ISSN: 2710-2165

Electroencephalographic (EEG) based Deep Learning (DL): A Comparative Review

Riyadh Salam Mohammed[*], Ammar A. Al-Hamadani [**]

[*]Department of Computer Engineering, College of Engineering, Al- Iraqia University, Iraq
riyadh.s.mohammed@aliraqia.edu.iq
https://orcid.org/0009-0008-7043-5516

[**]Department of Computer Engineering, College of Engineering, Al- Iraqia University, Iraq
ammar.aladin@aliraqia.edu.iq
https://orcid.org/0000-0001-9951-5431

Abstract

Deep learning (DL) has recently shown great promise in supporting knowledge of electroencephalographic (EEG) as a result of its ability to discover visual features (feature representation) from original (raw) data. This review will look at the latest developments in the research area of the EEG by analyzing a largest amount of the recent and definitive publications on EEG based on DL for biometrics identification. It covers the latest developments in different parts of the DL-EEG methodology and offers valuable information about them in order to improve its implementation. Also, it will provide interested researchers with a brief overview of the prospects of applying DL typical EEG processing methods. In addition to highlighting interesting methods and trends that used to acquisition and analyses brain signals, the stimulations, feature extractions and classifications. We summarize our review in some recommendations and proposals in the hope of promoting effective viable research in this field. We have highlighted interesting approaches and directions from this extensive research in order to provide ample information for future research. This review revealed that the duration of time spent trying to collect EEG data ranged from (10) minutes or less to a long time of hours, and interestingly, we found that more than 50 percent of the research design their models using publicly available datasets. Furthermore, There about half of the researchers used unprocessed or preprocessed EEG samples to train their models. Compared to traditional approaches, DL had an improvement in accuracy of 4% among the most applicable studies. More importantly, we discovered that the majority of previous studies have poor reproducibility: it is extremely difficult or impossible to replicate the majority of research due to a lack of data and codes. The importance of the paper lies in helping the research community to share and develop work more effectively. And We'll also offer a list of suggestions for more studies in the future.

Keywords- Electroencephalogram, Deep learning, convolution Neural Networks, Datasets, stimuli.

I. INTRODUCTION

Biometrics aim to identify individuals based on behavioral, physiological, or physical characteristics of the human body such as facial and finger prints, voice, hand written, and iris [8]. Recently, the research community has become interested in the use of EEG brain wave data as biometric identification, EEG brain wave (signals) can be acquired in response to a specific task or during the performance of a stimulus presented. Several EEG research has employed (DL) to find relevant data for brain classification. Despite the many advantages of brain biometrics, they have yet to be extensively embraced since there are still many studies to be done; one of this review's primary goals is to analyze the areas where an investigation is still needed. Seven criteria are used to evaluate how acceptable a biometric as a method of authentication method or identification (acceptability, uniqueness, permanence, circumvention, performance, universality, and collectability) [60]. This study attempts to give a comprehensive overview of the existing studies and highlight the researchers on EEG biometric systems utilizing DL that have been done. It gives a current analysis of cutting-edge techniques for acquiring brain signals, publicly accessible datasets, equipment, preprocessing tools, Feature Extraction (FE), and classifiers employed in the analysis of EEG signals, as shown in figure 1.

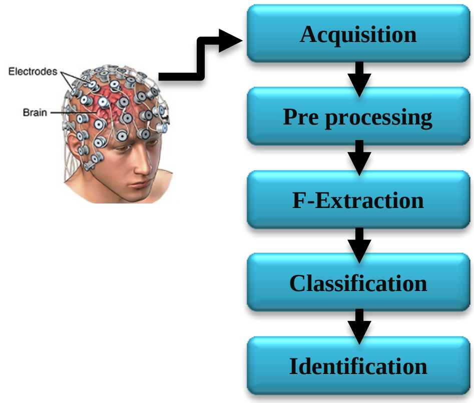

Figure1. General Identification model steps

There were more than (35) identified studies. According to the kind of different tasks, input data type, EEG preprocessing techniques, and DL architecture, those studies were analyzed, to provide the main results. Convolutional-Neural-Networks (CNN), Recurrent-Neural-Networks (RNN), and Multi-Layer-Perceptron-Neural-Networks (MLP) all perform well for EEG classifier. Motor-imagery (MI), mental-workload (MW), emotion-recognition (ER), seizure-detection (ZD), event-related-potential detection (ERP), and resting state (RS) were the six broad categories that the tasks that utilized DL fell within. Several previous research studies have shown that brain biometrics can be sufficiently distinctive, permanent, and universal. From the perspectives of signal capture and synthesis (preprocessing), recent studies have shown demonstrated that brain biometrics are robust against circumvention and spoofing [61]. And to enhance the acceptability, collectability, and performance of brain biometrics as identification, more study is necessary. Since that brain biometrics are becoming more practical, it's important to figure out what is and isn't understood about them. The significance of this evaluation summarizes the recent performs and practice results in the usage of DL for EEG data classification. Practical suggestions for the choice of several hyperparameters that provided the confidence that it will help or guide the deployment of DL to EEG data in future studies. In this review, we investigate the recent works between 2015 to 2023 and outline the scientific literature conducted on EEG signals for biometric identification. This review is prepared as follows: In first section, we introduce a descriptive introduction about EEG systems. In subsequential sub-Sections, each component of the typical system is thoroughly described. Includes the acquisition tools and EEG datasets used in section two. And Stimulation Process types were described in section three, FE and analysis of EEG data described in section four, and classification methods in section five. In section six, we discussed all parameters and tools used in literatures. The conclusion, in section seven, we outline a few of the research fields in the region.

