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Cheating Detection in E-exams System Using EEG Signals

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Abstract – Cheating in e-exams is a real problem that threatens academic integrity and undermines confidence in the feasibility of remote assessments. Many previous research papers and studies discussed the issue of cheating in e-exams to prevent or reduce it through the use of the available technologies such as the use of a web camera to monitor the examinee, some researchers proposed using specific software to restrict the examinee from accessing resources that are not permitted during the exam. This work aims to design a Semi-automatic, AI-based e-proctoring system that mitigates cheating in e-exams. This research proposed an innovative method to detect the possibility of cheating in the e-exams. This method relies on the use of IoT and the Muse2 devices to detect the examinee's physiological state and determine whether it is “Normal” or “Abnormal” through the examinee`s EEG signal, where the abnormal state indicates a possibility of cheating. Convolutional Neural Network (CNN) was used to distinguish the examinee's state. The collected data from 15 students at the fourth stage of the Computer Engineering Department/ University of Mosul ranging between 23 and 26 years old showed that there is an obvious difference between the “calm” or “Normal” state and “stress” or “Abnormal” state in the EEG signal of the volunteer. The accuracy of the system was obtained for many testing datasets. The dataset was divided into two main datasets; the 30 and 60 seconds duration time. The best accuracy obtained for the 30sec duration time was 97.37%, and 97.14% for the 60sec duration time. The researchers concluded that the EEG signal contains a lot of important information that can be utilized to detect the physiological state of the examinee and that the Muse2 device can be reliable to record the EEG signal.

Keywords – E-Proctoring; E-Exams; Cheating; Wearable Devices; EEG; Muse2; AI

I. Introduction

The trend towards electronic exams has taken a rapid expansion due to the development in information technology and communications [1]. Besides, The exam is the real assessment of a person's knowledge and for the evaluation to be fair and correct, electronic exams must be well-proctored and controlled so that there is no chance of cheating, and they must also be well-secured against cyber threats and attacks.

In previous works, we have discussed the types of e-proctoring systems, their advantages, possible threats and attacks against these systems [2], as well as the possibility of preventing cheating through the use of some applications and computer programs [3]. In this work, we will discuss the possibility of detecting cheating during exam sessions.

Many proctoring methods for online exams have been proposed previously by researchers and developers, like online webcam-based proctoring (also known as live proctoring), and biometrics-based proctoring that authenticates students depending on their biometrics and detects cheating by monitoring student`s activities such as head and eye movement, or mouse movement during the exam session. Others proposed combining several of these methods to obtain an integrated e-proctoring system.

In addition, the use of the Internet of Things (IoT) provides a lot of facilities for both teachers and students, where it enhances teachers' knowledge (through the data of learning) about their student`s performance and their learning progress, and at the same time informs teachers about the difficulties that the students may face, as well as it creates an interactive learning environment for both teachers and students.

Moreover, several techniques have been proposed and implemented that could contribute to addressing some cases of cheating in e-proctoring systems [4]–[8]. In this research, an innovative method was proposed to detect the possibility of cheating during the e-exam, we proposed to use the electroencephalogram (EEG) to detect the abnormal state of the examinee through the physiological changes that occur to him during the exam when he attempts to cheat. The examinee is expected to expose to several physiological changes during his attempt to cheat, and the EEG signals give good feedback on these changes [9], [10]. EEG signal can be obtained through the use of electrodes placed in certain places on the subject's head. These electrodes record the electrical signal of the brain. Nowadays, several commercial and medical devices are used to obtain EEG data, such as NeuroSky, Emotiv, OpenBCI, Neuroelectrics, Muse, etc. In this research, the Muse2 device was used to collect EEG signals of the examinees due to its features like ease of use, low cost, as well as its high-quality signal (more details about the device are explained later). In addition to other servers, the proposed system includes an AI server that uses Deep Neural Network (DNN) algorithms to classify the received signals into “Normal” or “Abnormal” depending on the examinee`s activity indicating if there is a malpractice or any possible cheating attempt.

