The Single-Channel SSVEP-based Biometric Approach Using RNN-based Deep Models: A Systematic Comparison

Kutlucan Gorur (✉ kgorur@bandirma.edu.tr)

Bandirma Onyedi Eylul Universitesi

Beyza ERASLAN

Bandirma Onyedi Eylul Universitesi

Research Article

Keywords: Biometric, SSVEP, Single-Channel, Recurrent Neural Networks, Discrete Wavelet Transform

Posted Date: March 1st, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1304515/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

The Single-Channel SSVEP-based Biometric Approach Using RNN-based Deep Models: A Systematic Comparison

Kutlucan GORUR^{1,*}, Beyza ERASLAN²

^{1,2} Electrical and Electronics Engineering, Bandirma Onyedi Eylul University, Balıkesir 10200, Turkey

Corresponding Author Email: *kgorur@bandirma.edu.tr

Abstract

Biometric technology is the branch of science dealing with identification and verification of individuals, focusing on physiological and behavioral traits. These traits can be reliable, permanent, unique, and capable of distinguishing one person from others. Fingerprints, the iris, and the face are conventionally used in biometric techniques involving ID cards and passwords. However, due to security threats and fraud, these static textures and approaches can be abused. Consequently, biometric studies based on electroencephalography (EEG) have received increasing attention because each individual has a dynamic and unique pattern. However, classic EEG-based biometrics have significant deficiencies, including noise-prone signals, gel-based electrodes, and the need for multi-training/multi-channel acquisition and high mental effort. In contrast, steady-state visually evoked potential (SSVEP)-based biometrics have the important advantages of low signal-to-noise ratio and untrained usage. The SSVEP signals also embrace a number of other advantages. First, the occipital lobe is the only suitable region for collecting SSVEP signals without obstruction. Second, because elicited dynamic brain responses are a natural subconscious activity, the omnipresent SSVEP signals are the most frequently emitted signals. Anyone can continuously look into flickering lights having distinct frequencies, such as cell phone flashes, without extra physical or mental effort. Few studies involving multi-channel/multi-trial SSVEP-based biometric research are available in the current literature. Moreover, there is a lack of research comparing them to the single-

channel single-trial SSVEP-based biometric approach using dry electrode-implemented recurrent neural network (RNN)-based deep learning models. To the best of our knowledge, no prior work has proposed such a biometric comparison of the RNN-based deep learning models and different sized time-series data compiled over raw and discrete wavelet transform (DWT)-based SSVEP signals. By achieving up to 100% accuracy using 11 individuals, the biometric recognition results are promising. This single-channel SSVEP-based biometric approach using RNN-based deep learning models may offer low-cost, user-friendly, and reliable individual identification authentication, leading to significant application domains.

Keywords: Biometric, SSVEP, Single-Channel, Recurrent Neural Networks, Discrete Wavelet Transform

1 Introduction

In modern life, with the use of passports, credit cards, laptops, and mobile phones, the demand is increasing for automatic methods of identifying people via anatomical characteristics or behavioral features [1, 2]. Biometric person recognition technologies have become an important research area in recent years and have earned an important place in many fields of application [3]. As security and privacy become more and more important, authentication systems based on biological traits are actively and widely used, even in daily life [4]. Unlike fingerprints, facial recognition, palm veins, or other external biological features, brainwave patterns can create an internal representation of traits that define a specific person [4]. However, each physiological and behavioral trait has advantages and drawbacks [2]. In order to advance an effective electroencephalographic (EEG) biometric approach, the imperative and fundamental approach is to form an EEG pattern that is consistent over time and that is a unique feature among individuals [4]. Moreover, this kind of EEG-based biometric model should have high inter-subject variability and low intra-subject variability [4]. Among

researchers, the identification of a person by employing EEG signals is an attractive concept. However, the nature of producing targeted EEGs involves some important challenges and complexities in sensing EEG signals [5, 6]. First of all, EEG-based human-machine interfaces require high concentration, continuous mental effort, and training [6]. Moreover, channel numbers/multi-channel recordings limit the use of EEG signals in real-world biometric applications, especially in wearable technologies [5–7]. At this point, steady-state visually evoked potentials (SSVEPs), when evoked in low-frequency signals, can provide high inter-subject variability and low intra-subject variability with a single-channel approach [2,8].

The visual evoked potential (VEP) signals form the most widespread brain pattern implemented in clinical and cognitive neuroscience. These signals are generally elicited by image stimulation [9]. Moreover, if the subject gazes at a flickering light of a specific frequency, the brain activity response can be acquired via electrodes placed on the occipital lobe. A clearly detectable and measurable signal occurs after the stimulus. After the transient visual, this stimulus can produce a stable VEP, known as the steady-state VEP (SSVEP), which occurs at the frequency of the stimulus and its multiples. The SSVEP has a robust characteristic against artifacts, including eye blinking and body movements, and exhibits a high signal-to-noise ratio [10]. Moreover, the SSVEP can provide a high information transfer rate (ITR) , with no training required for first-time usage [10–12]. Hence, these features can make the SSVEP a highly potential candidate for structuring real-time usage in human-computer interfaces consisting of biometric applications [10,11]. A great number of EEG-based and VEP-based biometric studies dealing with multi-trial and multi-channel recordings can be found in the literature [13–19]. However, few studies are based on the single-channel dry-electrode SSVEP approach with single-trial person identification [9,20]. Furthermore, to date, no investigation has been carried out systematically comparing the different types of recurrent neural network

(RNN)-based deep architecture for the single-channel and single-trial SSVEP-based biometric approach, including the discrete wavelet transform (DWT).

Min et al. studied SSVEP-based identification using the neurodynamics of the elicited brain responses and electro-ocular activity (Electrooculogram/EOG) while paying particular attention to the Korean letters. These evoked potentials and EOG activity were decoded using EEG channels over the F1 (for vertical EOG activity) and F7 and F8 (for horizontal EOG activity). Row segments (5, 6, and 7 Hz) and column segments (5.5, 6.5, and 7.5 Hz) were induced in a grid-shaped line array to construct a Korean letter. According to the study, 20 persons were classified using Support Vector Machine (SVM) with an accuracy score of 98.60% [21]. In another study, four flickering frequencies (6, 12, 18, and 24 Hz) were implemented to stimulate brain responses via nine green light-emitting diodes (LEDs). A total of 19 EEG channel recordings were obtained from the scalps of the subjects. Hence, using between 5 and 19 channels, 25 individuals were recognized within an accuracy range of 64.40-100%. Mel-Frequency Cepstral Coefficients (MFCCs) and Autoregressive Reflection (AR) coefficients were determined as discriminative features [22]. Another study was conducted to structure biometric authentication using deep learning (Convolutional Neural Network/CNN and Long Short Term Memory/LSTM) and traditional classifiers. It was noted that CNN and LSTM provided the highest average accuracies, 69.03% and 66.89%, respectively, for 11 persons. In the study, a leave-one-subject-out cross-validation (LOSO-CV) was carried out to process the SSVEP signals. In the experiment, 256 EEG channels and 5 non-overlapping flickering frequencies were used [23].

