number of the used channel to detect driver fatigue (drowsiness) to make EEG based drivers' fatigue detection methods more flexible and accepted. The current work also tried to overcome the EEG drivers' fatigue systems complexity by suggesting an EEG based system using only one or two EEG channels.

The most important characteristic of EEG is the frequency; it assists the diagnostics of abnormalities in EEGs and for understanding its cognitive and functional behaviours. Frequency refers to recurring repetitive activity (in Hz) [20].

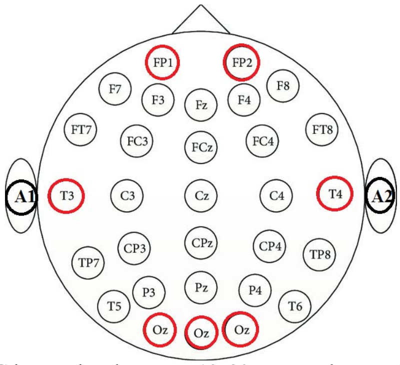


Fig. 2. EEG international montage10–20 system, the tested electrodes on the current study circled with red color.

EEG has five main frequency bands that could be distinguished, each of them related to a certain human activity [20]. These bands, as described in [20] and [21], are,

Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz) and Gamma (>30 Hz). Beta band activity is often identified clearly during relaxed wakefulness or early drowsiness [22].

Drivers' fatigue detection system generally used either machine learning technique with hand crafted features such as [14] [15], [16], [17], [18], [19] or deep learning techniques such as the proposed systems in [23], [2] or [24]. Although hand crafted feature-based systems show success in this field but it can't be adapted easily with new data [23]. So, the current study used deep learning classification technique to classify EEG signal either normal or fatigue.

Convolutional neural network (CNN) considered as one of the most important and successive deep learning methods. During the last few years, CNN shows excellent performance in the field of image classification and recognition. This performance exceeds the traditional machine learning techniques. The current study used it to classify the EEG signal of the drivers to either normal or fatigue, but the CNN expected to receive 2D or an image data type as an input, to solve this problem the author used EEG signal spectrogram to represent it as an image to the CNN. Signal spectrogram is a 2D representation of the usual 1D signal, or in other words, it is a frequency-time representation of the signal. It is a standard method used to display frequencies of a signal. In spectrograms the vertical axis represents frequency, with the lowest frequencies at the bottom and the highest frequencies at the top. The horizontal axis represents time, it runs from left to right of the axis. The colors represent the spectrograms third dimension, di□erent colors represent di□erent energy levels [25].

Ma et al. proposed a driving fatigue detection system based on EEG[23]. They used the 10-20 EEG channels standard system to capture the whole EEG 32 channels and use the whole 32 channels as an input to the system. They use PCANet classifier which was proposed in [26], but they used it as feature extractor then the output of the PCANet fed to two different classifiers to test both of them. This technique is one of the transfer learning techniques called freezing the convolutional base. Those two classifiers are SVM and KNN. The best classification accuracy reached 95%.

In [2], Guarda et al. proposed their own Deep CNN classifier. They used the 10-20 EEG channels standard system to capture the whole EEG 32 channels, but they only used Fz and Pz channels as an input to their proposed system. They started with converting the selected two channels to the spectrogram representation and convert it to its gray level

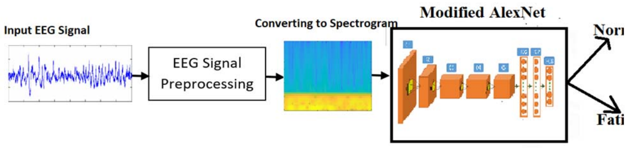


Figure 3. The proposed driver fatigue detection system architecture.

representation. The proposed Convolutional net model consists of three convolutional layers, each followed by a pooling layer then ended with two fully connected layers. They reached 86% of average accuracy classification ration.