II. Literature review

Many research papers presented the online proctoring systems and the factors affecting them, and many studies explored the matters that help these systems to be successful to overcome the obstacles that prevent e-exams to be smooth, reliable and safe. A systematic review was made by Karim and Shukur [11], the study focused on three main topics related to e-exams, user authentication methods, system design, and threats. The authors explored authentication methods that have been used in e-exam systems (e.g., username and password, challenge question, keystroke, timestamp, etc.) and they classified them as knowledge-based, possession-based, and biometric-based. They also presented e-exam systems in terms of authentication technologies used in these systems, and they identified three classes of these techniques, user identification, authentication, and continuous authentication, and summarized the strengths and weaknesses of these techniques. In addition, they presented threats that may occur during e-exams and may threaten the system. Finally, the study presented user authentication methods that are used in the existing e-exam systems like ProctorCam, ProctorU, BioSig-ID, SecureExam, and Webassessor. The authors concluded that the most accurate and popular method for user authentication is the biometric-based method. They also investigated that impersonation is the most type of threats that faces e-exams.

In reference [1], a study was made on e-proctoring systems and the motivational factors that motivate the transition from traditional examinations that require the physical presence of examinees toward online exams. The authors studied many factors which are considered the most motivational factors including Quality management, external conditioning, available information, attitude and intention, trust, perceived compatibility, and perceived usefulness, and as the authors thought, the trust factor (which represents security and privacy) is the most decisive factor between other factors in the process of online proctoring. The fuzzy cognitive maps (FCMs) method was used to analyse the gotten information from reviewers. According to recent studies, wearable computing can be used by teachers to enhance and facilitate their instruction while also enhancing students' access to course materials and their participation in and engagement with the curriculum [12].

In reference [13] the authors presented a multimedia analytics system that performs automatic online exam proctoring. The system hardware included one webcam, one wear-cam, and a microphone, to monitor the visual and acoustic environment of the testing location. The system included six basic components that continuously estimate the key behaviour cues: user verification, text detection, voice detection, active window detection, gaze estimation and phone detection. The authors proposed combining the continuous estimation components, and applying a temporal sliding window to design higher level features to classify whether the test taker is cheating at any moment during the exam. The authors evaluated their proposed system and collected multimedia (audio and visual) data from 24 subjects performing various types of cheating while taking online exams. The extensive experimental results demonstrated the accuracy, robustness, and efficiency of the online exam proctoring system.

In reference [12], the feasibility of using wearable devices and their contribution to improving the quality of education was studied. the authors presented the features of some devices, such as Google Glass, Muse, Virtual Reality and GoPro cameras, they also identified the obstacles and limitations that face the use of these devices in the educational process. The authors concluded that computing in education has several advantages, but it is also accompanied by some restrictions. In reference [14] the authors implemented deep learning and machine learning to recognize alcoholism disease through the EEG signal. The authors used Python to implement their proposed system. They applied various algorithms of machine learning and deep neural networks and they considered wavelet transforms and the fast Fourier transform to analyze the correlation of the signals from electrodes. The authors concluded that the deep neural network which operates only with a dataset of EEG correlation signals can anonymously classify the alcoholic and control groups with high accuracy.

Reference [15] addressed issues related to online assessments, the research included the utilization of an e-cheating intelligence agent can prevent and detect any malicious practices by using two major modules: the internet protocol (IP) detector and the behaviour detector. The authors applied several methods of machine learning like deep neural network (DNN); long-short term memory (LSTM) Dense-LSTM and recurrent neural network (RNN). The results revealed a high accuracy of 95% for the Dense-LSTM.

DEAP is a project conducted by the authors of the reference [16], the project presented a multimodal dataset for the analysis of human affective states. The electroencephalogram (EEG) and peripheral physiological signals of 32 participants were recorded as each watched 40 one-minute long excerpts of music videos. A novel method for stimuli selection is proposed using retrieval by affective tags from the last.fm website, video highlight detection and an online assessment tool. Finally, decision fusion of the classification results from the different modalities is performed.