Deep learning is a state-of-the-art machine learning algorithm that powers many areas of research studies and modern life applications (e.g., image processing, pattern recognition, and

brain-computer interfaces/BCIs) [24,25]. In the present research study, 11 participants were used for personal authentication performance based on the single-channel SSVEP approach via deep learning algorithms (Long Short-Term Memory/LSTM, Bidirectional Long Short-Term Memory/BiLSTM, and Gated Recurrent Units/GRU) with DWT. Recurrent Neural Network (RNN)-based deep learning algorithms, including LSTM, BiLSTM, and GRU, are specialized and recognize the pattern in the uncovering of temporal dependencies such as biological time-series data [26–28]. The EEG signals consisted of waves of various frequencies. Thus, the DWT was able to break them into frequency bands to assist the deep learning algorithms during the recognition of SSVEP patterns for each individual's signal [29]. In this study, the DWT was employed to separate the sub-bands of the recorded signals. The results were processed by the RNN-based deep learning algorithms over the raw signals, and the DWT-based signals showed very promising biometric classification, offering a single-channel SSVEP biometric approach using dry-sensor technology [8]. Unlike traditional BCI helmets, dry-sensor technology can greatly improve wearable comfort and therefore, can be used quite successfully in biometric person recognition, as one of the next-generation Internet of Things (IoT) applications [2,7,8].

The introduction has presented the dataset, methods, and performance metrics. The rest of the article is structured as follows. The Results section presents the biometric recognition outcomes for the deep architecture over the raw and sub-band signals. An estimation of all outcomes and a literature overview are found in the Discussion section. Finally, the Conclusion section defines precisely the aim and outcomes of the study and its contributions to the existing literature.

2 Materials and Methods

2.1 Experimental Setup and Mainframe of the Research

Security concerns against the threats and fraud, conventional biometric techniques, including passwords or ID cards, can be abused and sometimes can be easily accessed by imposters [2]. However, biometric recognition approaches are able to provide more robustness, high accuracy performances, and hard to spoof features [2]. Moreover, easy-to-use and wearable characteristics are also defined by single-channel and dry-electrode recordings [5–8]. In this study, single-channel SSVEP biometric approach was offered to provide reliable, highly accurate, and easy-to-use for individuals using deep learning algorithms.

Figure 1 Single-channel dry-sensor SSVEP-based biometric approach using RNN-based deep learning algorithms over the different flicker frequencies

Steady-State Visual Evoked Potentials (SSVEP) are defined as brain signals produced in the visual cortex area while focusing on a flickering light source emitted at a specific frequency [8]. In this study, 4 frequency signals (8.57, 10, 12, and 15 Hz) were reported to stimulate the brain activity for 16 seconds in collecting the dataset over the electrode of the Occipital area (Oz). The other electrode lead of the single-channel was located on the Frontal Parietal area (Fpz). The signals of the single differential channel were noted to be sampled at 256 Hz. These two active dry electrode pairs (CH- and CH+), embedded on the Olimex EEG acquisition device for a single-channel recording, were linked to the 10-bit analog-digital converter (ADC) for sampling before storing the data in the Raspberry Pi 3 minicomputer. Furthermore, a passive reference electrode was noted to be positioned on the earlobe. The 15.6-inch laptop screen

was used for the stimulating platform. Visual stimuli have been reported to consist of four alternating black and white 80×80 pixel squares on the black background with 60 Hz refreshing rate of the monitor. The dataset is named “A dataset of EEG signals from a single-channel SSVEP-based brain-computer interface” and can be accessed over this reference [8]. The bands of EEG signal and stimuli frequencies are presented in Table 1.

Table 1 EEG ranges and stimuli frequencies

Frequency Ranges (Hz)	Frequency Bands	Stimulation and Observed Frequencies
0-4	Delta	-
4-8	Theta	-
8-12	Alpha	8.57 (F1), 10 (F2)
12-30	Beta	12 (F3), 15 (F4)
>30	Gamma	-

Figure 1 shows the mainframe of the research and Figure 2 represents the components for the data acquisition process.

Figure 2 a) Headset b) Raspberry Pi 3 single-board computer c) FPz electrode d) Olimex EEG acquisition device e) Oz electrode [8] (upper) Experimental setup for trials during the stimulation process (lower)

2.1.1 Data Preparation

The single-channel recorded SSVEP signals for each stimulated frequency are obtained in a total of 4096 samples during 16 seconds. These signals are reshaped to merge the frequencies side by side to be recognized better via deep machine learning algorithms for 11 person biometric authentication task.

Figure 3 Resizing process for single-channel dry-sensor SSVEP signals for each person to obtain a better feature vector

2.2 Discrete Wavelet Transform

The EEG signal is constructed in rhythmic activity, creating different frequency bands. These various frequencies can be decomposed by Discrete Wavelet Transform (DWT). The feature vector of the EEG signals for pattern recognition consists of the coefficients of DWT extracted from the biological signals [30]. Hence these certain frequency bands may provide better classification results for single-channel SSVEP-based biometric recognition [25]. This study used the wavelet type of Sym10 (Symlets) at the 4th level to extract certain frequencies (0-16 Hz) over the recorded data with a sampling frequency of 256 Hz.

$$DWT(a, b) = \frac{1}{\sqrt{a}} \sum_n x(n) \psi^* \left(\frac{n-b}{a} \right) \quad (1)$$

The mathematical relation for DWT is represented in Eq.1, where a and b are named as translation and scaling parameters, respectively [25]. Figure 4 shows the decomposition process for EEG signals.

Figure 4 Wavelet decomposition process up to level-4 for the EEG frequency bands

2.3 Evaluation Metrics

The evaluation metrics chosen for pattern recognition are crucial to revealing the performances of the deep learning models. The appropriate metrics for this study are listed as; classification accuracy (ACC), sensitivity (SENS), specificity (SPEC), precision (PREC), F-score,

information transfer rate (ITR), receiver operating characteristics (ROC), and area under the curve (AUC).