Budak et al.[24] proposed a complex hybrid model for driver fatigue classification. Their classifier consisted of three basic blocks, where the final result is the fusion of the three blocks through a voting layer. They used three combination of the 32 EEG channel. These combinations are C3-O1, C4-A1 or O2-A1 channels. Two blocks of the classifier based on long-short term memory (LSTM)network. While the second block based on transfer learning it used EEG spectrogram as an input, then used AlexNet and VGG16 deep nets as a feature extractor and their output also fed to a LSTM network. The third block used EEG signal as an input and fed it tuneable Q-factor wavelet to get the mean and standard deviation of each sub-band separately, then feed then to a LSMT network. Finally, the output fused to get the final result. The maximum accuracy for each block separately reached 88.47%, while the fused output of the three blocks reached 94% present of correct classification. the This system reached 94% present of correct classification.

To summarize the proposed work, firstly the raw EEG signal filtered to limit its bandwidth between 0.5 and 45 Hz as this is the interested band to the current study, then each 1 sec. (sampling rate 1000 sample / second) length of the signal is converted to a 2D image representation using spectrogram. The current work used Short-time Fourier Transform (STFT) to get the signal spectrogram. Finally, the spectrogram image fed to the a modified AlexNet CNN model using transfer learning to classify it either Fatigue or Normal. The current work compared the accuracy of using the seven channels. These channels are FP1, FP2, T3, T4, O1, O2, and Oz. The current work compares the different EEG channels accuracy with the AlexNet CNN classification method to identify the highest effective EEG channels on driving fatigue.

The rest of this paper is rest of this paper is organized as follows: section II introduces the proposed system architecture; section III shows the results and finally section IV introduces the conclusion.

II. The Proposed System Architecture

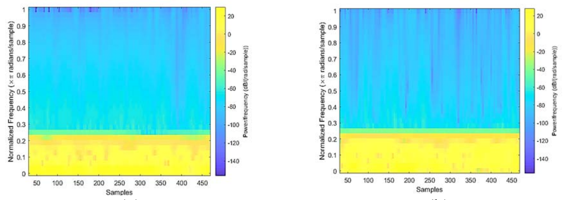
A. System overview

The proposed driver fatigue detection system architecture shown in figure 3. The system starts with feeding the raw EEG input signal to the system preprocessing stage, then the filtered EEG signal converted to the 2D spectrogram representation and finally, fed to the modified AlexNet [27]CNN model to classify it either as Normal or Fatigue driver state. The author chose to test seven channels out of the 32 channels of the EEG international montage 10-20 system. Those seven channels are FP1, FP2, T3, T4, O1, O2, and Oz. The seven channels chosen to be on the head circumference. The reason for this selection is to suggest only one of two of them to be used with simple wearable head bandage instead of the full 32 EEG channels.

The current work mainly aims to use transfer learning using AlexNet[27] CNN architecture model to classify the driver's EEG signal either Normal or Fatigue.

B. EEG Signal Pre-processing

The process started firstly with the EEG signal pre-processing. Band-Pass filtering was applied to the signal to remove noise below 0.5 Hz and limit the frequency higher than 45 Hz. Then the signal is downsampled from 1000 sample/sec. to 500 sample/sec. Then for each (500 sample size), the spectrogram is calculated, the current study used Short-time Fourier Transform (STFT) [28].For each channel, from the selected seven channels, this resulted in 3440 spectrogram image file for each class (Normal or Fatigue). Figure 4 shows a sample of EEG signal for FP1channel of.



(a) (b)

Fig .4 A sample of channel FP1 of EEG signal, (a) Normal signal and (b) Fatigue Signal.

C. The Used Dataset

The used dataset was exported from [29] web site as described in [29] and also in [30]. The dataset recorded using a static driving simulator in a controlled lab environment. The records include two states of drivers Normal and Fatigue in cnt file format. A twelve subjects participated in this dataset recording. All the twelve subjects were young, healthy men, whose ages ranged from 19–24 years, participated in a highway-driving simulator experiment. The data was recorded with a 32-electrodes Neuroscan data acquisition device as reported in [29], and the international 10–20 system was used for the EEG collection protocol. All Channels signal were digitized at 1000 Hz from a 32-channel electrode cap (including 30 effective channels and two reference channels) based on the international 10–20 system. Finally, the EEG signal had been stored in a computer for the offline analysis. The current study used only a set of channels on the head circumference. These Channels are FP1, FP2, T3, T4, O1, O2, and Oz).

