Computers & Security 135 (2023) 103520

Contents lists available at ScienceDirect

Computers & Security

journal homepage: www.elsevier.com/locate/cose

A robust brain pattern for brain-based authentication methods using deep breath

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ARTICLE INFO

Keywords:
BCI
Brain-based authentication
Brain-computer interface
Brain state stability
EEG signal

ABSTRACT

Security authentication involves the process of verifying a person's identity. Authentication technology has played a crucial role in data security for many years. However, existing typical biometric authentication technologies exhibit limitations related to usability, time efficiency, and notably, the long-term viability of the method. Recent technological advancements have led to the development of specific devices capable of reproducing human biometrics due to their visibility and tactile nature. Consequently, there is a demand for a new biometric method to address the limitations of current authentication systems. Human brain signals have been utilized in various Brain-Computer Interface (BCI) applications. Nevertheless, this approach also faces challenges related to usability, time efficiency, and most importantly, the stability of the method over time. Studies reveal that the stability of brain patterns poses a significant challenge in EEG-based authentication techniques. Stability refers to the capacity to withstand changes or disruptions, while permanency implies a lasting and unchanging state. Notably, stability can be temporary and subject to fluctuations, whereas permanency suggests a more enduring condition. Research demonstrates that utilizing alpha brainwaves is a superior option for authentication compared to other brainwave types. Many brain states lack stability in different situations. Interestingly, deep breathing can enhance alpha waves irrespective of the brain's current state. To explore the potential of utilizing deep breathing as a security pattern for authentication purposes, an experiment was conducted to investigate its effects on brain activity and its role in enhancing alpha brainwaves. By focusing on bolstering the permanency of brain patterns, our aim is to address the challenges associated with stability in EEG-based authentication techniques. The experimental results exhibited a high success rate of 91 % and 90 % for Support Vector Machine and Neural Network classifiers, respectively. These results suggest that deep breathing not only enhances permanency but could also serve as a suitable option for a brainwave-based authentication method.

1. Introduction

Biometrics has emerged as a compelling alternative to traditional password authentication for several decades. Various biometric authentication methods, such as fingerprints, face recognition, iris scanning, and voice recognition, have demonstrated significant success in enhancing security. However, these methods still suffer from certain disadvantages (Yousefi and Kolivand, 2019) (Alsunaidi et al., 2020; Alsaadi, 2021). As an example of biometric technology, consider the utilization of brainwave signals to control robots through Brain-Computer Interfaces, aimed at assisting visually impaired individuals in their daily tasks (Kavitha et al., 2023). This illustrates a practical and promising application of BCI technology in improving the quality of life for individuals with disabilities, offering them increased control and autonomy within their living environments through the use of an EEG-based smart home control system (Qin et al., 2020). Consequently, researchers have shifted their focus towards studying brainwaves as a potential new biometric authentication method, considering that brain patterns are invisible, potentially changeable, and could offer an ideal solution for disabled individuals.

In the pursuit of brain-based authentication, three primary EEG acquisition protocols have been explored: mental tasks, resting states,

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https://doi.org/10.1016/j.cose.2023.103520
Received 27 June 2023; Received in revised form 11 September 2023; Accepted 1 October 2023
Available online 6 October 2023

and tasks involving external stimuli (Zhang et al., 2021). Researchers have conducted experiments using various types of tasks, including finger movement, sports activities, audio listening, color identification, pass-thoughts, picturizing patterns, visual stimulus, and multi-tasking. While these studies have achieved successful results with high accuracy rates, a significant challenge remains: the reliability of brain-based authentication methods over time.

Human brainwaves are known to be non-stable during the course of a lifetime, as various events and experiences can lead to fluctuations in brain patterns. Factors such as sickness, drug addiction, high stress, mental health issues, alcohol consumption, anxiety, and other situations can affect brain functionality (Lees et al., 2020; Bremner, 2022; Satel and Lilienfeld, 2022). To address the challenge of brain state permanency, this research proposes a novel solution: utilizing deep breathing to enhance the permanency of brain patterns for authentication purposes. By focusing on Alpha brainwaves, which have shown promise in authentication applications compared to other brainwave types, we aim to achieve a reliable and enduring biometric authentication method. Our experimental results show that deep breathing significantly improves the stability of Alpha brainwaves, making it a suitable option for a brain-based authentication method that remains dependable across various mental states over time.

This paper is organized as follows. In Section 2, we provide a comprehensive literature review highlighting the gaps our research aims to address, including EEG-based authentication methods and Alpha brainwaves and deep breathing. Section 3 outlines the methodology, including data collection, pre-processing, feature extraction, and classification techniques. In Section 4, we present the analysis and findings of our study, emphasizing the achieved accuracy rates and their significance. Section 5 discusses the conclusion and the contributions of our research to the field, along with potential limitations and avenues for future exploration. Finally, Section 6 concludes with the references.

2. Literature

In recent years, Brain-Computer Interface (BCI) technology has experienced remarkable advancements across various fields, including biometric authentication and control systems. These systems hold immense potential for revolutionizing user authentication by utilizing brainwave patterns as unique identifiers. While numerous studies have delved into the feasibility of utilizing brainwave signals for authentication, a significant gap still exists in the creation of an authentication method that provides stability and adaptability across different mental states and situations.

2.1. EEG-based authentication methods

Biometric authentication using Brain-Computer Interface (BCI) technology has garnered substantial interest among researchers and scientists. BCI establishes a direct communication pathway between the brain and external devices, utilizing the brain's electrical signals for diverse applications, including biometric authentication (Hramov et al., 2021).

Electroencephalography (EEG), a non-invasive technique, records the brain's electrical activity through electrodes placed on the scalp (Niedermeyer, 2005). Brainwaves are categorized into five types based on frequency: Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–25 Hz), and Gamma (over 25 Hz), each corresponding to specific brain states (Sanei and Chambers, 2013).

EEG as a biometric authentication method remains a prominent subject of research. All biometric methods, including EEG-based ones, should meet four requirements: collectability, universality, uniqueness, and permanency (Armstrong et al., 2015). These prerequisites are crucial for utilizing brain signals in biometric authentication.