In this study, traditional validation was implemented to determine the biometric data process as 80% of the data for training and 20% for testing. In addition to this validation, the k-fold cross-validation technique has also been examined. The process divides into k subsets to use each separated part for both testing and training. The machine learning model is trained with $k-1$ subsets, and the other remaining subset is carried out for testing [25]. In this work, 3-fold cross-validation was implemented for data processing. Formulas used to calculate classification accuracy are given in Eqs.2-4.

$$Accuracy(N) = \frac{\sum_{i=1}^{|N|} estimate(n_i)}{|N|}, \quad n_i \in N \quad (2)$$

$$Estimate(n) = \begin{cases} 1, & \text{if } estimate(n) = cn \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

$$Classification\ Accuracy(ML) = \frac{\sum_{i=1}^{|k|} Accuracy(N_i)}{|k|} \quad (4)$$

where, N implies the test dataset, cn stands for the class of the value of n . $Estimate(n)$ is related to the classification result of n , and the k means for the k-fold cross-validation parameter. The accuracy metric alone is commonly seen as an unsatisfactory parameter when determining the proposed model is successful [25]. In this respect, it is useful to explain the statistical terms; specificity (SPEC), sensitivity (SENS), precision (PREC), and F-score. The term "specificity" refers to the ratio of correctly predicted true negatives, while the term "sensitivity" defines the ratio for correctly predicted true positives. The ratio of positive predictions that are correct is named as "precision". F-score is determined via the harmonic mean of the precision and sensitivity [31]. Formulas for SPEC, SENS, PREC, F-score and ITR are given in Eqs.5-9.

$$SPEC = \frac{TN}{TN + FP} \quad (5)$$

$$SENS = \frac{TP}{TP + FN} \quad (6)$$

$$PREC = \frac{TP}{TP + FP} \quad (7)$$

$$F\text{-score} = \frac{2TP}{2TP + FP + FN} \quad (8)$$

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 \frac{(1 - P)}{(N - 1)} \quad (9)$$

where, these terms are true positive (TP), true negative (TN), the false positive (FP), false negative (FN) [25, 31]. B means the number of bits per trial, N stands for classes, and the accuracy is named as P . The value of the ITR improves, when the number of various classes in a pattern recognition process increases [25]. Moreover, receiver operating characteristic (ROC) and area under the curve (AUC) evaluation metrics are employed to visualize the performance of the deep nets. The ROC curve is plotted as a two-dimensional probability graph with the false positive rate (X-axis) and the true positive rate (Y-axis) [32, 33]. AUC, which refers to the degree of separation between classes, is provided by determining the area under the entire ROC curve. Higher AUC values mean better classifier performances and are calculated in the range of 0 and 1 [32, 33].

2.4 Long Short-Term Memory Network

Long Short-Term Memory (LSTM) is a special type of Recurrent Neural Network (RNN) and has an especially ideal structure for sequenced data with long temporal dependencies between them [34, 35]. This type of network consists of repeating structures in the form of chains.

Let $x_i \in \mathbb{R}^d$ be given a series of input vector $[x_1, x_2, \dots, x_k]$. RNN generates a hidden sequence $[h_1, h_2, \dots, h_k]$ at each processing step. The activation of the hidden state at time t is a function of the current input x_t and the previous hidden state h_{t-1} . This process can be formulated as:

$$h_t = f(x_t, h_{t-1}) \quad (10)$$

The result of a continuous processing of state information in RNNs is considered unlikely to be transmitted without breaking long-term dependencies. LSTMs are structured to interest long-term dependencies. There are modules consisting of different gate combinations in the LSTM. The names of these gates are given as forgotten gate, input gate, and output gates. The volume of information is determined how much of it will be transmitted to the next stage in the forget gates. The sigmoid function is implemented for this operation. If the result of this function leads to 0, this means that no information will be transmitted. If it is 1, the whole information will be transmitted. The next step is carried out for deciding on the information to be stored. This task is accomplished with the sigmoid function at the input gate. It then

constructs the vector of candidate values $\tilde{C}_t$ implementing the $\tanh$ function. Hence two processes are then combined. After that, the new state information (C_t) for the memory cell is computed. Finally, the system output is calculated [35]. Figure 5 shows the internal structure of the LSTM module. The mathematical notations are given as:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (11)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (12)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (13)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (14)$$

$$h_t = o_t * \tanh(C_t) \quad (15)$$

In general, W describes the weight vector, b means the bias term, σ is the sigmoid activation function for non-linearity, x_t stands for the input sequence, h_{t-1} defines the output of the neuron at time $t - 1$ for feedback into the neuron. Moreover, i_t, f_t and o_t are input, forget and output gate, respectively [35]. The new status information of the memory cell must be calculated.

Figure 5 LSTM module internal structure [36]

2.5 Bidirectional Models and Gated Recurrent Unit

Representations of previous time steps are learned by LSTM models. However, understanding the content better and eliminating ambiguities are important to learn future representations in different application tasks. Bidirectional models offer a forward propagation process in two stages as main difference according to standard models. Firstly, it starts from the first step,

and the values up to the last step are computed. Then, starting the process from the last time step to the first time step is performed. Therefore this LSTM model is named as Bidirectional-LSTM or (BiLSTM) [37], as shown in Fig.6.

Gated Recurrent Unit (GRU) is designed as a simplified version of the LSTM, and it can be seen that GRU is comparable to LSTM because of the simpler structure and a lower computational complexity. GRU simplifies the structure via merging the cell state and hidden state. This merging process is developed by integrating the forget gate and input gate into a single update gate. When the LSTM structure has three gates (namely forget gate, input gate, and output gate), the GRU only contains two gates (namely reset gate and update gate). Furthermore, the number of parameters of GRU is fewer compared to the LSTM. This leads to less training time and better training loss with fewer training iterations [38].

Figure 6 The schematic of the BiLSTM structure

Table 2 Hidden neuron numbers for RNN-based deep models

Model-1	Model-2	Model-3
100	150	200

3 Results

Most of the EEG-based biometric works often force the users to perform some activities, including viewing a series of pictures or making/imaging a movement to trigger the signals of

interest [3]. However, EEG-based biometric systems have some usability issues for real-life scenarios when triggering the signals or multi-channel during acquisition. The actual performance of a biometric system depends on several factors. These are the specific biometric trait, sensor characteristics while capturing, the number and characteristics of the individuals. Moreover, environmental indoor and outdoor factors such as temperature and humidity are also important [1]. However, in this study, the single-channel dry-sensor SSVEP-based biometric approach via RNN-based deep learning investigation can provide a high signal-to-noise ratio and low susceptibility against artifacts as well as real-time and accurate usage without training [3, 10]. The great results of the research offer a good candidate for biometric recognition among the 11 people with SSVEP responses of the 4 stimulus frequencies.