II. DATASETS & DEVICES

Many datasets were used for experiments by researchers in public mode that available on online, like Brain-Computer-Interface (BCI), Physionet, DEAP, DREAMER, HEADIT, BED, CT2WS, and RSVP. Other mode founded in research center in University of Bonn, King Abdulaziz University [24], and Shanghai Mental Health Center [36]. Other researchers try another mode of acquisition EEG data by Self-Collected (SC) used in them researcher's. We founded a self-collected dataset by the researchers that consist of different numbers of subjects between (8 – 50) whose ages range between 15-50 years performed many tasks [7-10], [12-19], [21-22], [24], [26], and [32]. The ref. [1], [34], and [40] use BCI dataset that contains Thirty-two healthy subjects participated in the measurements. In [2] a large collection of EEG records with 100 participants from a BCI task evaluating driving tiredness, known as Baseline Driving for the BCIT Experiment (XB Driving), In [3] a self-collected EEG dataset from 20 Thai people in good health (10 females and 10 males, whose ages range from 15 to 50 years). Physionet data set used by the ref. [4-6], [11], [17], [20], [23], [25], [27-28], [33], and [37-39] and work on the publicly available dataset consisting of EEG of 109 participants completing various motor/imagery duties, it's a popular benchmark for biometric with EEG. In [9] datasets from four different experiments measuring endogenous brain functions (driving fatigue and emotion) in addition to time-locked artificially created brain responses from 157 subjects, [5] datasets including emotion and combined data. In [31][35] (DREAMER, HEADIT) datasets performed emotion recognition tasks were used in them experiments. In [29] a dataset created to evaluate EEG-based biometric methods, named (BED) created to test the effectiveness of consumer-grade hardware. The dataset includes EEG readings from 21 individuals in response to 12 various stimuli. There are several types of EEG recording systems, including [64]:

- Standalone EEG: These are compact and portable devices that can be used for bedside monitoring or in the clinic. They typically contain a few electrodes and a compact amplifier that can be connected to a computer for data storage and analysis.

- Video EEG Systems: These systems combine EEG recording with video and audio recording, providing a synchronized record of both the brain's electrical activity and the patient's behavior. They are commonly used to identify and treat neurological problems like epilepsy, sleep disorders, insomnia, and others.
- Wireless EEG: These systems allow for the collecting and recording of EEG signals without utilizing wires, making them more comfortable for the patient and allowing for greater mobility. The signals are transmitted wirelessly to a computer or other device for analysis.
- High-density EEG Systems: These systems use a great number of electrodes conductor (often 128 or more) to provide a high spatial resolution of the brain's electrical activity. They are commonly used in research studies because they provide a more comprehensive view of brain activity than other EEG systems.

Regardless of the type of EEG system used, the electrodes and amplifier must be properly placed and calibrated to ensure accurate and reliable recordings. Additionally, the signals recorded by EEG systems must be carefully analyzed and interpreted to get useful data regarding the brain's electrical activity. In [2], [4-6], [9], [11], [14], [16-19], [20], [23], [25], [27-28],[30], [33], and [37-39] worked on BCI2000 system to record and analyzed EEG using 32 electrodes, while [1][8][34][40] used AgCl electrodes EEG signals were recorded using a (Bio semi) Active Two system, EEG data were collected at a 512 sampling rate (Hz), AgCl with 32 electrodes works on the (10-20) of the international systems. Another device was using named GALILEO BE Light amplifier equipped with 19 channels/electrodes. [12] BrainLink electroencephalograph developed by Neurosky, [21] utilized Brain Devices called acti CHamp data collecting system, 64- scalp electrodes which works on the (10-20) of the international systems. [22] Synamps2 system (Neuroscan, Inc.). [31] Emotiv EPOC wireless EEG headset. [36] (BrainCap, Bavaria) 64-channel electrodes installed in an elastic cap were used to capture EEGs, along with two pairs of electrodes for electrooculography (EOG).

