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Adaptive Thresholds of EEG Brain Signals for IoT Devices Authentication

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ABSTRACT In this paper, a new authentication method has been proposed for the Internet of Things (IoT) devices. This method is based on electroencephalography EEG signals, and hand gestures. The proposed EEG signals authentication method used a low price NeuroSky MindWave headset. This was based on choosing the adaptive thresholds of attention and meditation mode for the authentication key. Hand gestures to control authentication processes by using a general camera. To verify that a new authentication method is widely accepted, it must meet two main conditions, security and usability. The evaluation of the prototype usability was based on ISO 9241-11:2018 standards usability model. Results revealed that the proposed method demonstrated the usability of authentication by using EEG signals with the accuracy of 92%, the efficiency of 93%, and user satisfaction is acceptable and satisfying. To evaluate the security of the prototype, we consider the most important three threats related to IoT devices which they are guessing, physical observation, and targeted impersonation. The results showed that the password strength, using the proposed system is stronger than the traditional keyboard. The proposed authentication method also is resistant to target impersonation and physical observation.

INDEX TERMS Electroencephalography, brain computer interface (BCI), convolutional neural networks (CNN), NeuroSky, human computer interaction (HCI), hand gestures recognition, Raspberry Pi, deep learning.

I. INTRODUCTION

In the world of the Internet of Things, smart things are in everywhere, indoor or outdoor. Therefore, simple precautions are not enough to protect against authentication key theft during the authentication process. Hence, a new method of authentication such as EEG signals is required. That is secure, invisible, imperceptible, and unimaginable.

The recent EEG devices with non-invasive, wearability, low cost, wireless, lightweight, and easy-to-use became a path of attraction and interest among researchers from various fields of study [1]. In this study, we used NeuroSky with a low-cost price nearly100 $ [2]. The main component of NeuroSky MindWave Mobile as shown in Fig.1 consists of a single EEG electrode and the ear clip.

EEG electrode is placed at FP1 in 10/20 International Standard Electrode Placement System. The ear clip functions as ground and reference to filter out the noise and focus on a brainwave. The ear clip picks up environmental noise generated from the body movement and other electrical devices such as laptops and power outlets then attenuates them. NeuroSky is based mainly on ThinkGear. ThinkGear is the name of NeuroSky's single dry sensor technology that allows the measurement, amplification, filtering, and analysis of EEG signals and brainwaves. The core of the ThinkGear technology is on-board ThinkGear chip and its built-in algorithms. ThinkGear chip takes its input from the raw brain signals using the dry electron sensor. The built-in algorithms extract the components of the EEG signals. ThinkGear built-in chip provides two types of algorithms. The first type of algorithms is to extract the raw brain wave such as alpha, beta, delta, gamma, and theta. Table 1, presents a brief description of each frequency band and the corresponding brain raw.

The second type of algorithms to extract raw activities such as attention, meditation, blink detection, mental effort, familiarity, appreciation, emotional spectrum, cognitive preparedness, and creativity. The ThinkGear technologies are also to magnify the raw brainwave signal and eliminate the noise

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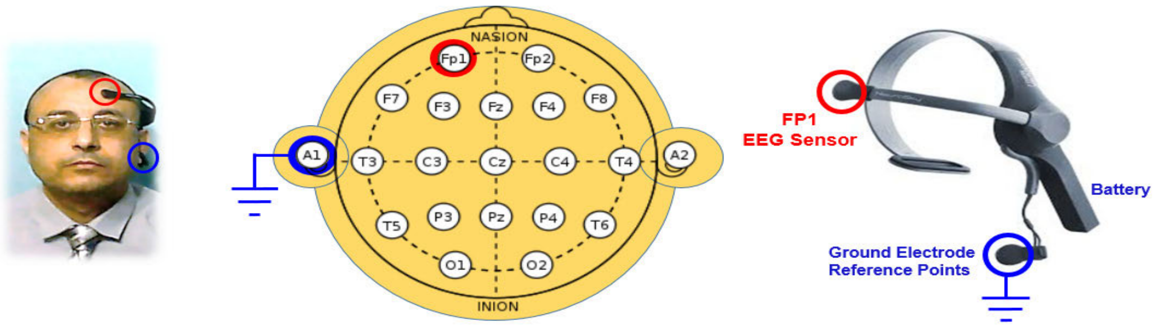

FIGURE 1. Places for the International 10-20 standard electrode placement system. (Fp1 circled in red).

TABLE 1. Main brainwave frequency bands and the corresponding activities.

Band Label	Frequency Range	Brain Activity
Delta	1 - 4 Hz	Deep Sleep
Theta	4 - 8 Hz	Meditation
Alpha	8 - 12 Hz	Relaxed and alert
Beta	12 - 25Hz	Attention and concentration
Gamma	> 25Hz	Switching between tasks

and muscle movement then send it through Bluetooth [2]. In this research, we used only two features which are attention and meditation. In this work, we suggested hand gestures to control the authentication process, facilitate, and speed up the authentication process especially that the brain signal is rapidly changing. We suggested classifying hand gestures based on lightweight CNN to create a lightweight model for compatibility with low computational and memory capabilities of IoT devices. We implemented the CNN deep learning model for hand gestures classification by TensorFlow then transformed it to TensorFlow Lite model then deployed it on the Raspberry Pi board. We used the Raspberry Pi camera for video capturing such as shown in Fig.2.

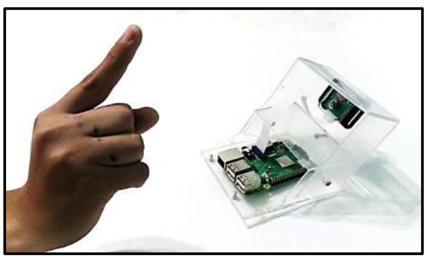

FIGURE 2. Hand gesture front of the Raspberry Pi camera to control EEG authentication.

The rest of the paper is structured as follows. In section 2 some of the significant related works are discussed. Section 3 presents the proposed EEG authentication method. Section 4 presents materials, and methods. Section 5 evaluation the proposed EEG authentication method. Section 6 results and discussion. Section 7 conclusion.

II. RELATED WORKS

Since NeuroSky MindWave appearance, has been used in many studies and researches, in the next section we will present the latest studies and research papers.

Avudaiammal *et al.* [3], Devasia *et al.* [4], Tiwari *et al.* [5] used a NeuroSky biosensor as the brain-computer interface for controlling Wireless wheelchair supporting paraplegics, quadriplegics to move from one place to another. This wheelchair is capable to move and change the direction of the wheelchair based on attention level and meditation level of mind and to control home appliances like light, fan through eye blinks.

Ruşanu *et al.* [6] proposed a simple chat application based on the counting of the voluntary eye-blinks acquired by a NeuroSky headset. One eye-blink determines the transition across emoticons/buttons, while two eye-blinks enable the selection of the emoticon corresponding to the desired information.