III. MATERIALS AND METHOD

A. *Muse2 headband*

Muse2 is a multi-sensor meditation device that provides real-time feedback on your brain activity, heart rate, breathing, and body movements to help you build a consistent meditation practice [17]. The MUSE2 shown in Fig.1, is a portable EEG measurement headband that is compact and user-friendly. It is widely applicable, simple to use, and reasonably priced (nearby USD 250), enabling the recording of EEG and head movement activities outside of a restricted laboratory environment [18]. This product is offered for commercial use, such as for sleep monitoring, meditation, or other relaxation-related activities. Dry electrodes in the MUSE 2 EEG system are situated similarly to AF7, AF8, TP9, and TP10. Along with two symmetrical forehead ground electrodes, the electrode at the centre of the forehead serves as a standard reference. The MUSE2 measures brain activity signals, which are broadcast via Bluetooth serial connection to a smartphone or specially created software on a PC/laptop to enable a further online or offline analysis of the data. The MUSE2 headband has been effectively utilized to monitor EEG dynamics, such as mental stress levels, and those related to people's level of pain perception, during neurofeedback or brain-computer interface (BCI) sessions [19], [20].

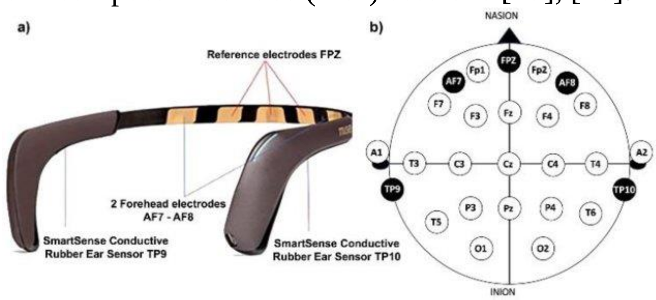


Fig. 1 a) Overview of MUSE2 headband sensors. b) The EEG electrode positions on the subject's head, a top-down view [18].

EEG brainwaves are divided into 5 bands which are Delta, Theta, Alpha, Beta and Gamma [21], as seen in Table 1.

Table 1. The power bands of EEG signal.

Power band	Frequency band	Nature of the wave
Delta	0.5Hz to 4Hz	Slowest frequency band in the brain.
Theta	4Hz to 8Hz	Observed in a state of drowsiness.
Alpha	8Hz to 12Hz	Observed in a state of relaxation.
Beta	12Hz to 30Hz	Observed in a state of active thinking.
Gamma	30Hz and above	Observed in emotional states

B. *Data acquisition*

In this study, the Muse2 headband was used to assess 15 subjects. To obtain EEG data from two various mental states; the first condition would be under calm state, while the second state would be under stress. To reduce signal noise, the EEG device would be placed as closely as possible to the participants' heads. The gadget gathers data using four electrodes; the electrodes are to be placed as shown in Fig. 1 above. The electrodes collect EEG data from the right frontal lobe of the brain, which is thought to be correlated with changes in emotion [22]. The testing must be relatively straightforward to avoid requiring the subjects to move during it. Heavy movement by the volunteers will affect the information gathered and could lead to inaccurate information. When the test begins, the participants will be relaxed. Our biggest worry is the volunteers' condition of stress. To observe the differences in the brain's waves under stress, the data collected from the second phase will be compared with that from the first condition. According to the study, stress causes a discrepancy between beta and alpha waves in the brain. The ratio's variations will be able to indicate the level of stress experienced. Stress appeared to be indicated by an increase in beta power and a reduction in alpha power [23], [24].

C. *EEG analysis methods*

EEG signal analysis is the procedure used in stress research to examine, purge, transform, and model EEG signals intending to discover relevant information, guide conclusions, and support decision-making. To measure mental stress based on EEG signals, a variety of data processing techniques have been documented in the literature. To reduce the cost, size, and dimensionality of data processing, it is crucial to choose the right analysis approach. The EEG signal analysis consists of two main stages:

1. *EEG signal pre-processing*

Before using data analysis techniques, the EEG signal goes through a lengthy preparation process to eliminate noise and artifacts. Getting useful information about the signal depends heavily on data preprocessing. Therefore, a thorough understanding of the many kinds of artifacts is necessary. Physiological artifacts are the most frequent kind of artifacts that alter EEG signals, according to Jiang et al. [25]. In addition, artifacts are a significant source of inaccurate information. Epochs can be created from the digitized EEG signal to visually identify and eliminate apparent artifacts. Researchers have used a range of techniques, including regression techniques, blind source separation (BSS), empirical-mode decomposition (EMD), correlation, windowing, and wavelet transform algorithms, to eliminate noise and distortions from EEG signals.