III. STIMULATION PROCESS

Stimuli are tools and items used to generate responses from study participants or volunteers in the field of human behavior research. Stimuli may come in many media including visual, physical, or auditory, and can be clearly observed in EEGs. So, what exactly are stimuli? The stimuli or (stimulus) are the foundation of the research study of brain signals. It's essential to know the nature of the stimuli and the best ways to apply them. The chosen stimulus should make the study scenario (or experiment) more interesting and interactive for the volunteers (selected category). And ought to be as accurate as feasible. In addition, it should focus attention on the research topic without too much pressure and provide a suitable and calm environment (place) for the volunteers [63]. EEG data acquisition can be enhanced by using various forms of stimulation, which can help to elicit specific responses from the brain and afford extra data about the brain activity. According to EEG standards, the initially proposed EEG-based identification techniques can be divided into three categories: resting states (modes), cognition tasks, and tasks with outside stimulus [41].

1- Resting states (RS), In a calm setting, individuals are told to rest totally while the EEG signals of the eye closed (EC) or the eye opened (EO) is recorded [42].
2- Cognitive tasks (CTs), such as driving (tiredness) fatigue [2], (MI) [43], and (MW) [44], Typically, volunteers need to undergo training and do specific activities due to external cues while having their EEG signals recorded. [45].
3- Tasks evoked by external stimulation, like visually evoked potential (VEP) [46], and auditory stimuli [47], some extra devices are usually necessary to make the appropriate stimulation for collecting the EEG signals. In comparison to the other two categories, (RS) essentially requires no subjects training and is easy to apply, which researchers have preferring. Some common forms of stimulation used in EEG include [5], [7], and [13]:
   3.1 Visual Stimulation: This involves presenting visual stimuli, such as flashing lights or patterns, to the patient and recording the resulting brain activity. This can be used to study visual perception and processing, as well as to elicit specific responses in the brain, such as the (VEP). Many references use this form of stimuli, such [15], [29], and [34].
   3.2 Auditory Stimulation: This involves presenting auditory stimuli, such as sounds or tones, to the patient and recording the resulting brain activity. This can be used to study auditory perception and processing, as well as to elicit specific responses in the brain, such as the auditory evoked potential (AEP) [21], [26].
   3.3 Somatosensory Stimulation: This involves applying tactile stimuli, such as vibrations or pressure, to the patient and recording the resulting brain activity. This can be used to study somatosensory perception and processing, as well as to elicit specific responses in the brain, such as the somatosensory evoked potential (SEP).
   3.4 Transcranial Magnetic Stimulation (TMS): This is a non-invasive kind of brain stimuli that works by stimulating the brain's cells using magnetic fields. TMS can be used in conjunction with EEG to study brain function and can also be used to treat certain neurological and psychiatric conditions.

The design was tested on two baseline scenarios in (RS), (EC, and EO) as shown in [4], [14], [20], [25], [28], [36-39]. in [10] EC Use this trigger only with the data to build the model and extract the results. And in [12] The volunteers are asked to close their eyes and sit still for 120 seconds. While in [11] employed (EO, EC) in RS, and two other tasks, including a picture narrative task, and an attention task. [17] use different motor/imagery tasks baseline tests (one with EO, other with EC). In [32], accumulation of cognitive brain load from lying down and closing your eyes to the end of a challenging game. In [38] three experiments applied, first experiment in Resting eye open (REO), and second experiment in Resting eye closed (REC), and third experiment (2 min) runs with (4) various (MI) activities.

The Cognitive Tasks (CT), [2], [30] A comprehensive study of an individual's discriminatory detail in the time-scale of EEG signals given from the XB Driving task. One standard driving BCI test is referred to as (BCIT) (XB Driving). In [18], The voluntary activation of private brain regions by the subjects involved is required for EEG responses to a (MI) protocol. This indicates that even when people are told to focus during EEG acquisition, some won't effectively perform the necessary imagined tasks. [27] use MI, the subjects were only asked to visualize and perform various motor tasks during the EEG signal capture phase. [33], a DL model based on attention was used to extract deep Delta wave representations from brain waves. In [34], use four different types of move imaging, including the tongue, the 2 feet, the right, and left hands, the short video was shown with various emotional classifications, there was a need for a resting stage of (1 min) EO and (1 min) EC. Second experiment, five minutes for each of the two video segments with various emotion classifications were shown, before 2 videos, there were 800 milliseconds of the black crosses. After then, respondents were instructed to imagine making left and right-handed movements every 25 times in time with the notification that appeared on the screen for 4 seconds. In [35], combine two protocols VEP and MI. Tasks Evoked (TE) by external stimulation, in ref. [1], While the EEG was being measured, they were told to watch effectively elicited music videos and give (40) video clips their subjective rankings (arousal and valence). In [16][22] used the stimuli the steady-states visually evoked potential (SSVEP), while in [3], suggested combining stimuli (SSVEP) and (ERP) to identify brain cues to discriminate between participants. [8], use ERP as a stimulus to collect EEG signals. [9] checked into how effectively it performed using EEG data from the XB driving test, with the rapid serial visual response (RSVP) experiment in the RSVP BCI paradigm with time locking. [21], use familiar-name auditory evoked potentials in the experiment. [26], use steady state Auditory Evoked Potential (AEP). Ref. [31], show percipients video clips selected to elicit specific emotions.