Ramírez-Noriega *et al.* [7], present an investigation that develops an Application Programming Interface (API) for a Brain-Computer Interface through the use of two MindWave NeuroSky headsets at the same time. The research designed and implemented a two-person attention game to test the operation of the two headsets. The results of the experiment were satisfactory since the API did not generate conflicts during the connection of both headsets.

D. L. Cuesta *et al.* [8] used NeuroSky to development of a Brain-Computer Interface Educational (BCIE) system. The system allows attention values to be obtained when the student interacts with different activities.

Jadon and Natarajan [9] in this paper, the methods used for preprocessing, feature extraction, classification, and conversion of signals into commands for typing done using the On-Screen Keyboard available on Windows Operating System by using single blinks is acquired from the NeuroSky MindWave headset.

Bala *et al.* [10], Rajmohan *et al.* [11] represent a brain-controlled EEG system for home automation that is designed to help physically disable and paralyze people. After the final implementation of the project, it can be observed that the attention level can be detected with 90% accuracy, with a blink rate accuracy between 60-70% which outweighs the performance of other conventional devices used for a similar purpose. Moreover, we were able to control the switching between 3 TV channels effectively with insignificant error and higher sensitivity.

Vardhan *et al.* [12] this work was to diagnose Insomnia using a single-channel Electroencephalogram (EEG) signal and to suggest some music to enhance sleep quality.

Nasir *et al.* [13] proposed EEG based human assistance rover for domestic application the rover uses this attention level and eye blink to control the rover wheel and a 5 degree of freedom (DOF) rover arm. The user controls the rover wheel and arm by changing the attention level and giving a different number of eye blinks simultaneously. This rover could be used to move an object from one place to another by controlling both the rover arm and wheel portion. This rover has a real-time IoT-based pulse monitoring system and a smoke detection system with GSM-based SMS alerts.

Sultanov and Ismailova [14] this work considered data from EEG rhythms in the eyes closed at rest and the eyes open condition during dynamic movements in real-time soccer training. The participants included professional male soccer players. Results from this study showed a reduction in the power spectrum of EEG rhythms during soccer training compared to the rest condition and demonstrated statistically significant differences (pp<0.03) between the rest and during dynamic movement conditions obtained as the summary value of bands in EEG power spectral estimates (1–50 Hz). In addition, the findings are interpreted to suggest that delta rhythm is a plausible neurobiological index of physical fatigue during sports training among soccer players. These findings encourage the application of wireless portable EEG systems for studies of brain functions among sportspersons.

Chaisricharoen *et al.* [15] this study identified the effect of Oolong tea during book reading state through the eSense meter values, including attention and relaxation. As a result, it indicates that some seniors have a change in the level of cognitive performance, while some participants remain at the same old level. It concludes that Oolong tea has a different effect on senior's cognitive performance in this study. Therefore, it is necessary to improve their learning ability in the long term.

Donmez and Ozkurt [16] the objective of this research is to classify the emotions by visual stimulus by using CNN (Convolutional Neural Networks). Therefore, in this study, the participants are presented with a video containing funny, scary, and sad excerpts, and simultaneously EEG signal is measured by NeuroSky MindWave EEG Headset. The result indicates that the spectrogram of EEG signals succeeds to classify three emotions are classified.

Benazzouz and Boudour [17] this paper attempts to show that it is possible to develop smell-based applications. The challenge is to infer correct smells from electroencephalography (EEG) signal, considering that a relationship between EEG data and smells was not admitted beforehand. In this work, a deep learning classification model is explored to deduce correctly the type of odor the user is smelling. Primary results are encouraging at least for a small-scale experiment.

Supoo and Sittiprapaporn [18] the objective of this study was the study of brainwave activity and cognitive performance by meditation yoga. The study design was experimental. This study compared the brainwaves of healthy people both before and after practicing meditation yoga. The results revealed that the post-test scores of all ten healthy people that practiced with 21 meditation postures yoga program had meditation and attention score higher than before training with a significant difference at 95% confidence level.

Aboalayon and Faezipour [19] this present paper is devoted to developing an easy-to-implement sleep stage classification algorithm that works fast (near real-time) in a proficient way. The results of analyzing our algorithm show that the run-time performance of this detection technique is quasi-linearly proportional to the size of the input samples and the execution time is fast, regardless of the time recording the data.

Li and Cha [20] In this paper, a new approach to extract features for EEG based biometrics is proposed, which can achieve high accuracy and efficiency. The proposed method uses the high order statistic and different entropy as features.

Abo-Zahhad *et al.* [21] In this letter, a novel technique is adopted for human recognition based on an eye blinking waveform extracted from electrooculogram signals. For this purpose, a database of 25 subjects is collected using the Neurosky Mindwave headset. Then, the eye blinking signal is extracted and applied for identification and verification tasks.

Al-Kaf *et al.* [22] In this study, they aimed to assess the effect of using NeuroSky Mindwave Mobile headset 2 on pulse rate variability (PRV) as a measure of relaxation in addition to the in-App real-time data. Six participants were recruited and provided information about the study once they contacted the university. Participants were required to use the brainwave visualizer application as part of the NeuroSky suite for relaxation for 10 minutes. They obtained multiple parameters including the average value of the inter-pulse intervals, standard deviation, root mean square of the successive differences, and stress index. The stress score from the MMH2 screen indicated a decrease in overall stress by the participants. RMSSD decreased from pre-MMH2 to Post-MMH2 (4.6±5.9; 2.9±0.9; p=) whilst the Kubios Stress Index decreased as well (0.74±1.5; 0.44±1.1, p =) MMH2 can be used to help reduce stress and anxiety levels, making it a potentially useful tool for home use.

Nasir *et al.* [23] In the work. Neurosky Mindwave Mobile 2 headset is used for collecting the desired brain data. This headset collects brain data and sends the data wirelessly to the main PCB circuit board using a Bluetooth module. The headset gives the output of attention level and number of eye blink based on EEG waves. According to the attention level and eye blinks, the system controlled Light, Fan, TV, Buzzer.

III. THE PROPOSED SYSTEM

The proposed system consists of two main parts. First, the EEG signal processing and, secondly the hand gestures. The following subsections provide an in-depth explanation for each part, such as shown in the following Fig. 3.

A. EEG SIGNAL PROCESSING

In this part, the signal passes through three stages, which are EEG signals acquisition, signals capture, and finally signal conversion, which is used to convert attention and meditation activity levels to binary digits. Then we present the proposed method to adapt threshold values. The following subsections provide an in-depth explanation for each stage.

1) SIGNAL ACQUISITION

In this work, the signal acquisition process is done using ThinkGear. ThinkGear chip takes the raw brain signals as input from the dry electrode sensor. Then the built-in algorithms extract raw signals for two activities, attention and meditation that are used in this research. The ThinkGear technology is also to magnify the raw brainwave signal and eliminate the noise and muscle movement then send it through Bluetooth.