The implementation of BCI for biometric purposes offers several unique advantages. Firstly, it provides a non-invasive means of capturing brainwave patterns, enabling authentication without the need for physical contact or specific user actions. This characteristic is particularly valuable in scenarios where traditional biometric methods, such as fingerprint or iris scanning, may not be feasible or practical. For example, individuals with physical disabilities that hinder their ability to use traditional biometric devices can benefit from brain-based authentication through BCI. Secondly, BCI-based authentication methods can offer enhanced security and anti-spoofing capabilities. Unlike traditional biometrics, which can be replicated or imitated using various techniques, brainwave patterns are inherently internal and difficult to mimic without direct access to the individual's brain signals. This intrinsic nature of brainwave patterns makes BCI-based biometrics a potentially robust and secure authentication method. Furthermore, BCI presents the potential for multi-modal authentication, where brainwave patterns can be combined with other biometric modalities to further strengthen security. For instance, a combination of EEG-based authentication with facial recognition or voice authentication can create a more comprehensive and reliable authentication system (Bidgoly et al., 2020) (Zhang et al., 2021). EEG-based authentication methods have been the focus of many studies due to their potential in enhancing security. These methods involve four main steps: signal acquisition, pre-processing, feature extraction, and classification. Each step plays a crucial role in determining the accuracy and effectiveness of the authentication process. Proper signal acquisition is vital to ensure high-quality EEG data, which directly influences the reliability of the results. Researchers have extensively explored different recording protocols and tasks to elicit brainwave responses for biometric identification. Resting state protocols, mental tasks, and tasks with external stimuli have been investigated to capture brainwave patterns under various conditions (Zhang et al., 2021). The selection of an appropriate EEG recording protocol bears crucial significance as it profoundly influences the accuracy and stability of brain-based authentication (Meng et al., 2018).

Resting state protocols, where individuals sit in a quiet environment, find widespread use in EEG signal recording, particularly for authentication purposes (Di et al., 2019). These protocols often lead to the prevalence of Alpha brainwaves, rendering them suitable for authentication. Resting state recordings are advantageous due to their simplicity, necessitating minimal additional equipment when compared to other protocols. However, it is essential to conduct these recordings in a tranquil environment (Barry et al., 2007).

Tasks involving external stimuli encompass various activities such as reading different types of texts (Ruiz-blondet et al., 2014), recognizing diverse images (Zuquete et al., 2010), identifying varied geometric figures (Das et al., 2016), and observing moving and static objects (Zhang et al., 2018). These protocols offer the advantage of long-term permanency, yet they require external equipment for stimulus presentation (Zuquete et al., 2010).

Mental tasks involve imagining body movements and other cognitive activities. Imaginary tasks have demonstrated superior outcomes compared to physical activities (Das et al., 2016). Studies have explored mental tasks like counting in the mind (Kumari and Vaish, 2016) and visualizing patterns through the imagination of 2D and 3D images (Yousefi et al., 2020), all for the purpose of authentication.

Numerous studies have achieved remarkable accuracy rates by employing distinct EEG recording protocols and tasks for authentication. Armstrong et al. (2015) utilized a text reading task along with Support Vector Machine (SVM) and non-SVM classifiers, resulting in an accuracy rate of 89 %. Patel et al. (2017) employed self-photo and non-self-photo visual stimuli combined with a Backpropagation (BP) neural network classifier that utilized fuzzy entropy features, yielding an average success rate of 87.3 %. Zhendong and Jianfeng (2011) employed visual/audio stimuli, attaining a recognition accuracy of 92 % for their specific subjects. Abo-Zahhad et al. (2016) introduced a multi-level EEG system that integrated eye blinking and a Linear Discriminant Analysis (LDA) classifier based on band power spectral features, achieving an impressive accuracy rate of 98.56 %.

However, a prevailing challenge in most studies within this domain pertains to the method's stability over time, a crucial aspect to ensure the permanency required for any authentication process. Human brain signals are susceptible to changes over time due to various life events. Instances where the brain might not function optimally could hinder the creation of a stable pattern for a given task. Such instances could arise from factors like illness, anxiety, intoxication, stress, and more. This variability underscores the importance of developing authentication methods that remain reliable and consistent across diverse mental and physiological states.

2.2. Alpha brainwaves and deep breathing

The human brain comprises a complex network of billions of neurons, where the intricate interconnections between individual neurons give rise to sophisticated electrical signals. These electrical impulses, commonly known as brainwaves, underlie a spectrum of emotions, behaviors, and cognitive processes that constitute the essence of human experience. These brainwaves encompass five primary categories: Delta, Theta, Alpha, Beta, and Gamma, each characterized by distinct frequency ranges that dynamically shift in response to an individual's psychological and physiological states. Of particular note, among these brainwave categories, alpha waves have garnered significant attention due to their potential relevance in authentication applications compared to other waveforms.

Alpha brainwaves are well-suited for authentication. The reported results from studies consistently support the advantages of using Alpha brainwaves as a reliable and secure biometric authentication modality. These studies have employed rigorous experimental methodologies, including various EEG recording protocols and classification algorithms, to assess the performance of Alpha brainwaves in biometric authentication scenarios. The evaluations are in three parts as follows:

2.2.1. Stability and consistency

One crucial aspect of a reliable authentication method is the stability and consistency of the biometric signal over time. Several studies have reported that Alpha brainwaves tend to demonstrate higher stability and consistency compared to other brainwave types. The relatively consistent presence of Alpha waves in resting states and relaxation periods makes them more reliable for identification and verification purposes (Cao et al., 2020; Ren et al., 2019).

2.2.2. Permanency

Effective biometric authentication methods necessitate the biometric trait to exhibit relative constancy and endurance over extended durations. Notably, alpha brainwaves have been observed to display a heightened degree of permanency over time relative to other brainwave types, which might exhibit more pronounced variations due to external influences or cognitive states (TajDini et al., 2023).

2.2.3. Usability and practicality

Alpha brainwaves are conveniently accessible and can be elicited through uncomplicated tasks or stimuli, rendering them pragmatic for real-world authentication scenarios. Resting state protocols, frequently employed in EEG-based authentication, frequently evoke alpha brainwaves, making them an accessible and user-friendly choice for the collection of biometric data (Tran et al., 2019).

The human brain's responsiveness is shaped by diverse life events, which produce a range of cognitive states. This variability can disrupt the brain's equilibrium and lead to abnormalities from its baseline condition, particularly when experiencing stress, anxiety, or illness. To restore a state of balance, the brain struggles to regain its normative operational status. This restoration process involves moderating brainwave activity to restore the preferred frequency patterns associated with optimal functioning.

In light of these challenges, the proposed method in this paper addresses the issue of brainwave stability by introducing deep breathing as a technique to enhance Alpha brainwave activity. Deep breathing has been associated with various psychological benefits, including reducing anxiety and stress, and has a direct positive impact on Alpha brainwaves. By stabilizing brainwave patterns through deep breathing exercises, the proposed method aims to create a robust and enduring authentication system that can adapt to changing mental states over time by leveraging deep breathing-induced brainwave patterns to enhance the permanency and longevity of brain-based authentication systems (Komori, 2018).