Figure 7 The single-channel raw SSVEP signals (*upper*), time-frequency analysis for 10 Hz (*lower*) (The related evoked potential responses from the Subject-3)

RNN-based deep architectures are specialized in the time series temporal dependencies. However, the size of the signals for EEG is also important to be better recognized by LSTM, BiLSTM, and GRU. Hence, the two sizes of the SSVEP signals are reconstructed, as shown in Figure 3. These datasets are obtained in the shape of the 64×256 and 128×128 matrices for each subject.

The SSVEP signals for 4 stimulus frequencies are processed by RNN-based deep architectures for classic validation (80-20% and 70-30%) and 3-fold cross-validation. The outcomes for the raw SSVEP signals and DWT-based SSVEP signals are presented in the tables and figures:

Table 3 Classic validation results for the size of 64×256 datasets (RNN Models-1)

		80% validation			70% validation		
Raw SSVEP Responses	%	BiLSTM	LSTM	GRU	BiLSTM	LSTM	GRU
	ACC	97.90	100	97.20	98.63	98.18	99.54
	SENS	100	100	100	100	100	100
	SPEC	100	100	100	100	100	100
	PREC	97.90	100	97.20	98.63	98.18	99.54
	F1	98.93	100	98.58	99.31	99.08	99.77
	AUC	1	1	1	1	1	1
	ITR	2.606	2.793	2.550	2.667	2.629	2.753
		80% validation			70% validation		
DWT-based SSVEP Responses	%	BiLSTM	LSTM	GRU	BiLSTM	LSTM	GRU
	ACC	99.30	100	97.20	99.54	95.00	100
	SENS	100	100	100	100	100	100
	SPEC	99.23	100	100	99.50	100	100
	PREC	99.30	100	97.20	99.54	95.00	100
	F1	99.64	100	98.58	99.77	97.43	100
	AUC	1	1	1	0.961	1	1
	ITR	2.729	2.793	2.550	2.753	2.391	2.793

According to Table 3, LSTM and GRU have provided the highest outcomes at the raw and DWT-based SSVEP signals for all evaluation metrics in 80-20% and 70-30% validation, respectively. In addition, it was observed that GRU found a high F-score of 99.77% as well as 99.54% ACC, 100% sense, and spec values for 11 people biometric recognition via single-channel evoked potential. The impact of the sub-band signals via discrete wavelet coefficients has been reported to be slightly higher than the raw signals except for the LSTM model for 70-30% validation. Figures 8 and 9 show the confusion matrices and ROC curves with t-SEN graph for 80-20% and 70-30% traditional validation prediction outcomes for 11 people biometric recognition.

Figure 8 Confusion matrices determined by BiLSTM for 80-20% (left) and 70-30% (right) training-testing validation, respectively in raw SSVEP responses

Figure 9 ROC curves and t-distributed stochastic neighbor embedding (t-SNE) presentation for 11 individual biometric recognition

Table 4 3-fold cross validation results for the size of 128×128 datasets (RNN Models-2)

Raw SSVEP Responses						DWT-based SSVEP Responses			
	%	fold1	fold2	fold3	Avg.	fold1	fold2	fold3	Avg.
BiLSTM	ACC	100	100	100	100	100	100	91.00	97.00
	SENS	100	100	100	100	100	100	100	100
	SPEC	100	100	100	100	100	100	100	100
	PREC	100	100	100	100	100	100	91.00	97.00
	F1	100	100	100	100	100	100	95.29	98.43
	AUC	1	1	1	1	1	1	1	1
	ITR	2.793	2.793	2.793	2.793	2.793	2.793	2.138	2.574
	%	fold1	fold2	fold3	Avg.	fold1	fold2	fold3	Avg.
LSTM	ACC	99.14	100	99.57	99.57	98.72	99.35	90.88	96.31
	SENS	100	100	100	100	100	100	100	100
	SPEC	100	100	100	100	100	100	95.33	98.44
	PREC	99.14	100	99.57	99.57	98.72	99.35	90.88	96.31
	F1	99.57	100	99.78	99.78	99.35	99.67	95.22	98.08
	AUC	1	1	1	1	1	1	1	1
	ITR	2.710	2.793	2.749	2.750	2.673	2.729	2.126	2.509
	%	fold1	fold2	fold3	Avg.	fold1	fold2	fold3	Avg.
GRU	ACC	99.57	99.14	99.14	99.28	100	99.57	89.74	96.43
	SENS	100	100	100	100	100	100	100	100
	SPEC	100	100	100	100	100	100	100	100
	PREC	99.57	99.14	99.14	99.28	100	99.57	89.74	96.43
	F1	99.78	99.57	99.57	99.64	100	99.78	94.59	98.12
	AUC	1	1	1	1	1	1	1	1
	ITR	2.749	2.710	2.710	2.723	2.749	2.749	2.062	2.520

At the biometric recognition results of 11 individuals according to Table 4, the BiLSTM model has achieved the highest average and fold performances (100%) for the metrics of ACC, SENS, SPEC, PREC, and F-score among the other deep architectures in the raw SSVEP signals. The

same deep architecture has also calculated 97.00 ACC with 1 of AUC score and 2.574 ITR value in the sub-band signals via DWT technique. On the other hand, LSTM and GRU have determined ACC values of over 99% and an AUC score of 1, respectively, in the raw SSVEP signals. In general, it is observed that the raw stimulated responses were classified better than the DWT-based SSVEP responses via all RNN-based deep architectures. In a concise comparison, 3-fold cross-validation outcomes were reported to be close to the traditional validation results. Whisker box plot and training process were represented in Figure 10 according to Table 4.