2. *EEG signal feature extraction*

This stage would involve the analysis of the pre-processed data; it would involve groups of time intervals, each of which would be analysed alone. Wavelet transform (WT) coefficient powers were used in [26] to extract features that have a strong correlation with mental stress. They discovered that as stress levels increased, the mean alpha rhythm power was considerably reduced. WT is a suitable technique for multi-resolution time-frequency analysis, as well. This is accomplished by breaking down the EEG signal into its frequency bands while keeping both frequency- and time-domain information. The average power and energy can then be calculated based on wavelet coefficients. The wavelet transform creates a time and frequency domain representation of the signal in addition to the frequency domain representation that the Fourier transform (FT) offers. This allows for quick access to the signal's localized information. Due to the no stationarity of EEG signals, utilizing the FT may cause minute changes in the spectrum, and the analysis may change depending on the length of the data. WT is therefore superior to FT [27]. The power spectral density (PSD), which seeks to determine the power distribution for time-domain EEG signals over a frequency range, yields important data on brain activation. PSD is particularly helpful for characterizing stochastic signal processes and assessing brief data recordings [21]. For example, fast Fourier transform (FFT), Welch, Burg, Yule walker, welch method, and periodogram are some of the techniques used to estimate the PSD [28]. The usefulness of utilizing PSD to gauge stress levels has been shown in a number of research. For instance, Al-shargie et al. [29] found that mental stress reduced the EEG's power spectral density in the band associated with alpha waves. Similar results were observed in the study in [30], which discovered a significant drop in alpha rhythm when stress levels were raised from level 1 to level 2 (based on increasing the complexity/difficulty of the math problem), and subsequently raised from levels 2 to level 3. In particular, by raising the integer numbers and operands employed in the math operation, the difficulty of the math work was enhanced from level 1 to level 3 in this manner. The right prefrontal cortex, on the other hand, is the major cortical region that is engaged in stress sensing.

D. *Data collection*

Since InteraXon stopped producing its Software Development Kits (SDK) (preventing software developers or researchers to create their custom applications), we used EEGEdu server [31] to record the brain signals in real-time, The server provides a live EEG tutorial that can be used with Interaxon's Muse and Muse2 headbands. Each channel in the headband (TP9, TP10, AF7, and AF8) records a raw EEG signal that is expressed in microvolts (μV). As a result, we have a total of four raw EEG signal data. These raw data are made up of 4 signals from the 4 channels. The five common brain wave frequency bands (Delta, Theta, Alpha, Beta and Gamma) are supported by the EEGEdu server, which also employs a 50 Hz notch filter to eliminate electrical interferences. Using the logarithm of the Power Spectral Density (PSD), this program automatically analyses the raw data arriving from each channel to produce the brain waves. Additional signals captured by the headband include accelerometer, heart rate, breath, and muscle movement sensors (allowing to record blinking and jaw clenching). However, several of these sensors are not supported by the EEGEdu tutorial or for developers [19].