2) CAPTURING EEG SIGNALS

In this study, we used the open-source library NeuroSkyPy 1.6 for capturing EEG signals [24]. NeuroSkyPy library written in python3.7 to connect, interact, get, save and plot data from NeuroSky MindWave EEG headset. This library is based on the MindWave mindset communication protocol published by NeuroSky and is tested with the NeuroSky MindWave EEG headset. Data is read in hex, then decoded. In this research, we used the NeuroSkyPy library to get the values of attention and meditation, which are received through Bluetooth port. This work, based on the two built-in algorithms in the ThinkGear chip which are the attention meter algorithm and the meditation meter algorithm. The following subsections provide an in-depth explanation for each activity meter.

a: ATTENTION

The attention meter algorithm indicates the intensity of attention or mental focus. The value ranges from 0 to 100. The attention level increases when a user focuses on a single thought or an external object and decreases when distracted. Users can observe their ability to concentrate using the algorithm. In educational settings, attention to lesson plans can be tracked to measure their effectiveness in engaging students. In gaming, attention has been used to create "push" control over virtual objects.

b: MEDITATION

The meditation meter algorithm indicates the level of mental calmness or relaxation. The value ranges from 0 to 100 and increases when users relax their minds and decreases when they are uneasy or stressed. The meditation meter quantifies the ability to find an inner state of mindfulness, and can thus help users learn how to self-correct and find an inner balance to overcome the stresses of everyday life. The algorithm is also used in a variety of game-design controls.

3) EEG BINARY CONVERTER

We proposed the EEG binary converter to convert attention and meditation modes to binary bit "1" or "0" under the control of hand gestures. The user enters binary bit with value "1" or "0" based on his mode (attention or meditation) and his threshold such as shown in Fig.4. The user enters a binary

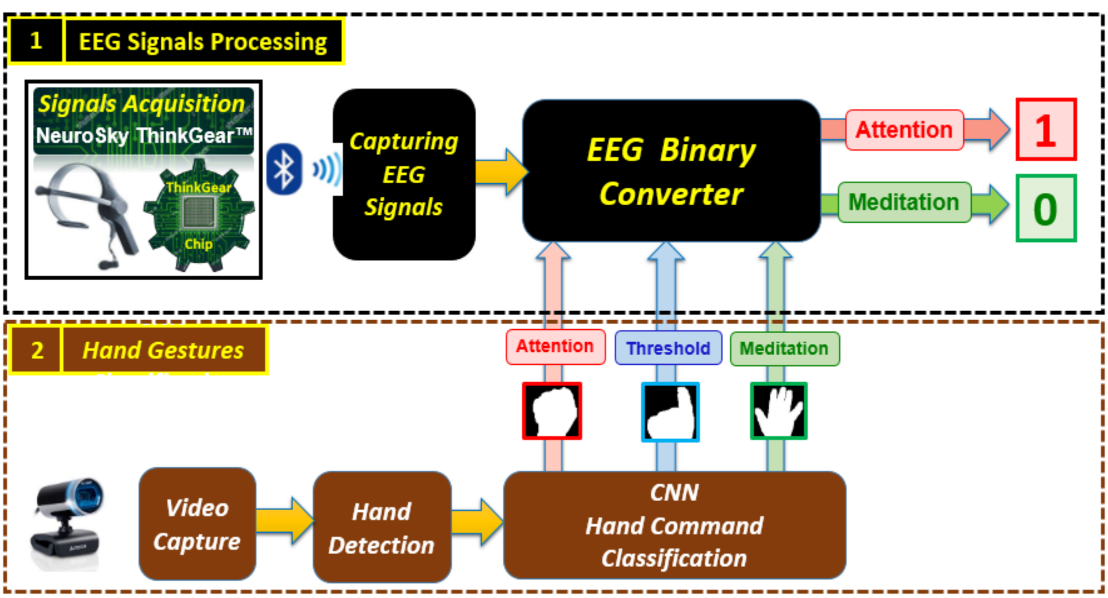

FIGURE 3. The main parts of the proposed system.

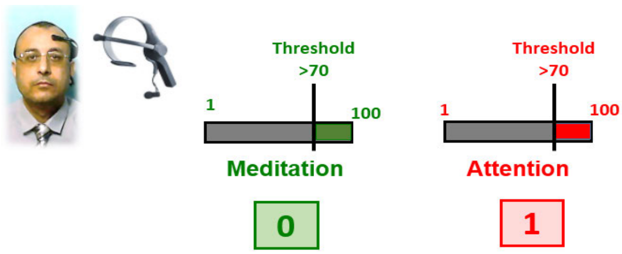

FIGURE 4. The converter of EEG signal to the binary digits.

bit with the value "0" when his meditation level reached greater than his threshold. For example when his meditation greater than 70. Also, the user enters a binary bit with the value "1" when his attention level reached greater than his threshold for example when his attention greater than 70.

To facilitate, simplify and accelerate the EEG authentication method especially the EEG signal is rapidly changing. We proposed three hand gestures to control authentication steps. The closed and opened hand gestures are used to read attention and meditation values. The opened index finger gesture is used to select the threshold value of attention or meditation. Also, hand gestures control is done without touch, which is recommended at the time of COVID-19. As was previously explained, each user can enter a different sequence of bits for his authentication such as shown in the following Fig.5. Thus, each user has a different sequence of bits and his threshold value to use for his authentication.

4) ADAPTIVE THRESHOLDS

In this study, we suggested adaptive thresholds value. This means that the user can choose different values for his threshold values for each bit or each attention or meditation such as shown in the following Fig.6. In the previous figure, the threshold for the first bit was greater than 70. The threshold for the second bit was greater than 60. The threshold for the third bit was greater than 50. The threshold for the fourth bit was greater than 80. The adaptive threshold is considered very useful for three main reasons, which are the following:

1- To make the method of authentication mechanism more confidential, we increased the number of the probabilities of guessing for one bit to 200 different values (100 for attention and 100 for meditation) such as will show in the security evaluation section.

2- To simplify the mechanism of authentication, as some values from attention or meditation, especially large values, are not easily accessible, especially for the elderly and psychiatric patients.

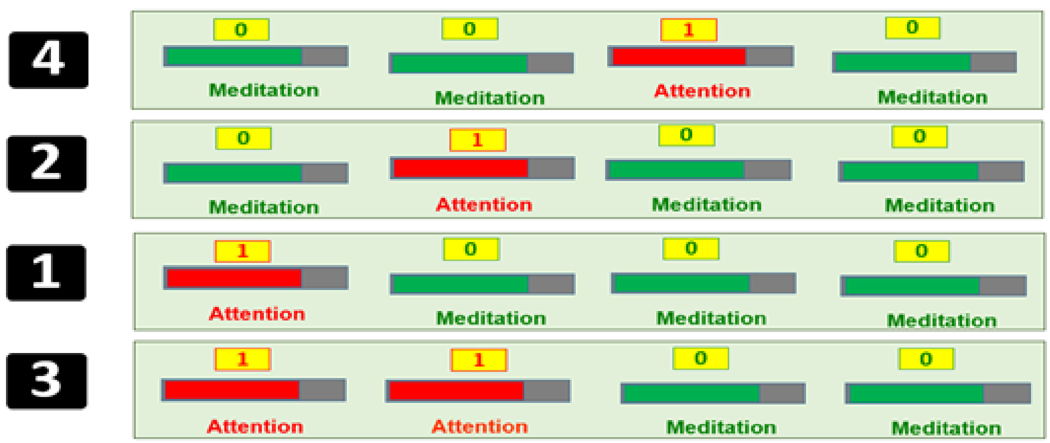

FIGURE 5. Examples of four authentications keys with a different sequence of bits.