In addition to these forms of stimulation, EEG recordings can also be obtained during tasks or other activities, such as cognitive or motor tasks, to study brain function in real-world situations. The combination of EEG and stimulation can provide a more complete picture of brain function and help to further our understanding of the brain and its role in perception, cognition, and behavior. [7], and [13] Use multiple protocols task-independent, EC, EO, MI, speech imagery (SI), visual stimulation (VS), and mathematical computation (MC). [29], use affective stimuli, (CSs), (VEP), and (RS). While [5-7], use (RS) with EO and EC, physical movement tasks (PHY) which calls for the participants to close or open both fists or feet, and (MI) tasks which asks the volunteers to imagine doing the previous movements without real physical activity, an image description task (IMG) and (ATT) [30].

IV. FEATURE EXTRACTION

Feature Extraction (FE) is a significant stage in the analysis of EEG data for DL models. The target of (FE) is to change the raw data of EEG signals into set of relevant and informative features that can be used as inputs for DL algorithms. Many techniques exist for extracting characteristics from EEG signals., including [1], [2], [4], [48]:

A. Time-domain features: These features are derived from the raw EEG signals and include measures such as mean, standard deviation, and amplitude from peak to peak. Time-domain features provide a simple and straight forward representation of the EEG waves and are commonly used as inputs to machine learning algorithms.

B. Frequency-domain features: These characteristics are determined from the EEG signals' frequency components. and include measures such as spectral entropy and power spectral (PSD) density. Frequency-domain features provide information about the distribution of energy across different frequencies in the EEG signals and can be utilized for detecting data patterns.

C. Temporal features: These features capture the temporal relationships between EEG signals and can include measures such as correlation, coherence, and phase locking value. Temporal features provide information about the interactions between various parts (regions) of the brain and can be used to identify functional connectivity patterns.

D. Spatial features: These features capture the spatial relationships between EEG signals and can include measures such as current source density and laplacian. Spatial features provide information about the distribution of electrical activity across the scalp and can be used to recognize activity patterns in different regions (parts)of the brain.

A recent evaluation review of the usability of EEG-based Personal Identification (PI) resulted in many main signal processing methods to support perform (FE) and several accepted types of features extraction were selected [11], [49], like the coefficients of the autoregressive models (AR), (PSD) functions [2], [9], [31], Wavelet Transform function (WT) [40], [50], and Hilbert Huang Transform (HHT) [51], are useful for (FE). Each of these features provide some information of individual uniqueness, and the researchers combined these features together to further boost the performance. DL models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been utilized to analyze EEG data and extract features automatically. These models can learn to identify patterns and relationships in the data and generate predictions or classifications based on these features. In

[1], [4], [6], [8], [14], [18], [20], [22], [25], [28], [32], [35-39] used the (CNNs) models or changing in the structure of the (CNN) [8], to extract features, while [10], [13] apply a model called Siamese CNNs, another researchers use the graph convolutional neural network (GCNN) to detain deep essential structural representations from EEG graphs immediately [5], and in [19] propose an adversarial inference learning with CNN to extend DL models. In [24], [33], used RNN and Long Short-Term Memory (LSTM) which is a special form of RNN architecture with FaceNet to create a new LSTM-RNN model that aided in the extraction of the feature vector for a given 100s EEG signal which leads with a support vector machine (SVM) used as a clustering tool. In addition to these methods, there are also more advanced techniques for feature extraction, such as Using neighborhood component analysis [27], wavelet transform [40], and independent component analysis, that can be utilized to extract more complex and nuanced characteristics from EEG signals. The choice of (FE) method will depend on the specific penalty area and requirements of the analysis, and the method that is best suited will depend about the EEG signals' nature and the questions being asked [49].

V. CLASSIFICATION

In EEG analysis, the aim of feature classification is typically to expect a particular outcome or to classify EEG signals into different categories based on their characteristics. There are several types of feature classification algorithms that can be used in the analysis of EEG data, including [53], [54]:

a) Supervised learning algorithms (SLA): These algorithms require labeled data, where the desired outcome or class label is known for each sample. Common (SLA) used for EEG data classification include SVM, decision trees, and random forests.
b) Unsupervised learning algorithms (USLA): These algorithms need no labeled data and instead attempt to detect patterns and structure in the data. Common (SLA) used for EEG data classification include self-organizing maps (SOM) and k-means clustering.
c) DL algorithms: These algorithms use artificial neural networks to model complex relationships in the data and can be used for both supervised and unsupervised learning. (CNNs) and (RNNs) are usually used for EEG data classification.