Figure 10 The biometric recognition variations of all RNN-based deep architectures (Whisker box plot) and training process of BiLSTM model in 3-fold cross-validation for the size of 128×128 dataset

Table 5 3-fold cross validation results for the size of 64×256 datasets (RNN Models-3)

		Raw SSVEP Responses				DWT-based SSVEP Responses			
	%	fold1	fold2	fold3	Avg.	fold1	fold2	fold3	Avg.
BiLSTM	ACC	100	100	90.55	96.85	100	100	90.98	96.99
	SENS	100	100	100	100	100	100	100	100
	SPEC	100	100	100	100	100	100	100	100
	PREC	100	100	90.55	96.85	100	100	90.98	96.99
	F1	100	100	95.04	98.34	100	100	95.28	98.42
	AUC	1	1	1	1	1	1	1	1
	ITR	2.793	2.793	2.108	2.564	2.793	2.793	2.132	2.572
	%	fold1	fold2	fold3	Avg.	fold1	fold2	fold3	Avg.
LSTM	ACC	99.14	97.00	91.06	95.73	100	100	90.79	96.93
	SENS	100	100	100	100	100	100	100	100
	SPEC	100	100	100	100	100	100	100	100
	PREC	99.14	97.00	91.06	95.73	100	100	90.79	96.93
	F1	99.57	98.48	95.32	97.79	100	100	95.17	98.39
	AUC	1	1	1	1	1	1	1	1
	ITR	2.710	2.535	2.138	2.461	2.793	2.793	2.120	2.568
	%	fold1	fold2	fold3	Avg.	fold1	fold2	fold3	Avg.
GRU	ACC	95.81	100	99.16	98.32	96.21	96.56	87.98	93.58
	SENS	100	100	100	100	100	100	100	100
	SPEC	98.15	100	100	99.38	100	100	100	100
	PREC	95.81	100	99.16	98.32	96.21	96.56	87.98	93.58
	F1	97.86	100	99.57	99.14	98.07	98.25	93.60	96.64
	AUC	1	1	1	1	1	1	1	1
	ITR	2.447	2.793	2.710	2.640	2.476	2.498	1.962	2.312

The performance comparison in respect of RNN-based deep architectures for the 64×256 dataset represents that GRU has carried out the greatest average values reaching the 98.32% ACC and 1 of AUC score in the raw SSVEP signals. Moreover, the ITR value has been calculated by GRU as 2.640. BiLSTM and LSTM have achieved the second and third best performances in biometric recognition for 11 subjects' evoked potential signals. However, the highest average performances were observed by BiLSTM (96.99% ACC and 98.42% F-score) and LSTM (96.93% and 98.39% F-score) deep architectures in the DWT-based SSVEP signals. Furthermore, it is investigated that RNN-based deep architectures have shown better classification performances for 11 subjects in the size of the 128×128 dataset than the dataset of 64×256 size. The spider plot presentations are provided for the raw and DWT-based SSVEP signals according to Table 5.

Figure 11 The comparison of the biometric recognition from the raw SSVEP signals and DWT-based SSVEP signals for the size of 64×256 dataset

Table 6 Biometric recognition results in 6 individuals for the size of 128×128 dataset (RNN Models-2)

80% validation	%	BiLSTM	LSTM	GRU
Raw SSVEP Responses	ACC	100	98.07	94.87
	SENS	100	100	100
	SPEC	100	100	100
	PREC	100	98.07	94.87
	F1	100	99.02	97.36
	AUC	1	1	1
	ITR	2.793	2.614	2.378

With respect to the 6 out of 11 individual biometric recognition, BiLSTM has the highest outcomes for all metrics. Then LSTM and GRU have achieved the second (98.07% ACC and 99.02% F-score) and third (94.87% ACC and 97.36% F-score) prediction performances. Sensitivity and specificity values are also determined as 100% for all RNN-based deep architectures. 6 individual biometric classifications are shown in Figure 12.

Figure 12 The graphical representation of the single-channel SSVEP-based biometric results for 6 individuals

4 Discussion

It is noticeable that EEG-based biometric systems with multi-channels pose the most relevant unsolved problems in real-world usage [39]. According to the biometric recognition results of 11 individuals, the single-channel and single-trial SSVEP signals stimulated via four distinct flickering frequencies provided a proof-of-concept for a robust and easy-to-use biometric system implementing the RNN-based deep architectures.

Our research also focused on the biometric performance and investigation of the RNN-based deep architectures and sub-band effect for different-sized datasets of the single-channel SSVEP responses. First, the biometric recognition processes were conducted via the traditional 80-20% and 70-30% validation (Table 3). The accuracy rates and the other evaluation metrics of the proposed deep architectures were remarkably in the range of 95-100% (ACC, SENS, SPEC, PREC, and F-score). The AUC scores and ITR values acquired were in the range of 0.961-1 and 2.391-2.793, respectively. It is obvious that the results determined for the 80-20% and 70-30% validation and the raw and DWT-based features of the SSVEP responses were close. However, a few successful variations of the deep architectures (BiLSTM, LSTM, and GRU) were also observed for both datasets. The 3-fold results and the average of those for the different-sized datasets (Tables 4 and 5) also offered great biometric recognition over 11 individual-evoked potentials. The average accuracy range (96.31-100%) and the other evaluation metrics demonstrated that the datasets of 128×128 in size, consisting of raw and DWT-based

features, provided better biometric recognition outcomes for 11 persons compared to the datasets of 64×256 in size (93.58-98.32% average accuracy). Furthermore, when the number of participants (Table 6) was reduced to six individuals, the biometric recognition results did not significantly increase or change (94.87-100% ACC and 97.36-100% F-score). This may prove that the RNN-based deep architectures had determined robust biometric recognition over the single-channel SSVEP responses for both numbers of individuals. The ROC curves, t-SEN, and confusion matrices presented the same achievements.

The flickering frequency set of 8.57, 10, 12, and 15 Hz in the single-channel SSVEP-based biometric approach can cause frequency dependence of the SSVEP amplitude. Moreover, significant variabilities in SSVEP responses for individuals in terms of the amplitude and peak values have been reported [40]. In this study, a resizing and merging process for the flickering frequencies was implemented to overcome these deficiencies. Hence, the success of the single-channel SSVEP-based biometric approach for 11 people may have been dependent on this implemented task. By using 12 and 15 Hz in our approach, the suggested frequency range (12-18 Hz) to provide maximum accuracy for BCI applications was included [40]. Furthermore, multi-channel recordings were also addressed and found to be helpful in capturing the high flickering frequencies as SSVEP responses [40]. However, the success of the flickering and low frequencies were not investigated for a single-channel SSVEP-based biometric approach using RNN-based deep architectures. Although Oz-Pz placement is generally recommended in the current literature as it produces better and stronger SSVEP responses, it has been noted that the optimum electrode placement can vary for individuals [40]. In the experiment, the EEG signals on the Oz-Fpz electrode pairs were recorded to detect the single-channel SSVEP responses. The electrode placement may have led to the high accuracy rates (up to 100%) and recognition results obtained in the single-channel SSVEP biometric approach.