E. *Classification using Deep Neural Network (DNN)*

Deep learning (DL) has lately been used to a number of domains, including computer vision, speech recognition, and natural language processing [32]. Additionally, DL has been successfully applied in EEG signals in recent years [33]. DL simulates the connections between the neurons in a brain by applying numerous iterative non-linear transformations to the data. By minimizing a cost function, the parameters of the transformations are adjusted iteratively (i.e., minimizing the error between the predicted and the real signal). Multiple neural network layers are referred to as DL. However, there is not a consensus on how many layers make it deep. In practice, several DL approaches use just three layers. In a neural network, we have neurons or units organized in these layers: one input layer, one output layer, and one or more hidden layers. The hidden layers of a deep neural network could be Fully Connected (FC, also known as the dense layer), Recurrent Neural Network (RNN), or Convolutional Neural Network (CNN). In an FC, the inputs of all neurons receive all the weighted outputs of the previous layer. Typically, every layer except the output layer is followed by a non-linear activation function (such as Relu and Sigmoid). Each neuron in an RNN receives both its own output from earlier values and the output of the previous layers. the long short-term memory (LSTM) layer is one of the most frequently employed layers in an RNN. LSTM layers keep track of the previous time step in memory. These layers are ideal for time series where the lags between occurrences are unpredictable because of this property. Neurons in LSTM hidden layers are called units, they are sited inside a cell. The LSTM cell, like RNN, has a state and may therefore recall data from the previous timestep. An LSTM receives a triplet as its common input, which consists of samples, timesteps, and features. One neuron in a CNN only accepts a portion of the output signals (the nearest outputs) from the preceding layers because the outputs are complicated (depending on the convolution of said outputs). The spatial component of the data is better detected by CNN layers, allowing them to choose the best features, whereas the temporal component is better detected by RNN layers [19]. CNN consists of 6 layers of Convolution_2D and MaxPooling2D layers after the second and fourth convolution. On all layers except the output fully connected layer, the ReLU activation function is used, and the last layer uses softmax. To regularize our model, after each subsample layer and the first fully connected layer, the Dropout layer was used. Fig. 2 shows CNN which was used in our model.

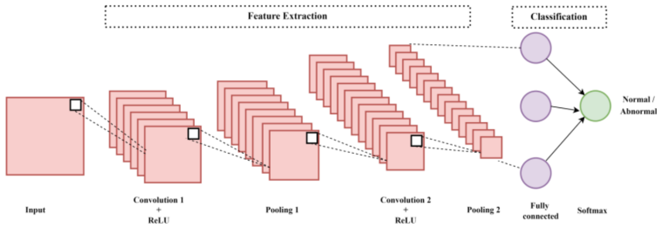


Fig. 2 CNN for the examinee`s status classification.

IV. EXPERIMENTAL RESEARCH

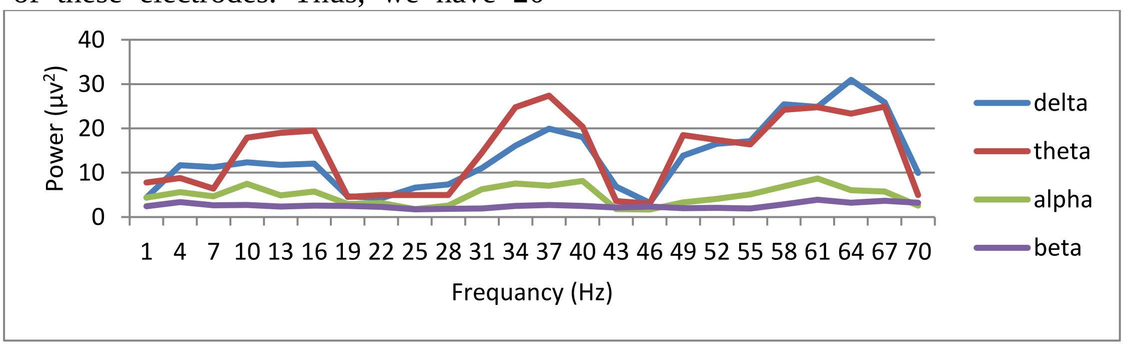
Our dataset of the EEG signals was collected from 15 volunteers from the fourth-stage students in the Department of Computer Engineering / College of Engineering at the University of Mosul, the data was recorded from the volunteers while they were attempting an experimental electronic exam, the EEG signals were recorded 3 times during the exam session for every volunteer with a duration period of 30 seconds and 60 seconds for each recording and the recordings were within the normal level, after that, some of the volunteers have been allowed to cheat, so they exposed to certain stress, and then the EEG signals were recorded again, so the signals were abnormal because the stress affected the physiological state of these volunteers (see Fig. 3). All volunteers ranged between 23 and 26 years old; they were all healthy and had an average body mass index (BMI).