3. Methodology

To address the research objectives, we conducted a comprehensive study that encompassed four key steps. Each step was carefully designed to contribute to the overarching goal of enhancing brainwave-based authentication systems. Through these steps, we not only aimed to investigate the effectiveness of deep breathing-induced brainwave patterns for authentication but also to establish a robust connection between our findings and the broader field of BCI research.

There are four steps in the proposed method for this project, which started with acquiring the brain signals from individuals for mental tasks including normal breathing, inhale, breathholding, and exhale; the second step was cleaning the raw data including pre-processing, and filtering by applying Finite Impulse Response (FIR) high-pass filter and Independent Component Analysis (ICA) methods. The final step was feature extraction and classification, Discrete Wavelet Transform (DWT) technique on the data for feature extraction and Artificial Neural Network (ANN) classifier for classification using Wavelet Transform and Neural Network toolboxes in Matlab software. Fig. 1 shows the whole process of the Deep Breathing (DB) method which includes 4 stages before training and testing the data. This process starts with Signal Acquisition for the deep breathing task and following that pre-processing the data using FIR and ICA methods, Feature Extraction using DWT method, Classification using Support Vector Machine (SVM) and ANN classifiers to train and test the data for authentication and verification purposes.

The proposed method contributes to enhancing the usability and stability of any brain-based authentication technique over time by introducing a deep breathing pattern. This method, irrespective of the various situations encountered in human life that may alter brain functionality, aims to restore the brain to its standard state. This restoration process facilitates the generation of brainwaves at the required frequency, ultimately yielding a distinct pattern.

3.1. Participant demographics and experimental setup

The study involved the participation of fifty healthy individuals, ranging in age from 25 to 45 years old. The selection of participants aimed to ensure a diverse representation of demographics, enhancing the generalizability of the study's findings. Participants engaged in a series of mental tasks, including normal breathing, inhalation, breathholding, and exhalation. These tasks were performed during different sessions held over three days. In each session, participants were instructed to follow specific breathing patterns, which were carefully timed and controlled.

3.2. Signal acquisition

In this study, data was collected using a non-invasive Brain-Computer Interface (BCI) device, specifically the 14-channel Emotiv Epoc + (Kumar et al., 2017). The data collection was spread across three days, with multiple sessions conducted during the morning, afternoon, and evening for each participant. Each session lasted approximately 30 min. The data collection process encompassed the following steps:

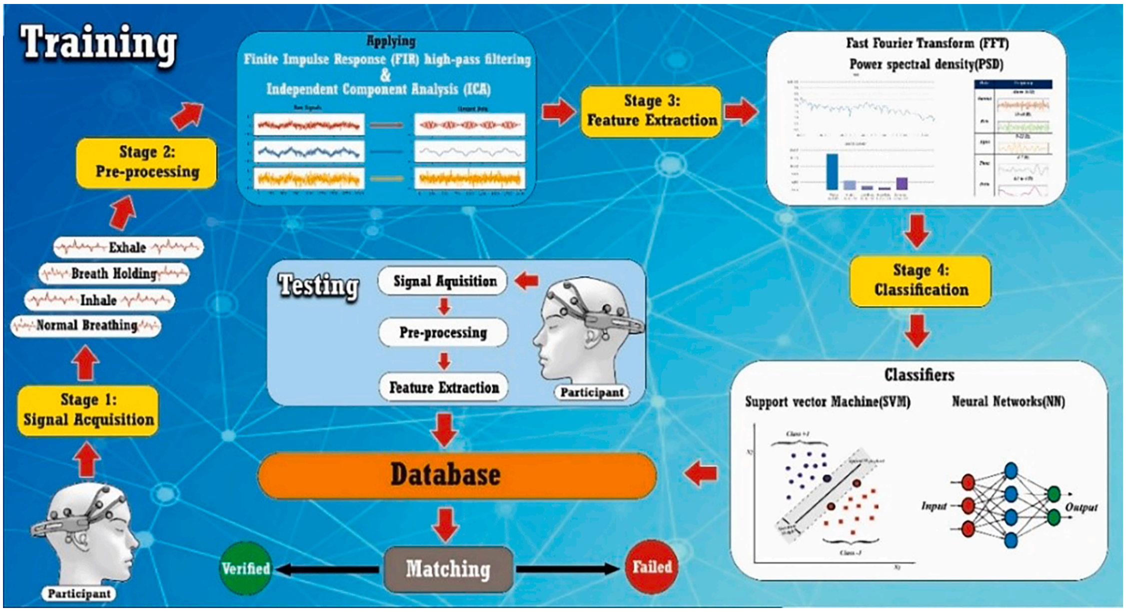

Fig. 1. The methodology of the whole process of this project.

3.2.1. Baseline recording

In the initial part of each session, participants were seated comfortably on a chair with their eyes closed. During this phase, participants were instructed to breathe normally for a duration of 2 min. The objective of this phase was to establish a baseline EEG recording under relaxed conditions.

3.2.2. Deep breathing task

The subsequent phase of each session involved participants engaging in a deep breathing task. During this task, participants followed a deep breathing pattern at a rate of six to seven breaths per minute. The deep breathing pattern consisted of approximately four seconds for inhalation, followed by a two-second breath-hold, and concluded with a four-second exhalation. Throughout each session, EEG data were captured and recorded, preserving them in their raw form for subsequent analysis. This comprehensive approach aimed to capture EEG responses under both relaxed and deep breathing conditions across multiple time slots, yielding a diverse dataset for examination.

3.3. Pre-Processing

EEG raw data represents a continuous and unprocessed signal that can be complex to interpret. To prepare it for measurement and comparison under different conditions, the data needs to undergo preprocessing to remove possible artifacts. These artifacts can interfere with the accurate assessment of the signal and noise ratio. In particular, amplitude artifacts often exceed the normal amplitude of brain data. In this study, a preprocessing step was applied to the EEG raw data to ensure its quality. A Finite Impulse Response (FIR) high-pass filtering technique (Kumar et al., 2017) was employed for this purpose. FIR is a method rooted in digital signal processing and linear time-invariant systems theory. It involves applying a sequence of weighted inputs (impulses) to obtain an output signal. FIR filters are characterized by their impulse response, which signifies how the filter responds to an impulse input. The design of FIR filters centers on determining filter coefficients that achieve specific frequency responses, such as low-pass, high-pass, or band-pass filtering. The mathematical formulation of FIR filters ensures their stability and linear phase response (Yang et al., 2021). By utilizing the FIR high-pass filtering technique, slow and large amplitude drifts were eliminated from the EEG data, enhancing the potential signal-to-noise ratio and facilitating more accurate outcomes in subsequent analyses.

The employed linear filtering technique operates by suppressing signals below a designated stopband frequency while permitting signals above a specified passband frequency. Independent Component Analysis (ICA) is a method that exhibits sensitivity to low band-pass frequency rates. Consequently, a band-pass filter with a range spanning from 0.5 Hz to 50 Hz was applied to prepare the data for utilization with the ICA technique. This band-pass filter serves to condition the data effectively for subsequent application of ICA.