The properties of the EEG signals are noted as being non-stationary and non-linear in form. This can make biometric pattern recognition difficult in both the time and frequency domains. Hence, the DWT decomposes these non-stationary signals at different intervals of frequencies with various resolutions to be captured in a more useful part [41]. In our study, 4-level DWT decomposition (Sym10) did not provide better classification success for all sizes of the datasets using RNN-based deep architectures. This may have resulted from the characteristics of the single-channel SSVEP signals. This kind of EEG signal has been reported to exhibit a robust

characteristic against noise and to provide high signal-to-noise ratio (SNR) values with clearly detectable flickering frequencies [10]. This may have led to the close biometric recognition success of the datasets for raw signal responses (8.57-15 Hz) and DWT-based signals (0-16 Hz).

An additional analysis was carried out to verify the effect of the different hidden neuron numbers used by the RNN-based deep architectures (BiLSTM, LSTM, and GRU) on the raw and DWT-based SSVEP signals. According to the proposed neuron numbers (100, 150, and 200), the BiLSTM and GRU achieved better biometric recognition over the DWT-based features for the traditional validation (see Table 3) via RNN model-1. On the other hand, RNN model-2 revealed better average and fold classification results over the raw SSVEP responses. Furthermore, except for the GRU over the DWT-based sub-band signals, RNN model-3 had few successful increments for the biometric recognition of the 11 individuals. These outcomes may reveal that the increment of the feature vector (from 128 to 256 in size) had been applied to the RNN-based deep architectures. The higher neuron numbers can help the models to learn long-term dependencies via time-series signals over the sub-band signals [42]. Hence, the capabilities and effectiveness of the deep neural networks can be improved by the neuron numbers and the different sizes of the datasets in order to identify better biometric patterns over the raw and DWT-based SSVEP signals.

Table 7 Overview of the state-of-the-art EEG-based biometric studies in recent years

Study/Year	EEG and Dataset Type	NFF	SB	CN	Pre. and FE Methods	MLs	Perf.
[22]/2017	SSVEP	4	25	19	Mel-Frequency Cepstral Coefficients (MFCCs) and Autoregressive (AR) Reflection Coefficients	Manhattan Distance	ACC: 91.47-96%
[43]/ 2018	SSVEP	3	5-12	8	Filtering Process	CNN, SVM, Random Forest (RF) and NN	ACC: 80.48-98.10%
[11]/ 2019	SSVEP and ERPs	1	20	6	Filtering Process and Cross-Correlation Analysis (CCA)	LSTM	ACC: 91.44%

[4]/2019	SSVEP	40	8	9	Filtering Process	CNN	ACC: >97%
[44]/2019	c-VEP (Code Modulated VEPs)	1	25	9	Filter Banks and CCA	Task-Related Component Analysis	ACC: 98.43-100%
[39]/2020	Motor Imagery EEGs	-	109	64	Empirical Mode Decomposition (EMD) and DWT	Support Vector Machine (SVM)	TAR: 0.822-0.927 TRR: 0.981-0.989
[45]/2020	EEG Signals Elicited by Music and Video	-	32	32	Filtering Process and Mesh Feature Technique	CNN-LSTM and CNN-GRU and SVM	ACC: 99.90-100%
[46]/2020	Mental Task EEGs	-	45	19	Common Average Referencing Filtering	CNN, RNN, LDA and SVM	ACC: >96%
[47]/2021	VEP	-	70	14	Filtering Process for Extracting Alpha Bands	CNN and LSTM	ACC: 81.78% FAR: 29.28% FRR: 7.14%
[17]/2021	Mental Task EEGs	-	45	19	Filtering Process	CNN	EER: 10.5-16.4%
[48]/2021	SSVEP and P300	4	10	3-12	Filtering Process and Canonical Correlation (CCA)	Bayesian Linear Discriminant analysis (BLDA)	ACC: 94.61-97.63%
[20]/2021	VEPs (Code Modulated VEPs)	2	15	9	Filtering Process	State-of-the-Art Task-Related Component Analysis (TRCA)	ACC: 98.93-100%
[49]/2021	SSVEP, ERP, MI and Hybrid Signals	4	54	32	Filter Bank Common Spatial Pattern (FBCSP) Algorithm	SVM, CNN	FRR: 0.12—7.36 FAR: 0.27-4.55
[50]/2021	SSVEP	2	15	30	Filtering Process	SVM	TAR: 84.12-95.51% FAR: 0.7-2.7

					and Independent Principal Component Analysis		
Our Study	SSVEP	4	11	1	Discrete Wavelet Transform and Data Resizing Process	LSTM, BiLSTM and GRU	ACC: 93.58- 100% F1: 96.64- 100% ITR: 2.312- 2.793

SB: Subject Number, NFF: Number of Flickering Frequencies CN: Channel Number, Pre: Pre-processing/ FE: Feature Extraction, ML: Machine Learning Models, Perf: Performances, TAR: True Acceptance Rate, TRR: True Rejection Rate, EER: Equal Error Rate

According to the literature survey (Table 7), the single-channel SSVEP-based biometric approach offers highly promising biometric recognition results compared to the multi-channel and multi-trial EEG-based biometrics. It is obvious that the accuracy range in our single-channel (93.58-100%) SSVEP-based biometric study is a significant achievement in view of the results of the other studies. It is worth noting that, with the single-channel performance of the Oz electrode with RNN-based deep architectures, our approach was comparable and provided better robust outcomes for raw signals and DWT-based features. It is crucial for SSVEP-based BCI studies that the test subjects are untrained and that small data block lengths are used [51]. Only one session and one trial were implemented and 16 s were allotted for each flickering frequency in the training models. Hence, our approach can offer these important features with single-channel SSVEP-based biometrics using RNN-based deep models.

5 Conclusion

Several light sources flickering at different frequencies and their responses on the EEG signals, i.e., SSVEP signals, can provide a highly promising and robust biometric approach. In this study, a single-channel and single-trial SSVEP-based biometric approach was developed using RNN-based deep architectures. Moreover, the biometric recognition results for 11 individuals were investigated and compared systematically for different-sized time series of raw signals and sub-bands signals. To date, the literature had lacked research using a single-channel SSVEP-based biometric approach with a systematic comparison using RNN-based deep architectures.

Hence, the single-channel, untrained, and singular dynamic of the SSVEP signals for each person can provide a more economical (due to the low set-up cost), easy-to-use, reliable, and high-accuracy (approaching 100%) biometric approach for real-time usage instead of the traditional static biometrics (face, fingerprints, etc.). In addition, this technique can serve as an important alternative to the noise-prone multi-channel EEG-based biometric methods.