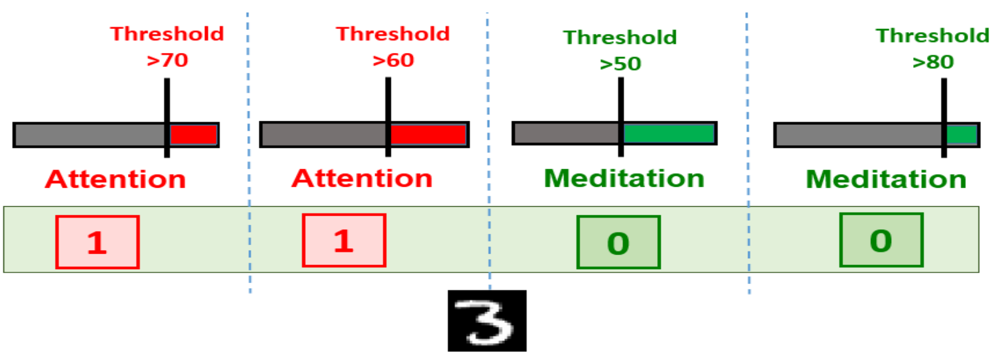

FIGURE 6. Example of adaptive thresholds authentication with different values.

3 - Creation of a new variety of scenarios for authentication by using different conditions to determine the threshold value. For example, greater than, smaller than, between, not between, or combination of two conditions for example " odd threshold and smaller than < 70 " such as shown in the following Fig.7.

Also, various scenarios make the EEG authentication process more flexible and comfortable for users.

B. HAND GESTURES

The second part is hand gestures which contain computer vision technique for hand detection then the lightweight deep CNN Convolutional Neural Network for hand gestures recognition to classify three-hand command (attention, threshold, and meditation) in real-time during when the hand in front of the camera.

1) HAND DETECTION

The target of this stage is to detect the hand based on skin color. To achieve this goal, the image is captured from the camera then passes through several filters., such as shown in Fig. 8. The following subsections provide an in-depth explanation for each part.

a: SKIN COLOR FILTER

Detecting skin color is an interesting problem in image processing. It is an important preliminary processing step for the proposed system, especially due to the difference in the color tone of the skin from one person to another. To avoid the problem of different skin tones from one person to another. We suggested that the calibration to be done before the authentication process. Calibration is done by placing the person's hand in front of the camera for five seconds. Then the camera captures the color of the skin of the hand in order to choose the appropriate range of skin tone for the user.

b: MASK STAGE (BACKGROUND SUBTRACTION)

Masking technique, an extremely powerful and useful technique in computer vision and image processing for background subtraction. We used a mask to focus only on the portions of the hand object. We apply the mask stage to find the hand in the whole image and ignore the rest of the content of the image.

c: BITWISE AND FILTER (BINARY IMAGE CONVERTER)

Bitwise operations work in a binary manner to convert images to binary images. In this filter, a particular pixel is turned off if its value is zero, and turned on if the pixel value is greater than zero. We apply a bitwise AND filter on the

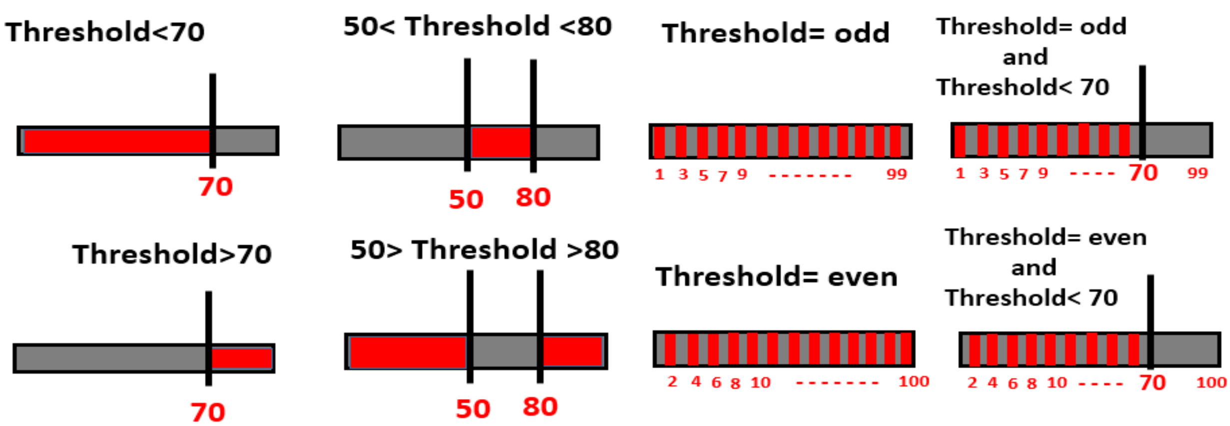

FIGURE 7. Different authentication scenarios by different conditions.

FIGURE 8. Steps for hand detection.

resulting images from the mask filter and original image. The output of the bitwise AND filter is a binary image with some noise.

d: OPENING FILTER
The opening filter is just an erosion filter followed by a dilation filter. It is used to remove noise around the hand.

e: DILATION FILTER
Another dilation filter is used to accentuate features of the hand object in the image by joining broken parts of the hand object and increasing the hand object area in the image.

f: HAND CONTOUR DETECTION
Hand contour detection was based on finding the largest contour in the whole image, which is the hand object.

2) HAND COMMAND CLASSIFICATION MODEL
Hand gestures recognition consists of two main parts, model training and model prediction such as shown in the following Fig. 9, the following subsections provide an in-depth explanation for each part.

a: MODEL TRAINING
In our work, the training images dataset was collected in two steps. First, we create a program for collecting 300 training images of three hand gestures (opened hand for meditation, closed hand for attention, and opened index finger for selecting threshold) with different situations in real-time. Second, based on the images augmentation technique we generated 40,000 artificial images for each hand gesture by using collected images in the previous step.

b: MODEL PREDICTION
In real-time, a hand gesture image is captured by the camera. Then the image passes through the processing stage to make its properties (size and black background color) like the previously trained images. Finally, the trained model predicts and classifies the image as one of the three (opened hand for meditation, closed hand for attention, and opened index finger for selecting threshold) gestures based on the training parameter of the model. Finally, the lightweight CNN with the following architectural in Fig. 10 is training on 100,000 images and testing on 20.000 images.