For illustration, Fig. 2 presents a visual representation of the recorded data from channel 11, both prior to and after the cleaning and filtering processes. This visual aid provides a clear depiction of the impact of the applied preprocessing steps on the EEG data.

Independent Component Analysis (ICA) is rooted in signal processing and statistical independence principles. The core concept is that a collection of observed signals is a linear amalgamation of independent source signals, and the objective of ICA is to disentangle these sources. The method is grounded in the assumptions of non-Gaussianity and statistical independence of the sources. ICA works by identifying the mixing matrix that links the observed signals to the sources, thereby enabling the recovery of the original sources. This theoretical framework proves especially valuable in scenarios where disentangling mixed signals is necessary, as is the case in EEG signal analysis (Maddirala and Shaik, 2017).

After conducting a thorough examination of all 14 channels, the ICA technique was employed on the EEG data. Fig. 3 visually presents the brain component mapping across all channels, illustrating the projection of scalp maps for the selected components. Eye artifacts are a recurrent phenomenon in EEG recordings, arising from eye movements such as blinking or rapid eye motions. These movements can introduce high-frequency noise to the EEG data, warranting appropriate detection and management.

In our analysis, we harnessed Independent Component Analysis (ICA) to disentangle the mixed sources within the EEG data, with one of the outcomes being the identification of distinct components representing diverse sources of activity, including artifacts. Detecting eye artifact components on a scalp map entails recognizing distinct patterns. These artifacts typically manifest spatial alterations around the eye regions, resulting in localized shifts in EEG signal amplitude near the frontal and temporal regions. Characterized by rapid, brief occurrences, these artifacts introduce high-frequency noise. Additionally, they may

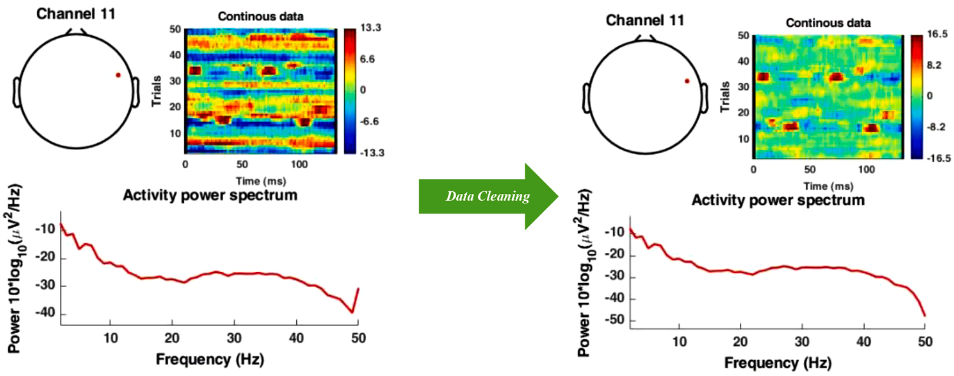

Fig. 2. An example of a cleaned data after filtering.

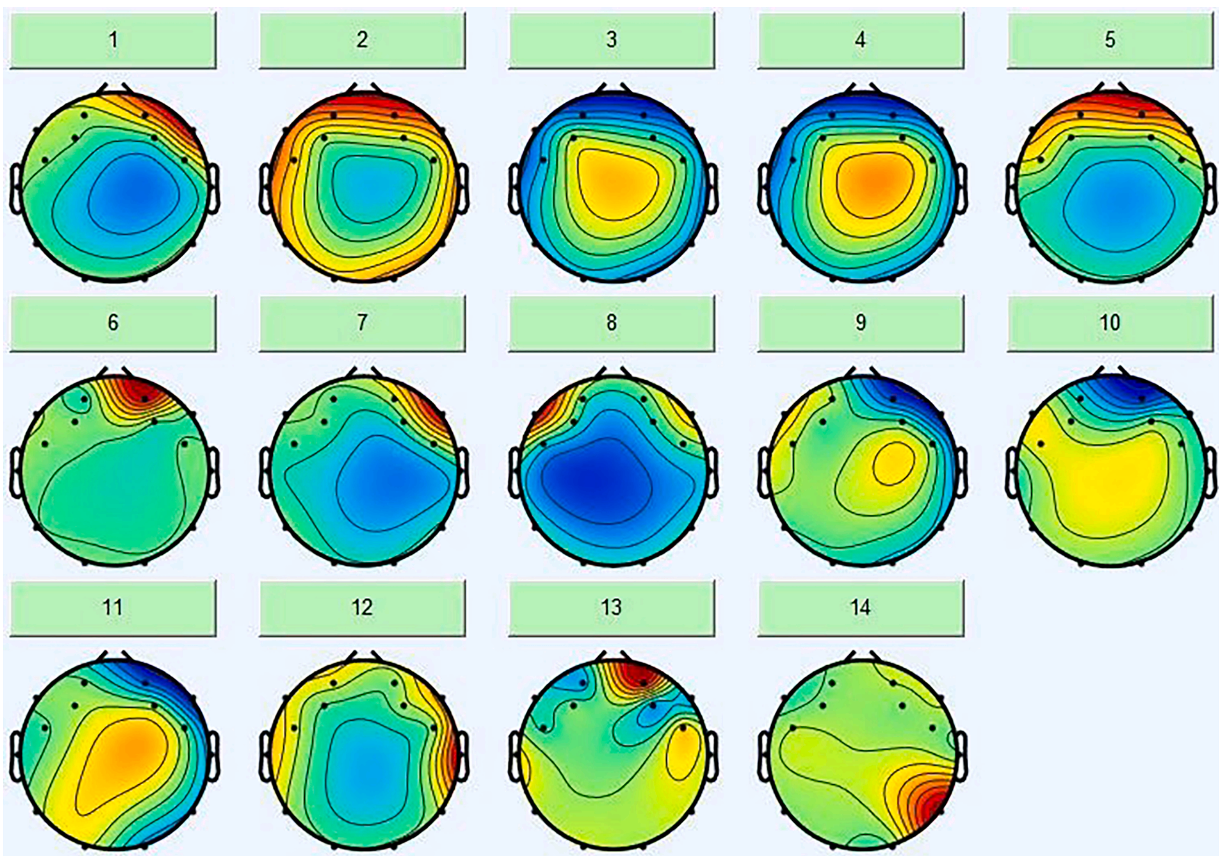

Fig. 3. Brain components map for all 14 channels after applying ICA.

exhibit contralateral distribution, indicating differences on one side of the scalp due to the type of eye movement. The identification process benefits from consistency across trials and recordings, coupled with unique topography. Expert judgment and familiarity with EEG data are instrumental in distinguishing eye artifacts from other neural activities or artifacts that might share similar attributes (Pontifex et al., 2017). For instance, an experienced observer would readily identify component scalp map numbers 2 and 5 as indicative of eye artifact components Fig. 3.