DL offers a possible solution for classification of EEG signals. Results of related work have showed that the representations automatically extracted by the DL models are more discriminative and robust over time than handcrafted features with conventional classifiers [12]. A DL model integrating functional connectivity was proposed for biometric identification in a recent work [16]. In recent studies CNNs have been proposed to EEG-based person identification and authentication, achieving promising results [2], [8-20], [22], [25], [28], [29], [31], [32] and [34-39]. These studies use CNNs model directly on the EEG amplitude fluctuations. However, as mentioned, EEG amplitudes are sensitive to many reasons such as mental states, noise, or simply signal acquisition solutions, making the extracted representations unacceptable to changes. A signal processing module that can provide stable inputs while facilitating the learning process is one way to improve performance and stability. In [3], [4], [6], [33] applied recurrent neural network (RNN)s with two approaches LSTM and gated recurrent unit (GRU) for classify the EEG signals and predicting the results. While in these studies [1], [21], [23], [30] proposed a combine CNNs with LSTM and with GRU, to handle spatial info, CNN is employed and RNN used for extract the temporal info, The combined use of CNNs and LSTMs can excellently improve the accuracy of personal identification systems by employing the spatio-temporal features of the EEG signals, and decreasing the number of EEG channels/electrodes employed in the systems to minimize their cost [23]. other researchers are used machine learning algorithms at standard classifier like LDA, SVM, KNN and MLP for the final clustering [5], [7], [24]. It is important to note that feature classification is just one step in the analysis of EEG data, and the choice of feature classification algorithm should be made in the context of the overall research question and analysis plan. In addition to feature classification, other techniques such as data preprocessing, feature selection, and model validation should also be considered to ensure accurate and robust results.

VI. DISCUSSION

In EEG analysis, the choice of feature extraction and classification algorithm will rely on the specific objectives and requirements of the analysis and the nature of the EEG signals. For example, DL algorithms may be more appropriate for complex and high-dimensional EEG signals, while traditional supervised learning algorithms may be better suited for simpler signals or when labeled data is readily available. All information in this review has been collected from many sites like (ScienceDirect, ieeexplore, springer and pubmed) were analyzed in details as seen in the table 1. The most used public dataset was Physionet with 109 subjects, while more than 15 papers using self-collected datasets in their experiments. And no. of subjects is between 5 to 157. The device that most be used in the experiments for acquisition EEG data BCI2000. And the maximum number of electrodes used 64, while the minimum number 2 electrode. In stimuli task the most of researcher prefer (EC) (EO) in resting state. While AEP used just in two papers for identification. In FE, 75 % of the papers use CNN as analyzer for extract features and also for classifier. The Accuracy was in between 63 to 100%, high accuracy achieved in ref. [34], which about 99.94 to 100 % by using five different datasets with 9-32 subjects, the MI, left and right hand, 2 feet and tongue attention EO, EC, VEP used as stimuli as input EEG data for Combining the BN, RL, GAP, and MGC models, RAMST-CNN. in-the-moment paradigm, we discover one study that employs various DL models based on

EEGNet, ResNet, and Inception along with a consumer-grade commercial EEG acquisition device (Emotiv EPOC) for biometric identification. They created a good DL EEGNet model with an accuracy of 86.74 percent using on the (BED) dataset.

Table 1: State-of-the-art topics related to our work, in summary.