Funding

This work did not receive any grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

K. Gorur: Conceptualization, Methodology, Software, Validation, Investigation, Writing - original draft. **B. Eraslan:** Writing - review & editing.

Declaration of competing interest

The authors declare that they have no conflict of interest.

References

1. Jain AK (2007) Biometric recognition. *Nature* 449:38–40. <https://doi.org/10.1038/449038a>
2. Dargan S, Kumar M (2020) A comprehensive survey on the biometric recognition systems based on physiological and behavioral modalities. *Expert Syst Appl* 143:113114. <https://doi.org/10.1016/j.eswa.2019.113114>
3. Yang S, Hoque S, Deravi F (2019) Improved Time-Frequency Features and Electrode Placement for EEG-Based Biometric Person Recognition. *IEEE Access* 7:49604–49613. <https://doi.org/10.1109/ACCESS.2019.2910752>
4. Yu T, Wei C-S, Chiang K-J, et al (2019) EEG-Based User Authentication Using a Convolutional Neural Network. In: 2019 9th International IEEE/EMBS Conference on Neural Engineering (NER). IEEE, pp 1011–1014
5. Jayarathne I, Cohen M, Amarakeerthi S (2020) Person identification from EEG using various machine learning techniques with inter-hemispheric amplitude ratio. *PLoS One*

15:e0238872. <https://doi.org/10.1371/journal.pone.0238872>

6. Gorur K, Bozkurt MR, Bascil MS, Temurtas F (2018) Glossokinetic potential based tongue–machine interface for 1-D extraction. *Australas Phys Eng Sci Med* 41:379–391. <https://doi.org/10.1007/s13246-018-0635-x>
7. Casson AJ, Smith S, Duncan JS, Rodriguez-Villegas E (2008) Wearable EEG: what is it, why is it needed and what does it entail? In: 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, pp 5867–5870
8. Acampora G, Trinchese P, Vitiello A (2021) A dataset of EEG signals from a single-channel SSVEP-based brain computer interface. *Data Br* 35:106826. <https://doi.org/10.1016/j.dib.2021.106826>
9. Singhal GK, RamKumar P (2007) Person Identification Using Evoked Potentials and Peak Matching. In: 2007 Biometrics Symposium. IEEE, pp 1–6
10. Angrisani L, Arpaia P, Casinelli D, Moccaldi N (2019) A Single-Channel SSVEP-Based Instrument With Off-the-Shelf Components for Trainingless Brain-Computer Interfaces. *IEEE Trans Instrum Meas* 68:3616–3625. <https://doi.org/10.1109/TIM.2018.2882115>
11. Puengdang S, Tuarob S, Sattabongkot T, Sakboonyarat B (2019) EEG-Based Person Authentication Method Using Deep Learning with Visual Stimulation. In: 2019 11th International Conference on Knowledge and Smart Technology (KST). IEEE, pp 6–10
12. Autthasan P, Du X, Arnin J, et al (2020) A Single-Channel Consumer-Grade EEG Device for Brain–Computer Interface: Enhancing Detection of SSVEP and Its Amplitude Modulation. *IEEE Sens J* 20:3366–3378. <https://doi.org/10.1109/JSEN.2019.2958210>
13. Carrión-Ojeda D, Fonseca-Delgado R, Pineda I (2021) Analysis of factors that influence the performance of biometric systems based on EEG signals. *Expert Syst Appl* 165:113967. <https://doi.org/10.1016/j.eswa.2020.113967>
14. Behera SK, Kumar P, Dogra DP, Roy PP (2021) A Robust Biometric Authentication System for Handheld Electronic Devices by Intelligently Combining 3D Finger Motions and Cerebral Responses. *IEEE Trans Consum Electron* 67:58–67. <https://doi.org/10.1109/TCE.2021.3055419>

15. Kumar MG, Narayanan S, Sur M, Murthy HA (2021) Evidence of Task-Independent Person-Specific Signatures in EEG Using Subspace Techniques. *IEEE Trans Inf Forensics Secur* 16:2856–2871. <https://doi.org/10.1109/TIFS.2021.3067998>
16. Palaniappan R (2004) Method of identifying individuals using VEP signals and neural network. *IEE Proc - Sci Meas Technol* 151:16–20. <https://doi.org/10.1049/ip-smt:20040003>
17. Maiorana E (2021) Learning deep features for task-independent EEG-based biometric verification. *Pattern Recognit Lett* 143:122–129. <https://doi.org/10.1016/j.patrec.2021.01.004>
18. Palaniappan R, Mandic DP (2007) Biometrics from Brain Electrical Activity: A Machine Learning Approach. *IEEE Trans Pattern Anal Mach Intell* 29:738–742. <https://doi.org/10.1109/TPAMI.2007.1013>
19. Palaniappan R, Ravi KVR (2006) Improving visual evoked potential feature classification for person recognition using PCA and normalization. *Pattern Recognit Lett* 27:726–733. <https://doi.org/10.1016/j.patrec.2005.10.020>
20. Zhao H, Chen Y, Pei W, et al (2021) Towards online applications of EEG biometrics using visual evoked potentials. *Expert Syst Appl* 177:114961. <https://doi.org/10.1016/j.eswa.2021.114961>
21. Min B-K, Suk H-I, Ahn M-H, et al (2017) Individual Identification Using Cognitive Electroencephalographic Neurodynamics. *IEEE Trans Inf Forensics Secur* 12:2159–2167. <https://doi.org/10.1109/TIFS.2017.2699944>
22. Piciuccio E, Maiorana E, Falzon O, et al (2017) Steady-State Visual Evoked Potentials for EEG-Based Biometric Identification. In: 2017 International Conference of the Biometrics Special Interest Group (BIOSIG). IEEE, pp 1–5
23. Thomas J, Maszczyk T, Sinha N, et al (2017) Deep learning-based classification for brain-computer interfaces. In: 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE, pp 234–239
24. LeCun Y, Bengio Y, Hinton G (2015) Deep learning. *Nature* 521:436–444.