The proposed CNN network consists of input and output layers composed of multiple hidden layers include

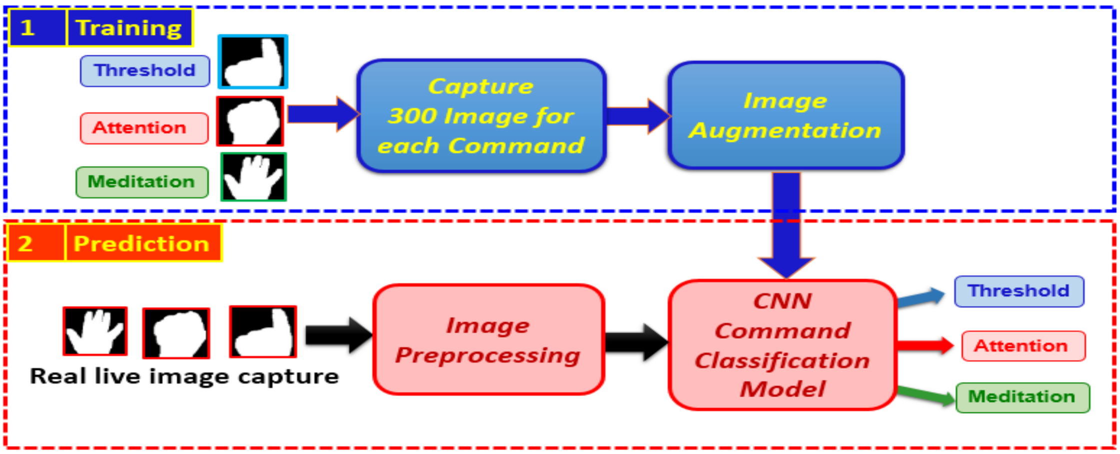

FIGURE 9. Steps of training and prediction for CNN model.

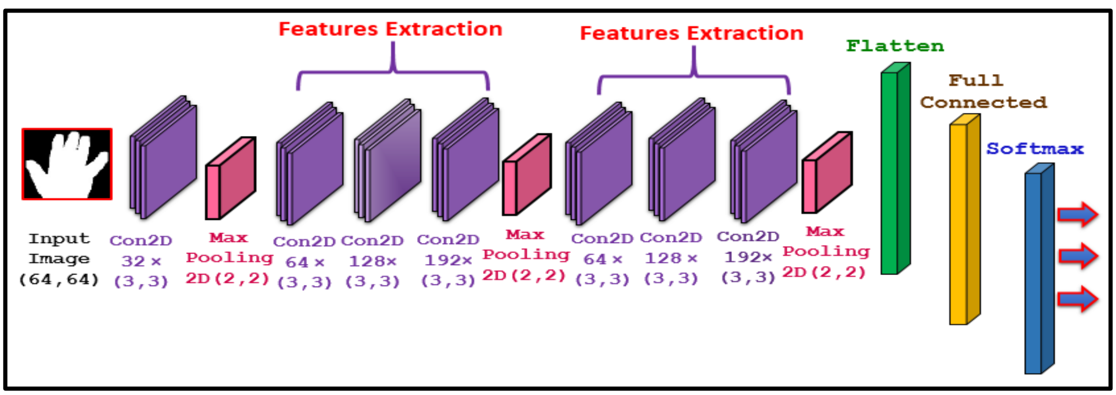

FIGURE 10. The lightweight CNN model for hand gesture classification.

convolution, pooling, and activation layers. The input layer is a 64 × 64 dimensional image. The two convolution stages consist of three layers contain 64, 128, and 192 channels, respectively for features extraction. The ReLU activation function is used for all the cases except the output layer. A dropout rate of 0.5 is used to reduce the possibility of overfitting during training. Adam is used as an optimizer with a learning rate of 0.0001 and categorical cross-entropy as a loss function. The softmax layer is used to convert the output of the fully connected layer into three classes (meditation, attention, threshold).

IV. MATERIALS AND METHODS

This section presents the overall methods that had been used in this study, from study objectives, participants, prototype development, resources required, experimental design, and experimental procedures were required for the evaluation of the new EEG authentication method.

A. STUDY OBJECTIVES

To verify that the new authentication method which based on adaptive thresholds EEG signals with four bits, and under control of hand gestures is acceptable from the following criteria:

1- Usability.
2- Security.
3- The cost time (authentication time).

B. PARTICIPANTS

The participants of this experiment were thirty (N=30) healthy users (12 males and 18 females) took part in the study. The participants have recruited a diverse range of ages and education. Their age ranging from 10 to 30 years old.

C. PROCEDURES

Before the experiment, the participants introduced themselves orally. All participants have been introduced and trained to use the brain-computer interface. The proposed system prototype is used to get the group familiar with the concept and the ways of using the new EEG authentication method. Participants were learned how to increase their attention, meditation, determine their threshold levels, and also trained to use hand gestures to control the authentication process.

D. HARDWARE

A Brain-Computer Interaction (BCI) device name NeuroSky Mind Wave headset is a single channel device that has been used in this study. Raspberry Pi board is such as an example of IoT devices. Raspberry Pi camera for video capture for hand detection and hand gestures classification to control operations of EEG authentication method.

E. PROTOTYPE DEVELOPMENT

The proposed lightweight CNN network for the hand gestures classification model was implemented, trained, and tested in TensorFlow on the Colab Google platform. The trained TensorFlow model was converted to TensorFlow Lite models to run on the Raspberry Pi board as an example of IoT devices. The GUI graphical user interface of the EEG authentication method was created by python programming language and computer vision filters for hand detection were implemented by using the OpenCV library (Open Source Computer Vision Library).

F. EXPERIMENTAL DESIGN

The experiment was done in a comfortable room. The participants were seated in a comfortable chair meter away from the screen that shows the GUI of the EEG authentication method. The EEG authentication application is controlled through attention or meditation under the control of hand gestures in front of the camera. The user can enter binary digit by his attention or meditation and select the threshold value by hand gestures such as the following two scenarios:

1) ENTERING *A* BIT WITH "1" VALUE

The user closes his hand to start read or get attention value from the NeuroSky brain sensor. Then user continues closing his hand and focus on the red circle until getting a value greater than his attention threshold. This value that appears above the circle such as shown in Fig.11

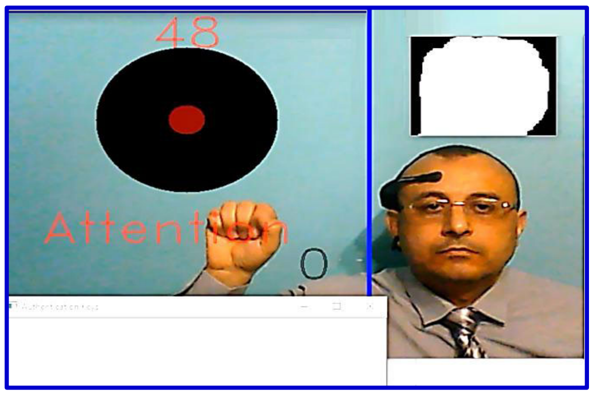

FIGURE 11. Entering one bit with "1" value by closing hand and focus on the red circle.

Then the user raises his index finger to select his attention threshold value, by that the user enters "1" in the authentication screen such as shown in Fig. 12.

FIGURE 12. Selecting the attention threshold value by raising the index finger.