3.4. Feature extraction

The pre-processing of the data has led to an enhancement in the signal-to-noise ratio, thereby facilitating a more accurate extraction of relevant features that correspond to distinct mental states (Abuhashish et al., 2014).

Wavelet transforms, widely employed in various engineering domains, offer a versatile tool for addressing real-world challenges. A wavelet is a concise waveform with intensified energy in time, making it a valuable instrument for analyzing transient, non-stationary signals or time-varying phenomena (Übeyli, 2008). In instances where a signal experiences minimal change over time, it can be considered stationary. Fourier transform is apt for analyzing such stationary signals, yielding satisfactory results. However, numerous signals, including EEG, exhibit nonstationary and transient characteristics, rendering direct application of Fourier transform less suitable. Instead, time-frequency methods, like wavelet transform, become relevant (Heckbert, 1995).

Discrete Wavelet Transform (DWT) is the method we employed, aids in extracting individual EEG sub-bands and accurately reconstructing information. DWT is rooted in signal processing and Fourier analysis.

Unlike the continuous Fourier transform, DWT divides a signal into discrete frequency components localized both in time and frequency. The theory is based on the decomposition of a signal using wavelet functions, which are small, oscillatory functions with varying scales and translations. These wavelets are scaled and translated to analyze different frequency bands within a signal. DWT's theoretical foundation allows it to capture both transient and steady-state characteristics in signals, making it valuable for analyzing non-stationary signals like EEG (Van Fleet, 2019). By leveraging the Discrete Wavelet Transform (DWT), detailed information can be extracted from signals in both the time and frequency domains. This property makes DWT a robust tool in biomedical engineering, particularly in tasks like detecting epileptic seizures. In our study, DWT is harnessed to analyze EEG signals across various frequency bands. The DWT operates by decomposing a given signal into approximation and detail coefficients at the first level. Subsequently, these approximation coefficients undergo further decomposition into the next level of approximation and detail coefficients (Faust et al., 2015). This approach enables us to dissect the EEG signals and extract vital frequency-related information. In the initial phase of the Discrete Wavelet Transform (DWT), the signal is subjected to simultaneous processing through Low Pass (LP) and High Pass (HP) filters. The outcomes from these filters are termed as the approximation (A_1) and detailed (D_1) coefficients of the first level. As per the Nyquist rule, the output signals, which contain half the frequency bandwidth of the original signal, can be down-sampled by a factor of two (Panda et al., 2010). This process is then iteratively applied to the first level approximation, generating second-level coefficients, both detailed and approximated.

Throughout each step of this decomposition process, filtering enhances the frequency resolution while down-sampling enhances the time resolution. This amalgamation works toward obtaining finer feature extraction outcomes. In this study, wavelet decomposition has been employed as a preliminary step for EEG segments, aiming to extract five distinct physiological EEG bands: delta (0–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–60 Hz) (as illustrated in Fig. 4). This extraction is facilitated through a sequence of filtering and down-sampling stages, contributing to the categorization of EEG signals into these key frequency bands.

In pursuit of this objective, a four-level Discrete Wavelet Transform (DWT) using the fourth-order Daubechies (db4) wavelet function (Benzy and Jasmin, 2015) has been applied. Given that our dataset spans a frequency range of 0–60 Hz, we focused on extracting specific coefficients: D_1, D_2, D_3, D_4, and A_4. These coefficients correspond to sub-bands of 30–60 Hz, 15–30 Hz, 8–15 Hz, 4–8 Hz, and 0–4 Hz, respectively. These sub-bands align closely with standard physiological divisions. The features extracted from each sub-band encompass the Maximum, Minimum, and Mean values of the wavelet coefficients. These values are determined according to Eq. (1), enabling a quantitative representation of the characteristics present within each sub-band (Benzy and Jasmin, 2015). This feature extraction process aids in capturing essential information within the EEG signals across these frequency sub-bands.

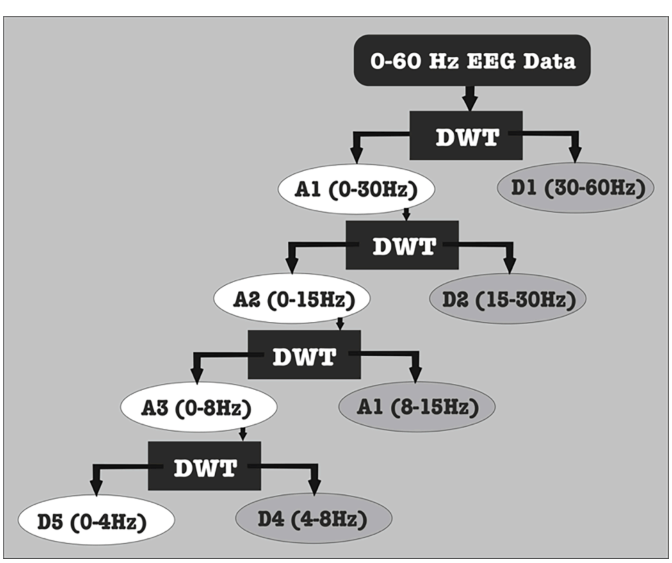

Fig. 4. Decomposition of EEG data in four levels.

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} Dij\, i = 1, 2, \ldots 1 \tag{1}$$

The final step of the process involves an analysis of the extracted features to make informed decisions based on the values obtained. In this context, a classifier is employed to determine the appropriate action based on the feature values. For this study, the Backpropagation neural network algorithm was selected as the classifier. This algorithm has been chosen with the goal of achieving the highest possible accuracy in classifying and categorizing the data based on the extracted features. The Backpropagation algorithm is known for its effectiveness in training neural networks, enabling them to learn and recognize patterns within the data.

3.5. Classification

The selected features were input into two classifiers: Neural Network (NN) and Support Vector Machine (SVM). These classifiers are commonly used for EEG signal analysis, particularly in authentication applications. To evaluate the performance and generalization capacity of the proposed method, the acquired EEG data underwent a meticulous process of division into distinct subsets for training, validation, and testing. To assess the performance and generalization capabilities of the proposed method, the acquired EEG data underwent a rigorous process of division into training, validation, and testing subsets.

3.5.1. Training data

A subset comprising 70 % of the total acquired EEG data was designated for training the classifiers. This training data encompassed EEG recordings obtained from participants' sessions and underwent essential pre-processing stages, including data cleaning, filtering, and feature extraction using the Wavelet Transform method.