ref. No.	Dataset	No. subjects	Devices & system	No. of electrode	stimuli	Feature extraction	Features Classification	accuracy
[1]	DEAP	32	AgCl a Biosemi	32	emotion or affective recognition tasks	(CNNs) &(RNNs)	CNN-LSTM CNN GRU	99%
[2]	BCI	100	BCI	64	BCIT (XB Driving)	(AR) (PSD)	CNN	97%
[3]	SC	20	-	6	(SSVEP) (ERP)	-	(RNN) (LSTM)	91.44%
[4]	Physionet	109	BCI2000	64	(EC) (EO).	(CNN)	(LSTM)	99.95% for EC 98% for EO
[5]	Physionet	109	BCI2000	64	task-independent (EO), (EC), (PHY) (IMA) (ATT) and (IMG).	(GCNN)	(SVM), (KNN), (MLP)	99.81%
[6]	Physionet	109	BCI2000	64	(EO), (EC) fists and feet both physically and imaginarily	(CNN)	(LSTM)	99.58%,
[7]	SC	45	GALILEO 19	19	(EC), (EO), (MI), (SI), (VS), (MC),	(CNNs) &(RNNs)	(LDA) , (SVM)	96%
[8]	SC	33	Ag/AgCl	64	(ERP)	(CNN)	(CNN)	(99.9%) 8-class , 99.3% for 10-class and 99.3% for 13-class
[9]	BCI	157	BCI	64	(RSVP) (XB), (XB R), X2 , CT2WS	(AR) (PSD)	(CNN)	96%
[10]	SC	45	GALILEO 19	19	EC	Siamese CNNs	Siamese CNNs	-
[11]	Physionet SC	109 59	BCI2000	64	EO, EC (ATT), and a picture narrative task	(RHO+CNN)	(RHO+CNN)	-
[12]	SC	15	Neurosky	1	EC	-	(CNN)	96.80%.
[13]	SC	45	GALILEO 19	19	task-independent (EC), (EO), (MI), (SI), (VS), (MC),	Siamese (CNNs)	Siamese (CNNs)	-
[14]	SC	10	BCI2000	64	(EO) (EC)	(CNN)	(CNN)	REO REC REO+REC 88% 86% 82%
[15]	SC	40	GALILEO19	19	(VEP)	(CNN)	(CNN)	98.8%
[16]	SC	17	BCI	8	(SSVEP)	(CNN)	(CNN)	97.60%, 95.90% for Dataset I and II
[17]	Physionet	109	BCI2000	64	(MI) (EO), (EC)	(CNN)	(CNN)	-
[18]	SC	50	GALILEO 19	19	(MI)	(CNN)	(CNN)	99.3%
[19]	SC	10	BCI	16	(RSVP)	Adversarial Learning + (CNN)	Adversarial Learning + (CNN)	98.6% ± 0.006
[20]	Physionet	109	BCI2000	64	(EO), (EC)	(CNN)	(CNN)	test 83.21% and [illegible]
[21]	SC	20	actiCHamp	64 Used 2 only	(AEP)	(1D-CNN) (LSTM) and (GRU)	(1D-CNN) (LSTM) and (GRU)	99.53 % (2) frontal electro 96.93 % a single frontal electro
[22]	SC	8	Neuroscan	9	(SSVEP)	(CNN)	(CNN)	97%
[23]	Physionet	109	BCI2000	64	-	(1D-CNN) (LSTM)	(1D-CNN) (LSTM)	99.58%
[24]	SC	-	-	16 18	-	(LSTM) (RNN)	(SVM) for the final clustering	97.84%
[25]	Physionet	109	BCI2000	64	(RS)	(CNN)	(CNN)	99.32%
[26]	SC	13	-	7	(AEP)	triplet loss as an objective function	(CNN+SVM)	-
[27]	Physionet	109	BCI2000	64	(MI)	neighborhood component analysis	(DNN) ML (DT), (KNN), (SVM), (RF) classifiers	98.630, 100%, 99.964%, 99.912% and 100%,
[28]	Physio Bank	109	BCI2000	64	(REO) (REC)	(CNN)	(CNN)	98.54%

[29]	BED	21	-	14	affective stimuli, cognitive stimuli, VEP, and RS	ResNet and Inception Time EEGNet	ResNet and Inception Time EEGNet	63.21%, 70.18%, and 86.74%
[30]	SC	109	BCI2000	109	MI,EO,EC	(CNN LSTM)	(CNN LSTM)	99.7%
[31]	DREAMER	25	Emotiv EPOC	-	(VEP)	(PSD)	(1DCNN)	94%
[32]	SC	21	-	-	(REC), cognitive brain load	(1DCNN)	(1DCNN)	99%
[33]	Physionet SC	8 8 109	BCI2000	**64**	Attention	(RNN)	(RNN)	0.982
[34]	MTED SEED P300 BCI DEAP	9 8 15 15 32	AgCl electrodes	32	(MI) left, right hand, tongue and both feet Attention (EO) , (EC), (VEP)	(RAMST-CNN), (BN), (RL), (MGC), and (GAP)	(CNN)	100.00 99.78 99.33 99.68 99.94
[35]	HEADIT	30		32	(MI), (VEP)	(DCNN net)	(DCNN net)	96%
[36]	SC	120	(Brain Cap, Bavaria, Germany)	64	(EO)	(CNN)	CNNV-RF CNNV-mSVM	81:6% for (CHR) individuals, 96:7% for (FES) 99:2% for (HC)
[37]	Physionet	109	BCI2000	64	(EO), (EC).	lightweight (CNN	lightweight (CNN)	99%
[38]	Physionet	109	BCI2000	64	(EO), (EC), (MI)	(CNN)	(CNN)	98%
[39]	Physionet	109	BCI2000	64	(REO) (REC)	(CNN)	(CNN)	98.54%.
[40]	DEAP	32	AgCl electrodes	32	a complex emotional for content-independent	(DWT)	(DNN)	94%

VII. CONCLUSION

From our comparison of existing methods in this review, the number of studies applying DL to EEG signal processing (PI) has increased significantly in recent years, indicating a growing community interest in these techniques. To this aim, several deep learning models have been successfully used to generate various classifiers that correctly classify EEG data to obtain satisfactory results. In this study, we examined more than 35 articles that applied DL to EEG data that were published between 2015 and 2023 in order to highlight recent trends in the DL-EEG field. We concentrated on a number of critical elements of the studies, including the datasets and devices they utilized, the technique for analyzing EEG data, the DL models, the claimed outcomes, and the degree of accuracy.