D. Transfer Learning

Transfer Learning is a well-known machine learning technique where a pre-trained neural network is used to solve a problem that is similar to the problem the network was initially trained to solve. Transfer learning is a commonly used technique with deep learning as it can overcome many problems associated with deep neural. Using transfer learning can reduce the training time, reduce efforts of tuning many hyperparameters. It is also suitable to be used in case of a relatively small dataset for training to avoid overfitting problems [31].

The use transfer learning with deep learning based on repurposing the pre-trained model for a new problem, similar

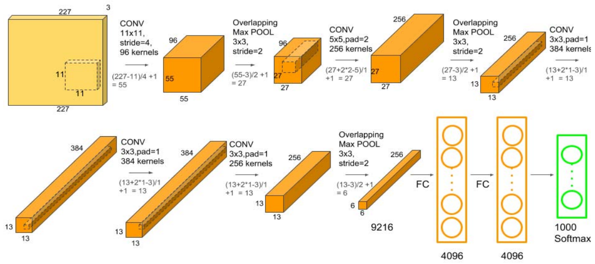


Fig.5 General architecture of AlexNet model and its' weights size[13]

to that was originally designed for, and it starts with removing the original classifier and adding a new classifier suitable for the new classification target. The change may reach other layers; on the current case, the last fully connected layer also changed. After modifying the model architecture, the model was fine-tuned. Fine-tuning is a common technique for applying transfer learning. Fine-tuning could be performed according to many strategies, in the current work the author selected to re-train the whole model with the new dataset.

The currently popular used techniques for knowledge transfer learning with CNN could be categorized into two major techniques. These techniques are freezing the convolutional base and fine-tuning based. The first category which is called freeze the convolutional base technique depends on using the pre-trained CNN as a feature extractor, where the output of a certain selected layer used to feed a classifier. The second category called fine-tuning usually starts with replacing the classification layer with another one suitable to the new problem and sometimes changing a part of the other layers. Then, re-training CNN, by either training the last layer or utilizing deep tuning where all the whole convolutional layers are trained[32].

With the appearance of AlexNet [33] in 2012, the use of deep and transfer learning grown and become more popular. AlexNet brought down the error rate significantly compared with the other proposed methods on ImageNet Large-ScaleVisual Recognition Challenge (ILSVRC) in 2012 [34]. This popularity extended to the fields of computer vision, medical aided diagnostics systems[35] and [36] and brain-computer interface (BCI)[37], [38] and [31]. AlexNet is a CNN consists of five convolution layers, three pooling layers, and two fully connected layers, as shown in figure 5 diagram. It contains 60 million parameters and 650,000 neurons. AlexNet has been adopted widely by many researchers using various transfer learning techniques as [32] and[35].

The current work applied transfer learning using fine tuning with the well-known AlexNet [27], figure 5 shows its general architecture. Firstly, the final classification layer was replaced with another layer according to the current classification problem it replaced with two nodes (Normal/Fatigue), the final fully connected layer size also reduced to 5 nodes. The whole net trained again with the used dataset. The author selected Adam optimizer (Adaptive Moment estimation) [39] to train the modified AlexNet. Adam optimizer is developed especially for deep neural networks, it is considered as the best optimizer for most cases during the last few years [40].

The training process required to tune many hyperparameters to reach the desired goal of the model. The model trained with Adam optimizer with initial learning rate of 0.0001, batch size of 32 and gradient decay factor of 0.7. The data set was divided into 70% for training and 30% for testing.

III. RESULTS

The system performance was evaluated using accuracy (Acc), receiver operating characteristics (ROC) curve and area under curve (AUC) [41]and [42].

These performance indicators described as follows:

$$Sn = \frac{TP}{TP+FN} \quad (1)$$

$$Sp = \frac{TN}{TN+FP} \quad (2)$$

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

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

A receiver operating characteristics (ROC) graph as defined in [42] " a technique for visualizing, organizing and selecting classifiers based on their performance." AUC shows how the performance of a binary classifier changed with the change of its threshold value. 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. ROC graphs usually used to show the tradeo between hit rates and false alarm rates of classifiers.[42], [41].