2) ENTERING *A* BIT WITH "0" VALUE

The user opens his hand to start the read or get meditation. Then user continues opening his hand and meditate, relax and waits until the radius of the green circle becomes greater than his meditation threshold value that appears above the circle such as shown in Fig.13.

FIGURE 13. **Entering one bit with "0" value by opening hand and relax.**

Then the user raises his index finger to select his meditation threshold value, by that the user enters "0" in the authentication screen such as shown in Fig. 14.

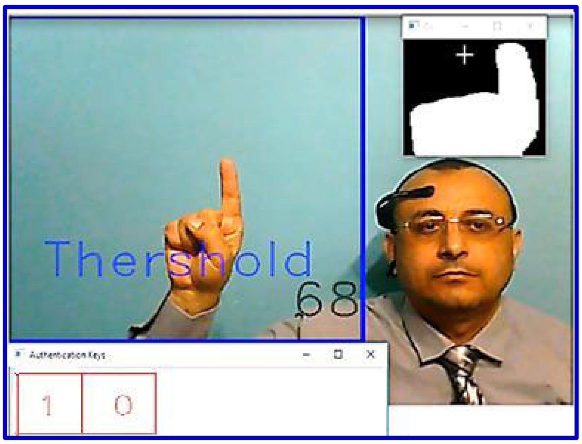

FIGURE 14. **Selecting the meditation threshold value by raising the index finger.**

G. *EXPERIMENTAL PROCEDURE*

The goal of the experiment is to assess and evaluate the usability of the EEG authentication method, which utilizes NeuroSky MindWave as a new method for IoT device authentication. Thus, as the previous section explained, the user enters 4 bits for his authentication. To evaluate the usability of the EEG authentication method each participant entered ten sequences for authentication each one consists of a different sequence of 4 bits.

H. *EXPERIMENTAL RESULTS*

The following Table 2 shows the data from the results of the experiment for the prototype.

TABLE 2. **The experiment results.**

Tasks	Task-1	Task-2	Task-3	Task-4	Task-5	Task-6	Task-7	Task-8	Task-9	Task-10
Authentication Keys	1110	1100	0111	0011	0001	1010	0101	1001	0101	0011
User-1	27	20	44	44	26	21	48	30	24	26
User-2	37	20	23	36	41	50	36	23	43	41
User-3	40	37	28	42	20	33	22	32	36	32
User-4	29	43	30	24	30	25	44	37	38	24
User-5	19	28	35	24	30	19	40	30	48	27
User-6	33	49	27	26	43	48	22	24	41	23
User-7	36	50	45	23	26	42	32	25	50	34
User-8	25	44	29	30	37	22	47	24	42	31
User-9	21	31	43	46	28	31	28	22	39	47
User-10	31	27	39	19	29	25	48	20	41	40
User-11	33	26	28	33	44	35	35	22	35	18
User-12	20	46	36	44	32	43	35	46	36	40
User-13	36	40	40	33	30	33	43	31	50	19
User-14	26	20	20	30	23	37	40	35	12	20
User-15	26	44	43	39	30	31	44	27	34	39
User-16	29	18	38	35	38	49	18	32	29	42
User-17	42	46	22	34	40	24	46	44	35	31
User-18	39	42	34	19	32	42	41	23	34	37
User-19	49	28	29	35	25	25	49	24	40	44
User-20	49	29	27	30	47	24	40	28	31	42
User-21	37	20	31	49	31	33	35	33	19	49
User-22	33	31	40	38	21	42	44	26	34	19
User-23	48	38	23	39	47	36	20	41	35	27
User-24	40	49	20	29	38	47	45	39	50	19
User-25	20	26	24	20	47	41	27	21	40	43
User-26	31	47	41	21	39	39	19	33	36	23
User-27	30	43	48	34	30	25	38	22	47	36
User-28	35	34	28	23	22	49	36	22	34	23
User-29	29	36	32	18	30	33	24	32	24	31
User-30	25	27	39	34	21	30	31	37	26	19

1- The orange cells in red indicate the failed attempts of the users and the remaining cells are the successful attempts.

2- The values in the cells represent the time in seconds to complete the task

3- Some statistical information to show the cost time of the task to enter four bits for authentication.

- The Average time for successful attempt = 33 seconds.
- The Median time for successful attempt = 31 seconds.
- The Mode time for successful attempt = 30 seconds.
- The maxim time for successful attempt = 50 seconds.
- The minimum time for successful attempt = 12 seconds.

V. EVALUATION

The goal of user authentication on the device is to prevent unauthorized access. This requires that the authentication mechanism to be secured against the associated threat models. But also, no matter how secure the system is, it will not be effective if it is difficult to use and thus is not approved by users. Thus, for the authentication method to be widely accepted, it must achieve security and usability. In this research, the usability and security of the EEG authentication method are evaluated. The usability of the EEG authentication method evaluated based on the ISO 9241-11:2018 usability standards model [25], [26]. To evaluate the security of the EEG authentication method, we consider the most three threats related to the IoT devices authentication method derived from Napa Sae-Bae *et al.*'s work [27]. The following subsections briefly present the two methods of evaluation.

A. *USABILITY EVALUATION OF EEG AUTHENTICATION METHOD*

The ISO - 9241-11 ISO 9241-11:2018 usability standards model recommends that usability metrics should include which are effectiveness, efficiency, and user satisfaction.

1) EFFECTIVENESS (ACCURACY)

The accuracy and completeness with which users achieve specified goals. Effectiveness can be calculated as the percentage of users successfully achieving their tasks vs. the total number of users: normally, as a result of coming through user tasks, users either achieve their goals or fail to achieve them. Then, overall integral product effectiveness E will be calculated as:

$$\mathbf{E} = \frac{\text{Number of tasks completed successfully for all users}}{\text{total number of tasks}} \times 100 \quad (1)$$

In this work, to calculate the effectiveness of the EEG authentication method, we proposed ten tasks for thirty participants. Each task is an authentication key that consists of a different sequence of 4 bits such as (0011, 1010, 1110, 0010, …etc.).

2) EFFICIENCY

According to ISO-9241, product efficiency is defined as "resources spent by the user to ensure accurate and complete achievement of the goals". With regards to software products and information systems, the most key measured resource is time spent by the user to achieve the goals. Efficiency is measured in terms of task time. So that, overall integral product efficiency F can be calculated as the percentage of the time in seconds or minutes the participants take that successfully complete a task vs. the total time number of all participants that successfully or unsuccessfully complete a task such as:

$$\mathbf{F} = \frac{\text{The total time of tasks completed successfully for all users}}{\text{The total time of all tasks}} \times 100 \quad (2)$$

3) USER SATISFACTION

ISO-9241 standard defines satisfaction with the product as "comfort and relevance of application". user satisfaction is measured through a formalized questionnaires featuring satisfaction scales. In this study, a survey has been distributed to the 30 users of the experiment to get their feedback to evaluate the usability satisfaction of the new EEG authentication method. The questions were designed based on the metrics as outlined by the ISO 9241-11:2018 standards [26]. We designed the survey questionnaire consists of five questions based on Likert scale questionnaire with 5 levels of user satisfaction. Each user rated the satisfaction on a scale between 1and 5 (1=strongly disagree, disagree=2, neutral =3, agree=4 and 5=strongly agree) such as shown in Fig.15. The survey questionnaire was developed based on the prototype functions and the experiment tasks of the EEG authentication method.