As we mentioned previously, Muse2 gives several types of data recording of the body's vital activities. In this research, the power bands (delta, theta, alpha, beta and gamma) were recorded, where the Alpha and Beta bands are affected by the state of stress of the examinee during the cheating attempt. Muse2 device contains 4 electrodes, and the power of delta, theta, alpha, beta and gamma bands were recorded for each of these electrodes. Thus, we have 20 columns of recorded data with a duration time of 30 seconds, and 60 seconds, the data was obtained as an excel sheet by connecting the Muse2 device to the EEG server which receives the data and stores it in an excel sheet, and because of the high rate of the recorded data and to regulate it, the average of every column was taken and fed into the deep neural network.

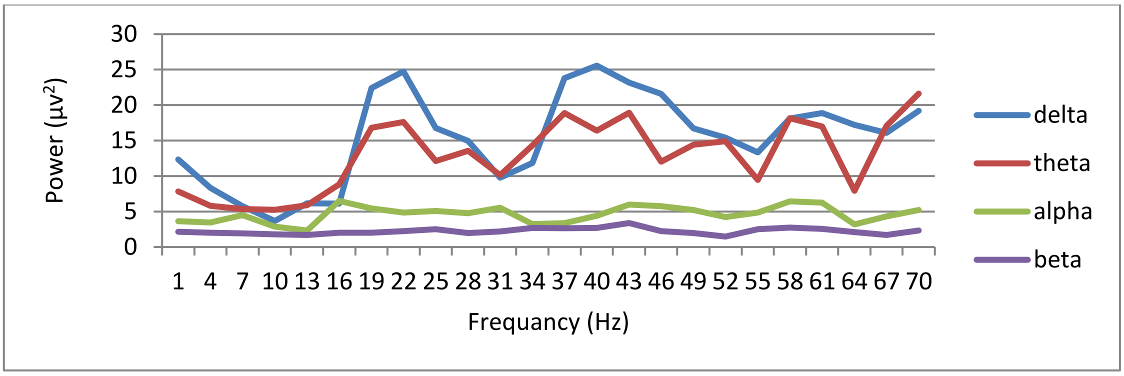
2.2 GHz core i7 is the machine which was used to implement our proposed system. Python (3.9) is the programming language which was used to apply the classification algorithms as a development tool. For classification, Convolutional Neural Network (CNN) algorithm was conducted. The recorded data taken from the volunteers was labelled as "0", and "1", where the data which were within the “Normal” level were considered "0", while the data which were within the “Abnormal” level were marked as "1". The data was divided into two parts, 70% for network training, and 30% for network testing. First of all, we divided the data into seven datasets; delta dataset, theta dataset, alpha dataset, beta dataset, gamma dataset, alpha-beta dataset, and all-bands dataset. For the dataset of 30 sec duration time, we obtained accuracy as follows; 73,68% for the delta band dataset, 63.16% for the theta band dataset, 71.05% for the alpha band dataset, 63.16% for the beta band dataset, 57.89% for the gamma band dataset, 81.58% for the alpha-beta bands dataset, and 97,37% for the all-bands dataset (see Fig. 4). Table 2. shows the obtained results of accuracy for each dataset.

Table 2. Obtained accuracy for each dataset of 30 sec duration time.

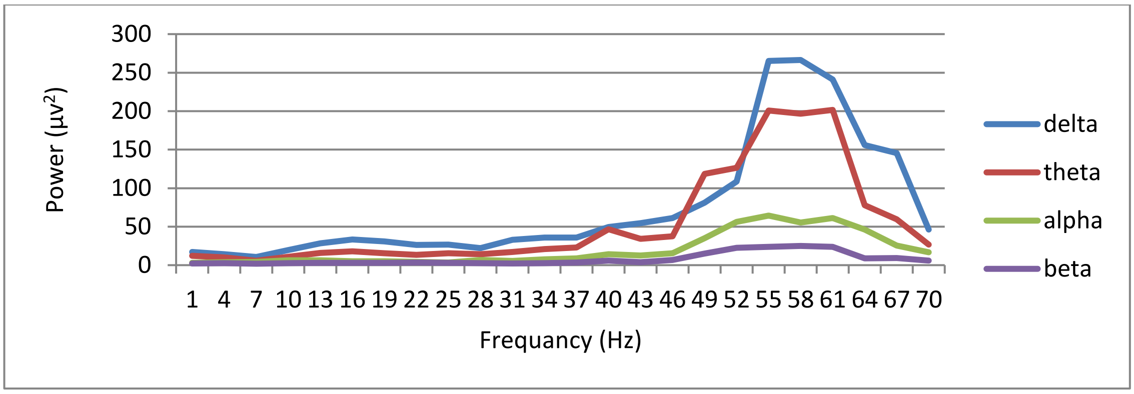
Power band	Accuracy %
Delta	73.68
Theta	63.16
Alpha	71.05
Beta	63.16
Gamma	57.89
Alpha-Beta	81.58
All bands	97.37