3.5.2. Validation data

An additional 15 % of the dataset was set aside for validation purposes. This subset was instrumental in fine-tuning the neural network model during the training phase. The validation data allowed us to optimize the model's ability to recognize and generalize relevant patterns present in the EEG signals.

3.5.3. Testing data

The remaining 15 % of the data was reserved as an independent test dataset. This dataset was deliberately not utilized during the training phase. Instead, it was used to rigorously evaluate the performance of the trained classifiers. The independent test data provided insights into the algorithm's generalization capabilities, assessing its accuracy, False Acceptance Rate (FAR), and False Rejection Rate (FRR).

By clearly distinguishing between training, validation, and testing datasets, we aimed to ensure the robustness and reliability of our results. This approach allows us to demonstrate the algorithm's ability to generalize beyond the data it was trained on and effectively identify relevant features or factors influencing the outcome.

3.5.4. Support vector machines (SVM)

SVM is rooted in the theory of supervised machine learning and pattern recognition. It is based on the idea that a decision boundary, known as a hyperplane, can be found to optimally separate data points of different classes. The theory relies on the concept of "support vectors," which are the data points closest to the decision boundary and crucial for determining its position. SVM aims to maximize the margin between classes, leading to better generalization to new data. The theoretical basis involves convex optimization, finding the optimal parameters that define the hyperplane, and the use of kernel functions to transform data into higher-dimensional spaces for handling non-linear separations (de Jesús Rubio, 2009).

Formula 2, shows the solution of the given training data, $X_i \in R^m, y \in R^1$ and $i = 1, \ldots, l$ as an indicator vector such that $y_i \in \{1, \ -1\}$:

$$min \frac{1}{2}\omega^T\omega + C\sum_{i=1}^{1}\varepsilon_i subjected\ to\ y_i\left(\omega^T\theta(x_i) + b\right) \geq 1 - \varepsilon_i\ \varepsilon_i \geq 0, i = 1, \ldots, l \tag{2}$$

where $C > 0$ is the parameter for regularization and $\theta(x_i)$ maps x_i into a higher-dimensional space and. The SVM optimization, convergence, classifying multi-classes issues were solved using LIBSVM. It is a library for subsequent analysis for support vector machines by Chang and Lin (Walczak, 2019).

3.5.5. Artificial neural network (ANN)

The classification network selects the category based on which output response has the highest output value. Classification neural networks become very powerful when used in a hybrid system with the many types of predictive neural networks. There are three important types of neural networks that form the basis for classification process: Artificial Neural Networks (ANN), Convolution Neural Networks (CNN), and Recurrent Neural Networks (RNN). In this project, ANN are used for the classification part of the second proposed method. ANN theory draws inspiration from neuroscience and is grounded in the concept of interconnected artificial neurons, organized in layers. The theory's core idea is that complex functions can be learned by adjusting the weights between neurons through training. This learning is achieved via back-propagation, where errors between predicted and actual outputs guide weight updates to minimize the error. The universal approximation theorem suggests that ANNs with a sufficient number of neurons can approximate any continuous function, enabling them to capture intricate patterns in data (de Jesús Rubio, 2017).

After the EEG signals were recorded from the participants, we leveraged the Matlab Wavelet Analysis Toolbox and Neural Network Toolbox for processing these signals. These tools were utilized to carry out critical tasks such as filtering the signals, extracting pertinent features, and building a classification model. Through these processes, we aimed to determine the level of accuracy that the proposed methods could yield. By employing these toolboxes, we were able to implement a comprehensive pipeline encompassing data preprocessing, feature extraction, and classifier development. The ultimate goal was to quantitatively assess the performance of the proposed methods in terms of their accuracy and effectiveness. This was measured by utilizing FAR and FRR as follows:

$$FRR = \frac{False\ Rejection}{Unauthorized\ Attempts} \times 100\% \tag{3}$$

$$FAR = \frac{False\ Acceptance}{Unauthorized\ Attempts} \times 100\% \tag{4}$$

An additional key metric is EER, which is the value where FRR and FAR are equal. The actual processing steps included: load data, specify computational approach, specify parameters, learn a model, visualize a model, and apply the model to a new data set. As mentioned, selected features were fed into two classifiers: Neural Network (NN), and Support Vector Machine (SVM) using Matlab. SVM and NN methods are the most common used techniques in EEG authentication studies. However, in a simple way, SVM without kernel is a single neuron inside neural networks, nevertheless with diverse cost function. By adding a kernel function, it will be comparable with two-layer NNs. Actually, in terms of the model performance, SVMs are sometimes equivalent to a shallow neural network architecture [51]. Generally, a NN will outperform an SVM when there is a large amount of data.

Neural networks are intricate models inspired by the structure of the human brain. They are engineered to discern diverse patterns within data. Neural networks consist of multiple layers of interconnected neurons. Each layer receives input from the preceding layer and transmits its output to subsequent layers. Neural network methods have gained widespread popularity in EEG-based studies, particularly for authentication purposes, due to their robust capabilities, especially when dealing with substantial datasets. For this study, we employed the MATLAB Artificial Neural Network Toolbox to implement this approach.

The dataset was fed into the neural network system, organized into three distinctive layers: input, hidden, and output layers. The input layer receives the initial data, and through a series of weighted connections and activation functions, information is processed across the hidden layer(s). Eventually, the output layer generates the final outcome or prediction based on the patterns learned by the network during training. This approach allows the neural network to learn intricate relationships and capture intricate patterns present within the EEG data, ultimately leading to accurate classification outcomes.

Fig. 5 illustrates the Artificial Neural Network (ANN) diagram that was constructed using Matlab. In this diagram, a hidden layer comprising fifteen neurons was incorporated. The chosen algorithm for training the network was the feedforward back-propagation algorithm. For the network's output layer, a configuration of five possible outputs was established, corresponding to the different phases of the deep breathing task (inhale, breath-hold, and exhale).

The process involves five Decibel-based frequency spectrum values, which serve as the inputs for the Artificial Neural Network (ANN). Following this, the results are calculated using the same weights that were established during the training phase of the network. Subsequently, the output is categorized into three classes: inhalation, breath-holding, and exhalation. During the training stage, the neural weights within the ANN are computed, and these weights are then applied in the testing phase. In the testing phase, the output is generated and used to determine the biometric authentication decision ID. This decision ID is derived from the binary values of 0 and 1, signifying whether the EEG signal segment is authenticated or rejected. Specifically, when the decision ID is 0, it indicates that the signal segment has been authenticated. Conversely, a decision ID of 1 indicates that the segment has been rejected. This process underscores the core functionality of the proposed method, wherein the trained neural network takes the frequency spectrum values as inputs, applies the learned weights, and makes authentication decisions based on the network's outputs, effectively determining whether the EEG signal segment belongs to one of the specified classes or not.