B. SECURITY EVALUATION OF EEG AUTHENTICATION METHOD

To evaluate the security of the EEG authentication method, we considered the most important three threats related to IoT devices are guessing threat, physical observation threat, and targeted impersonation threat, which are derived and recommended from Napa Sae-Bae *et al.*'s work [27]. The following subsections briefly present the three threats.

1) GUESSING THREAT

In this scenario, an attacker does not have access to information about the authentication credentials and attempts to guess the appropriate input credential to gain access to the system. Guessing is one of the more common threats to an authentication system. Guessing could be random or based on a dictionary. The quality or security of the authentication method based on password strength. The main challenge with the strength of the password, how easy (or how hard) it can be "guessed" by an attacker. We evaluated password strength generated by the proposed authentication method based on the electronic authentication Guideline for (NIST) Guideline National Institute of Standards and Technology [28]. NIST estimating password strength by measuring password entropy. The notion of entropy was introduced by Claude Shannon [29] as a measure of the uncertainty associated with a random variable. In other words, it is the expected value of the information contained in a message in bits. Entropy essentially measures how many guesses an attacker will need to make to guess your password. The password entropy (PE) calculates as:

$$PE = \mathrm{Log}_2 S^L \quad (3)$$

where (L) is the password length; a number of symbols in the password. Where (S) is the size of the pool of unique possible symbols (character set). Based on the previous equation, the strength of the password depends on two factors, the first: the number of possible guesses, and the second: the length of the password. Therefore, we evaluate the password strength of binary EEG by comparing it with the traditional keyboard

No.	Questions	Disagree Strongly	Disagree	Neutral	Agree	Strongly Agree
1	Attention mode is easy-use.					
2	Meditation mode is easy-use.					
3	Selecting your threshold is easy-use.					
4	Felt excited.					
5	EEG authentication method is easy.					

FIGURE 15. The five questions for user satisfaction questionnaire.

password in the two previous factors numbers of guesses and the length of the password.

2) PHYSICAL OBSERVATION THREAT

Here the attacker learns authentication credentials by monitoring the victim (during entry or later) which credentials are entered into the authentication system, with or without a digital recording device. This type of attack is called a "shoulder-surfing attack" or a "display attack."

3) TARGETED IMPERSONATION THREAT

Here the attacker attempts to impersonate the victim by exploiting knowledge about the victim's personal information. This type of attack applies to authentication systems that use information in the "what you know" and "what you" categories.

VI. RESULTS AND DISCUSSION

A. EFFECTIVENESS (ACCURACY)

The results show the overall effectiveness of the prototype is 92% which is considered acceptable, as some researchers previously indicated that the BCI effectiveness 82% [25]. The 10% increase in effectiveness can be explained because the use of the adaptive thresholds helped the users to choose the appropriate value for their thresholds, and also use the appropriate scenario for each user from the various proposed scenarios which helped the users to succeed in the required tasks.

B. EFFICIENCY

The results show that the overall efficiency of the prototype is 93% which is a high value, as some research previously indicated that the efficiency of BCI is 77% [25]. The 16% increase in efficiency can be explained by the use of the hand gesture in the control because it is quick and easy, which made users successfully achieving their tasks in a short time, especially as the EEG signal changes quickly.

C. USER SATISFACTION

1 - The first question is about the easiness of entering binary digits with the value "1" through EEG attention mode. Fig.16 shows the percentage of the neutral response is the highest with 30%, the strongly agree with 27%, and 23% for the agree response. Overall, this indicates ease of use of entering binary digit with value "1" through EEG attention mode.

2 - The second question is about the easiness of entering binary digits with the value "0" through EEG meditation mode. Fig.17 shows the percentage of the neutral response is the highest with 37%, the strongly agree with 23%, and 17% for the agree response. It is clear that the results are close to the first question, which is clear that there is no difference when using attention or meditation to enter binary digit through attention or meditation modes.

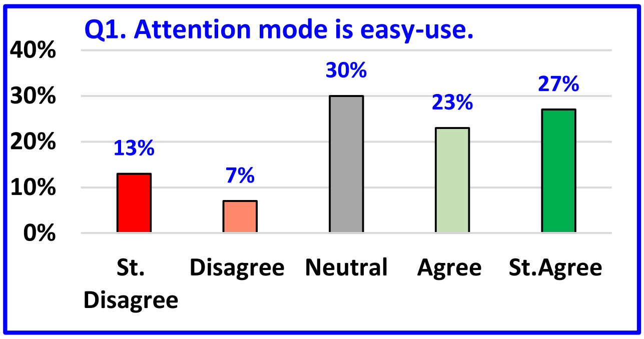

FIGURE 16. The results of the first question.

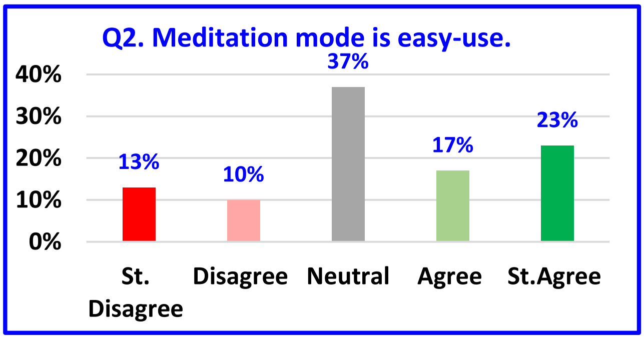

FIGURE 17. The results of the second question.

3 - The third question is about the easiness of selecting the threshold value. Fig.18 shows the percentage of the strongly agree response is 20%, the neutral with 27%, and the agree with 23%. 17% strongly disagree with the statement, this could be affected by the NeuroSky EEG Headset itself because the low quality of EEG signals of the dry and semi-dry EEG sensors. However, the overall easiness of performing to select threshold values is acceptable, especially with its low price.

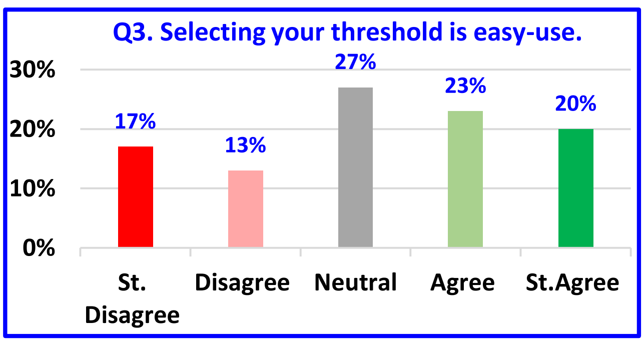

FIGURE 18. The results of the third question.