(a)



(b)



(c)

Fig. 3 EEG signal for the "Normal" state (a) & (b), and the "Abnormal" state (c) for the same person.

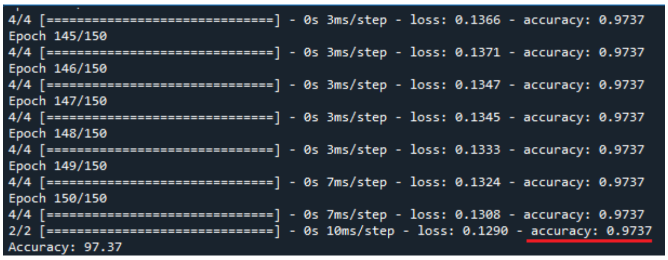


Fig. 4 Achieved accuracy of the proposed system for data with 30 sec duration time.

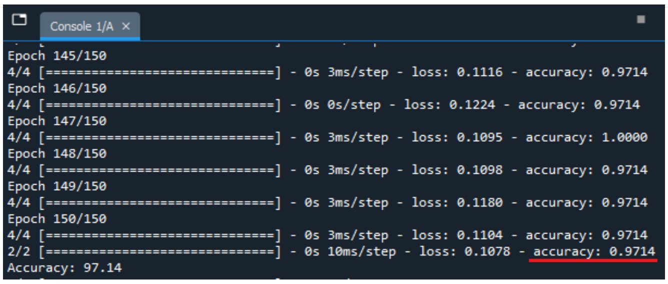


Fig. 5 Achieved accuracy of the proposed system for data with 60 sec of duration time.

For the dataset of 60 sec duration time, we obtained accuracy as follows; 51.43% for the delta band dataset, 54.29% for the theta band dataset, 71.43% for the alpha band dataset, 57.14% for the beta band dataset, 60% for the gamma band dataset, 82.86% for the alpha-beta bands dataset, and 94.14% for the all-bands dataset as seen in Fig. 5. Table 3 summarizes the results of obtained accuracies depending on the chosen power band.

Table 3. Obtained accuracy for each dataset of 60 sec duration time.

Power band	**Accuracy %**
Delta	51.43
Theta	54.29
Alpha	71.43
Beta	57.14
Gamma	60
Alpha-Beta	82.86
All bands	97.14

The system achieved a False Acceptance Rate (FAR) which represents the rate of not detecting cheating attempts and a False Rejection Rate (FRR) which represents the rate of false alarms indicated depending on the equations below:

$$FAR = \frac{No.of\ false\ acceptance}{No.of\ tests} * 100 \quad ....(1)$$

$$FRR = \frac{No.of\ false\ rejection}{No.of\ tests} * 100 \quad ....(2)$$

The Equal Error Rate (EER) was achieved at a threshold of "**0.45**", as shown in Fig. 6.

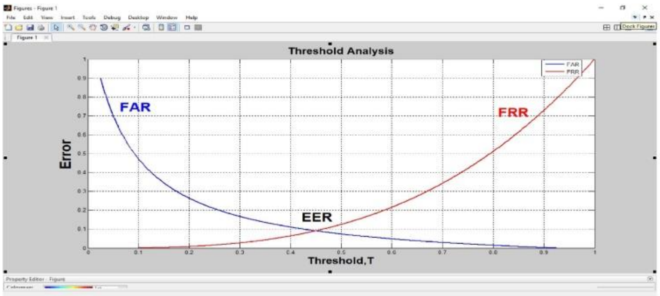


Fig. 6 EER of the proposed system.