The dataset was divided into two distinct phases: training and testing. In order to assess and evaluate the performance of the proposed method, two key metrics were computed: accuracy (Acc) and the F-Score measure. These metrics provide insights into the method's effectiveness and its ability to accurately classify EEG signal segments. The calculations for these metrics are presented in Equations 5 and 6 respectively:

$$Acc = \frac{TA + TR}{TA + FR + TR + FA} \times 100\% \tag{5}$$

$$F - Sc = \frac{2TA}{FA + FR + 2TA} \times 100\% \tag{6}$$

In this context, FA stands for False Acceptance, FR denotes False Reject, TA corresponds to True Acceptance, and TR signifies True Reject. The confusion matrix encapsulates the classification outcomes by organizing them into four categories: TA, TR, FA, and FR. This matrix is pivotal in comprehending the performance of the classification method

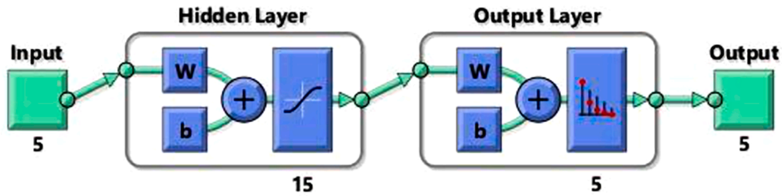

Fig. 5. The ANN diagram for EEG brainwave segments.

by detailing the distribution of correct and incorrect classifications.

The process of generating these metrics and the confusion matrix was carried out within MATLAB, leveraging its neural network toolbox. Initially, a neural network was constructed and configured, involving decisions about the number of layers and the algorithms to be employed for network configuration. Following this, the network's weights and biases were initialized, initiating the training and testing phases using the provided dataset. This process allowed the neural network to learn from the training data and subsequently classify the testing data, yielding the outcomes necessary for constructing the confusion matrix and computing the accuracy and F-Score metrics.

4. Results and discussion

The rhythm of breathing creates electrical activity in the human brain that enhances emotional judgments and memory recall. These effects on behavior depend on whether it is inhale, exhale or breath holding. It means that deep breath can bring back brain signal to its own normal state and help remembering, picturizing memorised patterns. Human brain is not stable during life and depends on different situations it could lose its normal state to create any patterns. Deep breath can improve any brain-based security patterns in the long term. This experiment is done to prove the effects of deep breath on brain and see if the deep breath itself could be used as a security pattern for authentication purposes.

The primary objective of this study was to investigate the potential of using deep breathing as a brain pattern for biometric authentication. EEG data were acquired from 50 individuals while performing two tasks: normal breathing and deep breathing. The deep breathing task was divided into three phases: inhalation, breath-holding, and exhalation. The recorded datasets were pre-processed, and relevant features were extracted for classification.

The importance of deep breathing in promoting relaxation and enhancing Alpha brainwave activity has been widely recognized in previous research. This existing evidence aligns with our study's findings, confirming that deep breathing can create a consistent brainwave pattern, even amidst varying mental states and situations. This capability makes deep breathing an ideal choice for establishing a dependable authentication system.

The results of the experiments demonstrated that all three phases of the deep breathing task achieved successful recall percentages. However, the breath-holding phase consistently exhibited the highest successful recall rate, indicating its significance in establishing a stable brain pattern for authentication purposes. This finding leads us to conclude that the breath-holding phase of the deep breathing task is the most suitable brain pattern for the authentication process.

The achieved true positive rates (TPR) and true negative rates (TNR) for both the Support Vector Machine (SVM) and Neural Network (NN) classifiers are notable. These high TPR and TNR values underscore the classifiers' capability to accurately identify both positive and negative instances, indicating their suitability for authenticating users based on their brainwave responses.

The calculated false acceptance rate (FAR) and false rejection rate (FRR) provide insights into the trade-off between security and user convenience, a crucial consideration in authentication systems. The slight differences in FAR and FRR between the SVM and NN classifiers suggest nuanced preferences in the balance between false acceptance and false rejection. This indicates that while the SVM classifier may lean towards higher false acceptance, the NN classifier might err slightly more towards false rejection. This trade-off can be fine-tuned to align with specific security requirements and user preferences, further highlighting the adaptability of the proposed method. Table 1 shows the results of the classifiers for all 50 participants.

The extracted features from the EEG data were used as inputs for the classification models, namely Support Vector Machine (SVM) and Neural Network (NN) classifiers. The classifiers demonstrated impressive performance, achieving an average accuracy rate of 91 % for SVM and 90 % for NN, with a precision of 95 % in recalling the breath-holding phase of the deep breathing task. These results provide robust evidence supporting the effectiveness of deep breathing as a stable and reliable brain pattern for biometric authentication.

The assessment of precision, recall, F-score, and accuracy metrics provides a nuanced evaluation of our brainwave authentication method's performance. Precision values of 0.95 for both SVM and NN classifiers emphasize their capability to accurately identify genuine users, minimizing false positive identifications. Meanwhile, recall rates of 0.88 and 0.89 for SVM and NN, respectively, underscore their adeptness in recognizing a substantial portion of genuine instances. The F-scores of 0.86 and 0.85 for SVM and NN, respectively, showcase the balanced equilibrium achieved between accurate identification and comprehensive recognition of authentic users. These metrics collectively reflect the strength of our method in effectively differentiating between legitimate and unauthorised users, regardless of potential variations in brainwave patterns due to external factors.

The high accuracy rates of 0.90 for SVM and 0.91 for NN, coupled with the notable precision, recall, and F-score values, affirm the alignment of our approach with our research objectives and application requirements. These metrics collectively underscore the method's robustness and reliability in biometric authentication scenarios. Furthermore, the comparable performance of SVM and NN classifiers emphasizes the adaptability of our approach, offering a flexible choice to suit varying security and user experience preferences. In conclusion, the precision, recall, F-score, and accuracy metrics collectively highlight the effectiveness of our proposed brainwave authentication method, not only meeting the research objectives but also addressing the needs of practical applications where security and usability converge Table 2.

Table 3 presents a comprehensive comparison of notable experiments that have achieved remarkable performance results within the EEG-based authentication domain. Evidently, these experiments have all attained notably high accuracy rates. Specifically, Patel et al. secured the highest accuracy rate of 92.5 % among these experiments. Subsequently, Armstrong et al. recorded an accuracy rate of 89 %, followed by

Table 1
The average results of both SVM and NN classifiers for breath-holding pattern.