Our study revealed several key tendencies, including the following:

1. DL has been mainly used for EEG classification in areas such as EEG brain-computer interface, sleep disorders, identification of diseases such as epilepsy and schizophrenia, cognitive and emotional recognition, etc.
2. The amount of data used varied greatly, ranging from 9 to over 200 people.
3. Many architectures have been successfully used with EEG data, the most commonly used being CNNs, and RNNs.
4. Use raw EEG as input instead of hand-selected features.
5. Using raw EEG showed a benefit in almost all studies.

The most recent findings were attained utilizing the DL technique, and they showed a different accuracy and the majority of papers achieved high scores. It is encouraged to conduct more research on these combinations, especially the number and configuration of various layers including DL models recurrent layers, and convolutional layers. Many factors must be met before an EEG-based biometric identification system can be used in real-world applications. The number of electrodes utilized for data acquisition (collection) has an important effect on the system's usability: A big number of (connectors) electrodes could make it more challenging to use the system in real-life situations. The volume of EEG data used to train and test the system, as well as the processing duration in seconds, user time spent, and computational efficiency are all important considerations and are factors that are focused on in research studies. in the future, Further research on non-resting state EEG features is possible and going forward. Also, it is important to consider the difficulties of EEG-based personal identification systems in real-time applications which are also worth highlighting and studying. finally, the Classification of EEG data for medical diagnosis is another area of scientific research where deep learning algorithms can be applied to brain diseases.

REFERENCES

[1] T. Wilaiprasitporn, A. Ditthapron, K. Matchaparn, T. Tongbuasirilai, N. Banluesombatkul and E. Chuangsuwanich, "Affective EEG-Based Person Identification Using the Deep Learning Approach," in *IEEE Transactions on Cognitive and Developmental Systems*, vol. 12, no. 3, pp. 486-496, Sept. 2020, doi: 10.1109/TCDS.2019.2924648.

[2] Z. Mao, W. X. Yao and Y. Huang, "EEG-based biometric identification with deep learning," *2017 8th International IEEE/EMBS Conference on Neural Engineering (NER)*, Shanghai, China, 2017, pp. 609-612, doi: 10.1109/NER.2017.8008425.

[3] S. Puengdang, S. Tuarob, T. Sattabongkot and B. Sakboonyarat, "EEG-Based Person Authentication Method Using Deep Learning with Visual Stimulation," *2019 11th International Conference on Knowledge and Smart Technology (KST)*, Phuket, Thailand, 2019, pp. 6-10, doi: 10.1109/KST.2019.8687819.

[4] Das, B.B., Kumar, P., Kar, D. et al. A spatio-temporal model for EEG-based person identification. Multimed Tools Appl 78, 28157–28177 (2019). https://doi.org/10.1007/s11042-019-07905-6

[5] M. Wang, H. El-Fiqi, J. Hu and H. A. Abbass, "Convolutional Neural Networks Using Dynamic Functional Connectivity for EEG-Based Person Identification in Diverse Human States," in *IEEE Transactions on Information Forensics and Security*, vol. 14, no. 12, pp. 3259-3272, Dec. 2019, doi: 10.1109/TIFS.2019.2916403

[6] Sun, Yingnan and Benny P. L. Lo. "EEG-based Authentication With 1D-Convolutional Long Short-Term Memory Neural Networks." (2018).

[7] Emanuele Maiorana, "Deep learning for EEG-based biometric recognition," Neurocomputing, Volume 410, 2020, doi.org/10.1016/j.neucom.2020.06.009

[8] Y. Di, X. An, S. Liu, F. He and D. Ming, "Using Convolutional Neural Networks for Identification Based on EEG Signals," *2018 10th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC)*, Hangzhou, China, 2018, pp. 119-122, doi: 10.1109/IHMSC.2018.10134.

[9] Chen, J.X., Mao, Z.J., Yao, W.X. et al. EEG-based biometric identification with convolutional neural network. Multimed Tools Appl 79, 10655–10675 (2020). https://doi.org/10.1007/s11042-019-7258-4

[10] Maiorana, Emanuele. "EEG-based biometric verification using siamese CNNs." New Trends in Image Analysis and Processing–ICIAP 2019: ICIAP International Workshops, BioFor, PatReCH, e-BADLE, DeepRetail, and Industrial Session, Trento, Italy, September 9–10, 2019, Revised Selected Papers 20. Springer International Publishing, 2019.

[11] M. Wang, J. Hu, and H. Abbass, "Stable EEG biometrics using convolutional neural networks and functional connectivity," Australian Journal of Intelligent Information Processing Systems, vol. 15, no. 3, pp. 19–26, 2019.