In the e-proctoring systems, the FAR is more important than the FRR because the increase in FAR means that there are many attempts of cheating that the system has not detected, so if we increase the FRR at the expense of the FAR, we will be sure that the system has detected all the cheating attempts even if the system indicates false alarms.

V. A COMPARISON WITH A SIMILAR WORK

To validate our proposed system, we compare it with another system in the literature. Atoum et al. [13], presented a multimedia analytics system that performs automatic online exam proctoring. The system was designed to monitor the visual and acoustic environment of the testing location. The system included six basic components that continuously estimate the key behaviour cues: user verification, text detection, voice detection, active window detection, gaze estimation and phone detection. The authors proposed combining the continuous estimation components and applying a temporal sliding window, and they applied a correlation process between all the obtained signals to design higher-level features to classify whether the test taker is cheating at any moment during the exam. The authors collected multimedia (audio and visual) data from 24 subjects performing various types of cheating while taking online exams. The extensive experimental results demonstrated the accuracy, robustness, and efficiency of the online exam proctoring system. Table 4. Shows a comparison between our proposed system and Atoum et al. system.

VI. CONCLUSION

- AI technology can be utilized with wearable devices to implement a reliable, robust, and efficient e-proctoring system, hence enhancing remote learning.
- Muse2 is a good, useful, and cheap wearable device to record EEG signal for processing and analysis. Multi forms of brain wave signal measures can be obtained by using this device like: Heart beats, Heart rate, Frequency spectra, Frequency bands, Spectrogram, etc.
- EEG signal contains a lot of important information that can be utilized to detect the physiological state of the examinee.
- The most volatile bands are observed in the Delta and Theta bands, in contrast to the Alpha and Beta bands where they are more stable, and the more affected power bands by the stress are the Alpha and Beta bands.
- The duration of recorded data fed to the DNN did not affect the accuracy of the system, where the accuracy of the 30s and 60s of duration was almost the same as obtained in the results, and a more accuracy rate was achieved when a combination of all the bands.

Table 4. A comparison with a similar work.

Features	Atoum et al. work [13]	Our work
Work description	The system presented a multimedia analytics system that performs automatic online exam proctoring.	Design of an innovative e-proctoring system using AI algorithms and Muse2 EEG device.
The system hardware	The examination room`s hardware included one webcam, one wearcam, and a microphone.	The examination room`s hardware included one 360º webcam, one webcam with a microphone integrated into the examinee`s device, and a wearable EEG device (Muse2).
Components	The system included six basic components that continuously estimate the key behavior cues: user verification, text detection, voice detection, active window detection, gaze estimation and phone detection.	The system included one component which detects physiological changes in the vital activity of the test taker.
No. of data types that have to be diagnosed	Two types of signals, audio and visual signals.	One type, EEG brain wave signal.
No. of subjects	24 subjects.	15 subjects, each with four times of data recording with 30sec and 60sec duration time.
Signal analysis methods	The authors applied a correlation on the combined signal of all six components.	Power spectral density (PSD) is the method that is usually applied to the EEG signal, we collected the data through the EEGEdu server which automatically processes the raw data coming from each channel to obtain the brain waves, using the logarithm of the power spectral density (PSD).
Classifier type	Support Vector Machine (SVM).	Convolutional Neural Network (CNN).
Using of lockdown browsers	Free of lockdown browsers due to the use of active window detection method.	We suggested the use of SEB because of its advantages and benefits.
Achieved accuracy	Many values of accuracy were obtained depending on the signal type. The top accuracy achieved for the audio signal was **99.72%**, and the top accuracy for the visual signal was **94.25%**.	Many values of accuracy were achieved depending on the power band classified and the duration time of data recording. The top accuracy with the 30sec duration time achieved was **97.37%**, and the top accuracy with the 60sec duration time was **97.14%**.

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