Performance Metrics	SVM (Support Vector Machine)	NN (Neural Network)
TPR (True Positive Rate)	**0.82**	**0.86**
TNR (True Negative Rate)	**0.97**	**0.97**
FAR (False Acceptance Rate)	**0.17**	**0.15**
FRR (False Rejection Rate)	**0.02**	**0.03**

Table 2
The average performance of the classifiers for recalling Breath-Holding vs not recalled.

Classifier	Precision	Recall	F-Score	Accuracy
SVM (Support Vector Machine)	**0.95**	**0.88**	**0.86**	**0.90**
NN (Neural Network)	**0.95**	**0.89**	**0.85**	**0.91**

Table 3
A comparison between this paper and previous works.

Author	Brain State Tasks	Accuracy	Permanency Test
Armstrong et al. (2015)	Text reading	89 %	Yes
Patel et al. (2017)	Visual stimulus	92.5 %	No
Zhendong and Jianfeng (2011)	Visual stimulus	87.3 %	No
Proposed technique	Deep Breathing	91 %	Yes

Zhendong et al. with an accuracy rate of 87.3 %. It is worth noting that both the Armstrong et al. study and the current thesis successfully cleared the permanency test, demonstrating the stability of the authentication method over time. However, this thesis surpasses Armstrong et al. with a 3 % higher accuracy rate, achieving a commendable 91 % accuracy.

What sets the deep breathing method used in this thesis apart is its distinct advantages. Unlike other mental tasks and brain patterns explored in various studies, the deep breathing pattern requires no additional equipment, incurs no costs, and is highly accessible. Importantly, deep breathing can be practiced anywhere, by anyone, regardless of their situation in life or the circumstances they find themselves in. This inherent flexibility and universality contribute to the appeal of the proposed deep breathing-based authentication method as a practical and convenient approach that holds potential to enhance security in various contexts.

The stability and permanency of the brain pattern are critical considerations for any brain-based authentication system. Deep breathing's ability to promote relaxation and enhance Alpha brainwave activity contributes to its effectiveness in maintaining a stable brain pattern, even during challenging situations such as stress, anxiety, sickness, and distraction. These attributes reinforce deep breathing's suitability as an appropriate brain pattern for authentication purposes.

The findings of the study clearly demonstrate the effectiveness of deep breathing in restoring brainwave patterns to a state of equilibrium. This practice not only has the capability to normalize brainwave activity but also showcases its potential to enhance the presence of alpha waves. As alpha waves are associated with mental relaxation, the utilization of deep breathing can prove to be immensely beneficial for establishing a consistent pattern for authentication purposes. This holds true regardless of the individual's mental or physical condition, such as instances of stress, fear, anxiety, illness, or other factors that might otherwise disrupt the brain's typical state.

Furthermore, it's noteworthy that deep breathing has the additional capacity to encourage the generation of other brainwave types. For instance, the promotion of Delta brainwaves, which emerge during the deepest phases of relaxation, and Theta brainwaves, indicative of profound mental tranquility, are among the advantageous effects of deep breathing. This amplifies the potential benefits of the method, extending beyond alpha waves to encompass a wider spectrum of brainwave patterns.

The overarching implication of these findings is that deep breathing not only contributes to the permanency of brainwave patterns but also holds the promise of being an appropriate and versatile option for establishing a secure brain-based authentication pattern. This versatility arises from the ability of deep breathing to foster different brainwave states, ultimately making it a strong contender for the development of a robust and adaptable authentication method that is less susceptible to the fluctuations of an individual's mental or emotional state.

5. Conclusion

In near future, biometric authentication methods will be the most useful methods for devices and applications because of the usability, security level, ease of use, and fast execution. Many brain computer interface experiments were performed to use brain signals as alternative biometric authentication method, where some of them achieved high accuracy for their experiences. However, there are several limitations such as usability, security level and permanency of the system through time associated to such methods which needs to be resolved for any brain-based authentication in the future.

In conclusion, this study has demonstrated the feasibility and effectiveness of using deep breathing as a secure brain pattern for biometric authentication. The breath-holding phase of the deep breathing task emerged as the most reliable brain pattern for authentication, supported by the impressive classification performance of SVM and NN classifiers.

Different mental tasks or brain-based paradigms will have different outcomes. According to the literature, it is shown that better results have been achieved from imaginary tasks and protocols in comparison to the physical ones. Many different mental tasks have been tested and good results achieved. However, most of them are very complex and time-consuming for the authentication process. The big challenge for all brain-based authentication studies is that the brain patterns can change depending on the brain situation.

The significance of deep breathing in promoting relaxation and enhancing Alpha brainwave activity has been well-documented in the literature, aligning with our study's findings. Deep breathing offers a stable and consistent brainwave pattern, making it a viable choice for establishing a dependable authentication system.

Compared to existing EEG-based authentication studies, our proposed deep breathing pattern method achieved high accuracy rates and surpassed some previous experiments. Its simplicity, accessibility, and applicability to diverse mental states and situations make it a practical and cost-effective approach for biometric authentication.

Overall, this work provides compelling evidence for the potential of deep breathing as a brain pattern for authentication purposes. The study's findings contribute to the advancement of brain-based authentication research and lay the groundwork for future investigations in accurate predictions for long-term memory tasks. Our study offers valuable insights that pave the way for future research directions in the realm of brain-based authentication. Building upon our findings, we recommend that future studies explore the integration of deep breathing-induced brainwave patterns with existing BCI frameworks. This integration could potentially augment the accuracy and stability of authentication processes, addressing the limitations observed in previous studies. Additionally, investigating the applicability of our approach across diverse user groups, including individuals with specific mental conditions, could shed light on the universality and robustness of the proposed authentication method.

While the proposed deep breathing pattern method enhances authentication permanency and brain pattern stability, it is essential to acknowledge potential drawbacks. For instance, the need for an individual to achieve a relaxed state through deep breathing may introduce time variability in the authentication process. This aspect, particularly in emergency situations, poses a challenge worth exploring. Furthermore, we encourage researchers to explore the potential synergies between deep breathing-induced brainwave patterns and emerging technologies such as machine learning methods and different neural network architectures, as these avenues hold promise for enhancing authentication efficiency and effectiveness. Lastly, the developed system showcases feasibility for implementation in smart homes and offers promising potential for integration into smart automation frameworks. However, it's important to note that the requirement for customized training, validation, and testing for individual data may necessitate careful consideration due to its time-consuming nature.

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CRediT authorship contribution statement

Fares Yousefi: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Resources. **Hoshang Kolivand:** Supervision, Writing – review & editing, Project administration.

Declaration of Competing Interest

The authors confirm that there is no conflict of interest with this submission and this is an original work.

Data availability

Data will be made available on request.

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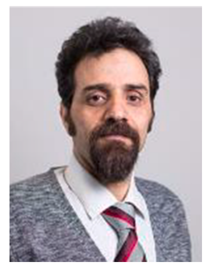

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