4 - The fourth question is about the users who felt excited during the experiment. Fig.19 shows the percentage of the agree response with 37%, the neutral with 30%, and 23% for the strongly agree response. The reason for the high approval

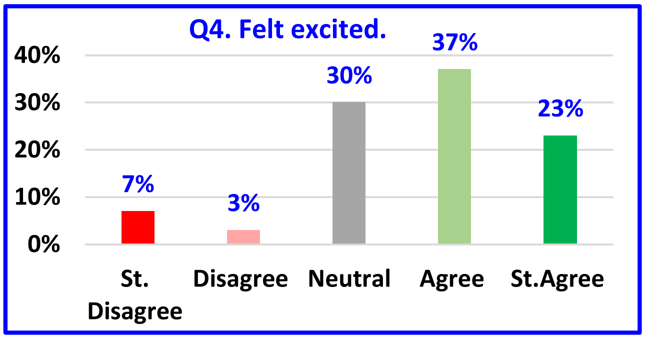

FIGURE 19. The results of the fourth question.

scores is that the users felt excited during the experiment because the users had a successor to the new technology but had never used it before and were excited to experiment.

5 - The fifth question was about the easiness of using the EEG signals for authentication. Fig.20 shows the percentage of the agree response with 50%, the neutral with 17%, and 23% for the strongly agree response. These results reflect easy to perform tasks during the experiment especially since some of the users are children from the age of ten years. Thus, generally, we can conclude that the overall usage of the prototype is acceptable and easy.

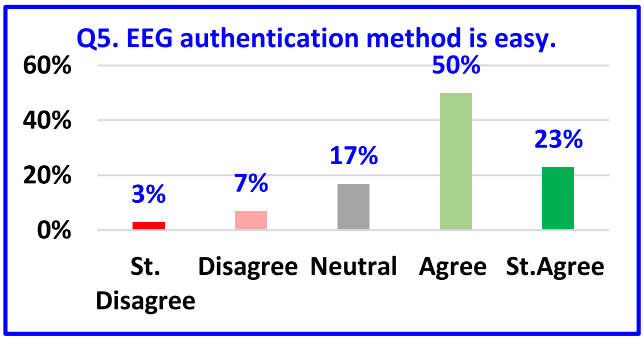

FIGURE 20. The results of the fifth question.

D. GUESSING THREAT

Therefore, we evaluate the password strength of binary EEG by comparing it with the traditional keyboard password in the two factors numbers of guesses and the length of the password.

1) FIRST FACTOR (NUMBERS OF POSSIBLE GUESSES)

Traditional keyboard writes 95 different symbols consisting of numbers, lower and upper case letters, and special symbols such as shown on the left side of following Fig.21. So based on (3) the password entropy for one ASCII symbol equals 6.56 where the size of unique possible symbols equals 95($S = 95$) and $L = 1$. But the EEG binary bit may be "1" or "0" with a threshold value from 1 to 100 for attention or meditation such as shown on the right side of following Fig.21.

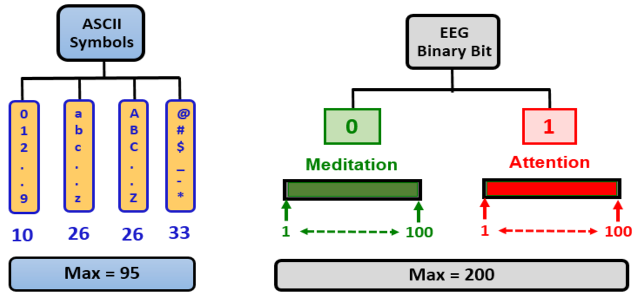

FIGURE 21. The possible symbols for ASCII and EEG binary bit.

This means that each bit can be defined by 200 different values. So the password entropy for one EEG binary bit equals 7.64 where the size of unique possible symbols equals 200($S = 200$) and $L = 1$. These results show that the entropy of one EEG binary is greater than the entropy of a single symbol from the keyboard this means that the password from EEG binary bit is more strength than a password that consists of one symbol from the traditional keyboard password by 1.08.

2) SECOND FACTOR (THE LENGTH OF THE PASSWORD)

We have calculated password entropy (Eascii) for ASCII symbols and (Eeeg) for EEG binary bit with different lengths from 1 to 8. Also, we calculated the difference between them (Edif = Eeeg - Eascii) to observe the strength of a password from one to another such as shown in Table 3.

TABLE 3. Password entropy with different lengths from 1 to 8.

Password Length	EEG Binary Bits E_{eeg}	ASCII Symbols E_{ascii}	$E_{dif} = E_{eeg} - E_{ascii}$
1	7.64	6.56	1.08
2	15.28	13.13	2.15
3	22.93	19.7	3.23
4	30.57	26.27	4.3
5	38.21	32.84	5.37
6	45.86	39.41	6.45
7	53.5	45.98	7.52
8	61.15	52.55	8.6

The result shown password entropy of EEG binary bits is greater than that of ASCII symbols with different password lengths. Also, the difference between EEG binary bits password entropy (Eeeg) and ASCII symbols entropy (Eascii) increases with the length of the password. The most important result is the password strength of the proposed system, with a length of four, from EEG binary bits is stronger than that with a traditional keyboard by 4.3.

E. PHYSICAL OBSERVATION THREAT

EEG authentication method is used electroencephalography electrical signal as a communication channel between a user and a machine. EEG signals are confidential because they correspond to a secret mental task, which cannot be observed. EEG signals do not require any physical movement or effort by the user. All of the above confirms that the (EEG) authentication method resistant to physical observation.

F. TARGETED IMPERSONATION THREAT

EEG signals are very difficult to mimic because the signals of similar mental tasks are person-dependent. EEG signals are almost impossible to steal because the brain activity producing them is sensitive to the stress and the mood of the person. An aggressor cannot force a person to reproduce the same signals while he or she is under stress. EEG signals, by nature, require a living person to produce the record. All of the above confirms that (EEG) authentication method resistant to target impersonation.

G. COST TIME (AUTHENTICATION TIME)

The average cost time or time of authentication of the prototype 33 seconds that is acceptable. Because the prototype is based on four adaptive thresholds bits or four selection consist of attentions or meditations so the average selection is four per 33 seconds.

The average number of selections of a prototype is very acceptable compared to the previous study based on BCI usage like Gaber *et al.* [30] which result was the average number of selections was 3.22 selection per minute.

We can be explained low cost time or fast selection because of reliance on the hand gesture to control the authentication process which is quick and easy.

VII. CONCLUSION

This paper proposed a new authentication method for the Internet of Things IoT devices based on electroencephalography EEG signals and hand gestures. The results showed that our proposed EEG signals authentication method in respect of usability parameters such as effectiveness, efficiency, and user satisfaction are acceptable and significant. Also, our proposed EEG signals authentication method is secure and resistant to target impersonation and physical observation. These satisfactory results indicate the usability and security of EEG signals from a single dry sensor NeuroSky's headset for using on authentication method for IoT devices. The difficulty and disadvantage of using EEG signals for authentication are that it is very weak and susceptible to contamination from many artificially created signals.

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