<https://doi.org/10.1038/nature14539>

25. Gorur K, Bozkurt M, Bascil M, Temurtas F (2019) GKP Signal Processing Using Deep CNN and SVM for Tongue-Machine Interface. *Trait du Signal* 36:319–329. <https://doi.org/10.18280/ts.360404>
26. Kim B-H, Pyun J-Y (2020) ECG Identification For Personal Authentication Using LSTM-Based Deep Recurrent Neural Networks. *Sensors* 20:3069. <https://doi.org/10.3390/s20113069>
27. Kumar S, Sharma A, Tsunoda T (2019) Brain wave classification using long short-term memory network based OPTICAL predictor. *Sci Rep* 9:9153. <https://doi.org/10.1038/s41598-019-45605-1>
28. Ruffini G, Ibañez D, Castellano M, et al (2019) Deep Learning With EEG Spectrograms in Rapid Eye Movement Behavior Disorder. *Front Neurol* 10:. <https://doi.org/10.3389/fneur.2019.00806>
29. Kaushik P, Gupta A, Roy PP, Dogra DP (2019) EEG-Based Age and Gender Prediction Using Deep BLSTM-LSTM Network Model. *IEEE Sens J* 19:2634–2641. <https://doi.org/10.1109/JSEN.2018.2885582>
30. Chen D, Wan S, Xiang J, Bao FS (2017) A high-performance seizure detection algorithm based on Discrete Wavelet Transform (DWT) and EEG. *PLoS One* 12:e0173138. <https://doi.org/10.1371/journal.pone.0173138>
31. Abdar M, Yen NY, Hung JC-S (2018) Improving the Diagnosis of Liver Disease Using Multilayer Perceptron Neural Network and Boosted Decision Trees. *J Med Biol Eng* 38:953–965. <https://doi.org/10.1007/s40846-017-0360-z>
32. Fawcett T (2006) An introduction to ROC analysis. *Pattern Recognit Lett* 27:861–874. <https://doi.org/10.1016/j.patrec.2005.10.010>
33. Metz CE (1978) Basic principles of ROC analysis. *Semin Nucl Med* 8:283–298. [https://doi.org/10.1016/S0001-2998\(78\)80014-2](https://doi.org/10.1016/S0001-2998(78)80014-2)
34. Ozer I, Cetin O, Gorur K, Temurtas F (2021) Improved machine learning performances with transfer learning to predicting need for hospitalization in arboviral infections

- against the small dataset. *Neural Comput Appl* 33:14975–14989. <https://doi.org/10.1007/s00521-021-06133-0>
35. Ozer I, Efe SB, Ozbay H (2021) A combined deep learning application for short term load forecasting. *Alexandria Eng J* 60:3807–3818. <https://doi.org/10.1016/j.aej.2021.02.050>
 36. BAYRAM MA, ÖZER İ, TEMURTAŞ F (2021) Deep Learning Methods for Autism Spectrum Disorder Diagnosis Based on fMRI Images. *Sak Univ J Comput Inf Sci* 4:142–155. <https://doi.org/10.35377/saucis.04.01.879735>
 37. Rhanoui M, Mikram M, Yousfi S, Barzali S (2019) A CNN-BiLSTM Model for Document-Level Sentiment Analysis. *Mach Learn Knowl Extr* 1:832–847. <https://doi.org/10.3390/make1030048>
 38. Deng Y, Wang L, Jia H, et al (2019) A Sequence-to-Sequence Deep Learning Architecture Based on Bidirectional GRU for Type Recognition and Time Location of Combined Power Quality Disturbance. *IEEE Trans Ind Informatics* 15:4481–4493. <https://doi.org/10.1109/TII.2019.2895054>
 39. Moctezuma LA, Molinas M (2020) Towards a minimal EEG channel array for a biometric system using resting-state and a genetic algorithm for channel selection. *Sci Rep* 10:14917. <https://doi.org/10.1038/s41598-020-72051-1>
 40. Ajami S, Mahnam A, Abootalebi V (2018) Development of a practical high frequency brain–computer interface based on steady-state visual evoked potentials using a single channel of EEG. *Biocybern Biomed Eng* 38:106–114. <https://doi.org/10.1016/j.bbe.2017.10.004>
 41. Zarei A, Asl BM (2021) Automatic seizure detection using orthogonal matching pursuit, discrete wavelet transform, and entropy based features of EEG signals. *Comput Biol Med* 131:104250. <https://doi.org/10.1016/j.compbiomed.2021.104250>
 42. Xu G, Ren T, Chen Y, Che W (2020) A One-Dimensional CNN-LSTM Model for Epileptic Seizure Recognition Using EEG Signal Analysis. *Front Neurosci* 14:. <https://doi.org/10.3389/fnins.2020.578126>
 43. El-Fiqi H, Wang M, Salimi N, et al (2018) Convolution Neural Networks for Person

- Identification and Verification Using Steady State Visual Evoked Potential. In: 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE, pp 1062–1069
44. Zhao H, Wang Y, Liu Z, et al (2019) Individual Identification Based on Code-Modulated Visual-Evoked Potentials. *IEEE Trans Inf Forensics Secur* 14:3206–3216. <https://doi.org/10.1109/TIFS.2019.2912272>
 45. Wilaiprasitporn T, Ditthaporn A, Matchaparn K, et al (2020) Affective EEG-Based Person Identification Using the Deep Learning Approach. *IEEE Trans Cogn Dev Syst* 12:486–496. <https://doi.org/10.1109/TCDS.2019.2924648>
 46. Maiorana E (2020) Deep learning for EEG-based biometric recognition. *Neurocomputing* 410:374–386. <https://doi.org/10.1016/j.neucom.2020.06.009>
 47. Chakladar D Das, Kumar P, Roy PP, et al (2021) A multimodal-Siamese Neural Network (mSNN) for person verification using signatures and EEG. *Inf Fusion* 71:17–27. <https://doi.org/10.1016/j.inffus.2021.01.004>
 48. Rathi N, Singla R, Tiwari S (2021) Towards a role-based authentication system based on SSVEP-P300 hybrid brain–computer interfacing. *Behav Inf Technol* 1–17. <https://doi.org/10.1080/0144929X.2021.1979655>
 49. Debie E, Moustafa N, Vasilakos A (2021) Session Invariant EEG Signatures using Elicitation Protocol Fusion and Convolutional Neural Network. *IEEE Trans Dependable Secur Comput* 1–1. <https://doi.org/10.1109/TDSC.2021.3060775>
 50. Zhang Y, Li M, Shen H, Hu D (2021) A Permanency Investigation of SSVEP Signals in Brain Biometrics. In: 2021 IEEE 4th International Conference on Electronics Technology (ICET). IEEE, pp 758–762
 51. Bassi PRAS, Rampazzo W, Attux R (2021) Transfer learning and SpecAugment applied to SSVEP based BCI classification. *Biomed Signal Process Control* 67:102542. <https://doi.org/10.1016/j.bspc.2021.102542>