Table II, Figure 6 and 7 shows the CNN classifier accuracy and AUC respectively with each channel of the selected individual EEG channels (FP1, FP2, T3, T4, O1, O2, and Oz). As shown in the figures and table I, channels FP1 and T3, got the highest accuracy and AUC. Figure 8 shows the ROC of the individual EEG channels (FP1, FP2, T3, T4, O1, O2, and Oz) with the proposed classifier. It is clearly concluded from the ROC graph as shown in figure 8, that channel T3 and FP1 got the highest AUC. The author concluded that each one of these EEG channels (T3 or FP1) could be used separately as a single channel with the proposed classifier to detect the driver fatigue with a good performance.

TABLE I. THE ACCURACY AND AUC OF EACH INDIVIDUAL EEG CHANNEL WITH THE PROPOSED CLASSIFIER.

Channel	Accuracy	AUC
FP1	90	0.94
FP2	79	0.856
T3	91	0.936
T4	83.9	0.907
O1	70	0.81
O2	78	0.86
Oz	84	0.88

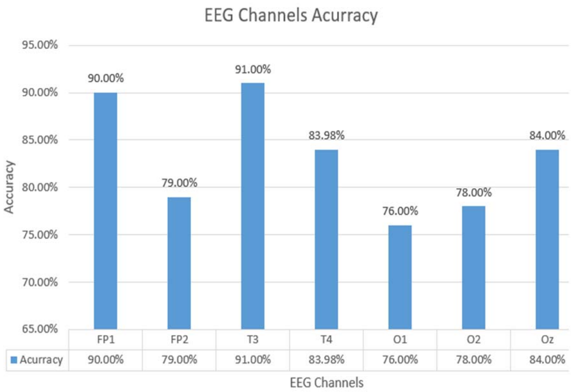


Fig. 6. The CNN classifier Accuracy for EEG channels (FP1, FP2, T3, T4, O1, O2 and Oz).

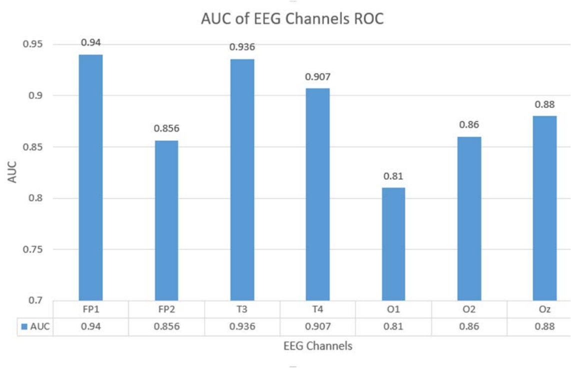


Fig. 7. The AUC for the classifier for each channel of the selected EEG channels (FP1, FP2, T3, T4, O1, O2 and Oz).

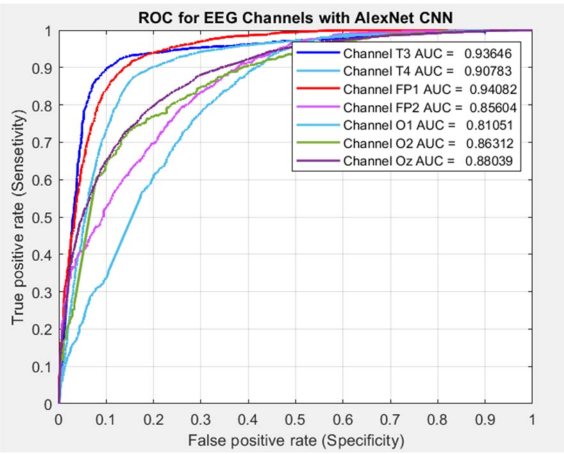


Fig. 8. The ROC of the proposed system with each individual EEG Channel.

IV. Conclusion and Discussion

The current work proposed a drivers' fatigue detection system based on fine-tuning transfer learning using AlexNet. The study tested seven out of the 32 channels of the EEG international montage 10-20 system. The seven channels have chosen to be on the head circumference. The results show that the proposed system got good accuracy for channels T3 and FP1. The author suggested to use only one of the two channels or fuse the two channels to make the drivers' fatigue detection system flexible and accepted to wear by drivers. In future a further investigation could be performed by applying transfer learning using freezing technique.

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