[12] Tsai MH, Hsia CY, Wu SK, Chen TL. An individual specifc electroencephalography signal pattern verifcation model based on machine learning and convolutional neural network. J Adv Comput Netw. 2020;8(1):1–9. https://doi.org/10.18178/JACN.2020.8.1.272

[13] Emanuele Maiorana, "Learning deep features for task-independent EEG-based biometric verification," Pattern Recognition Letters, Volume 143, 2021, doi.org/10.1016/j.patrec.2021.01.004

[14] L. Ma, J. W. Minett, T. Blu and W. S. -Y. Wang, "Resting State EEG-based biometrics for individual identification using convolutional neural networks," *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Milan, Italy, 2015, pp. 2848-2851, doi: 10.1109/EMBC.2015.7318985.

[15] R. Das, E. Maiorana and P. Campisi, "Visually evoked potential for EEG biometrics using convolutional neural network," *2017 25th European Signal Processing Conference (EUSIPCO)*, Kos, Greece, 2017, pp. 951-955, doi: 10.23919/EUSIPCO.2017.8081348.

[16] H. El-Fiqi, M. Wang, N. Salimi, K. Kasmarik, M. Barlow and H. Abbass, "Convolution Neural Networks for Person Identification and Verification Using Steady State Visual Evoked Potential," *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Miyazaki, Japan, 2018, pp. 1062-1069, doi: 10.1109/SMC.2018.00188.

[17] Schons, T., Moreira, G.J.P., Silva, P.H.L., Coelho, V.N., Luz, E.J.S. (2018). Convolutional Network for EEG-Based Biometric. In: Mendoza, M., Velastín, S. (eds) Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications. CIARP 2017. Lecture Notes in Computer Science(), vol 10657. Springer, Cham. https://doi.org/10.1007/978-3-319-75193-1_72

[18] R. Das, E. Maiorana and P. Campisi, "Motor Imagery for Eeg Biometrics Using Convolutional Neural Network," *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Calgary, AB, Canada, 2018, pp. 2062-2066, doi: 10.1109/ICASSP.2018.8461909.

[19] O. Özdenizci, Y. Wang, T. Koike-Akino and D. Erdoğmuş, "Adversarial Deep Learning in EEG Biometrics," in *IEEE Signal Processing Letters*, vol. 26, no. 5, pp. 710-714, May 2019, doi: 10.1109/LSP.2019.2906826.

[20] Lai, C.Q.; Ibrahim, H.; Abdullah, M.Z.; Abdullah, J.M.; Suandi, S.A.; Azman, A. Arrangements of resting state electroencephalography as the input to convolutional neural network for biometric identification. Comput. Intell. Neurosci. 2019, 2019, 7895924.

[21] C.M. Jijomon, A.P. Vinod,"Person-identification using familiar-name auditory evoked potentials from frontal EEG electrodes," Biomedical Signal Processing and Control, Volume 68, 2021, doi.org/10.1016/j.bspc.2021.102739.

[22] T. Yu, C. -S. Wei, K. -J. Chiang, M. Nakanishi and T. -P. Jung, "EEG-Based User Authentication Using a Convolutional Neural Network," *2019 9th International IEEE/EMBS Conference on Neural Engineering (NER)*, San Francisco, CA, USA, 2019, pp. 1011-1014, doi: 10.1109/NER.2019.8716965.

[23] Yingnan Sun, Frank P.-W. Lo, Benny Lo, "EEG-based user identification system using 1D-convolutional long short-term memory neural networks," Expert Systems with Applications, Volume 125, 2019, doi.org/10.1016/j.eswa.2019.01.080.

[24] G. Bouallegue and R. Djemal, "EEG Person Identification Using Facenet, LSTM-RNN and SVM," *2020 17th International Multi-Conference on Systems, Signals & Devices (SSD)*, Monastir, Tunisia, 2020, pp. 22-28, doi: 10.1109/SSD49366.2020.9364129.

[25] Fan Y, Shi X, Li Q. CNN-Based Personal Identification System Using Resting State Electroencephalography. Comput Intell Neurosci. 2021 Dec 13;2021:1160454. doi: 10.1155/2021/1160454. PMID: 34938327; PMCID: PMC8687816.

[26] S. N. A. Seha and D. Hatzinakos, "Longitudinal Assessment of EEG Biometrics under Auditory Stimulation: A Deep Learning Approach," *2021 29th European Signal Processing Conference (EUSIPCO)*, Dublin, Ireland, 2021, pp. 1386-1390, doi: 10.23919/EUSIPCO54536.2021.9616098.

[27] Tatar, A.B. Biometric identification system using EEG signals. Neural Comput & Applic 35, 1009–1023 (2023). https://doi.org/10.1007/s00521-022-07795-0

[28] Lai, C.Q.; Ibrahim, H.; Suandi, S.A.; Abdullah, M.Z. Convolutional Neural Network for Closed-Set Identification from Resting State Electroencephalography. *Mathematics* 2022, *10*, 3442. https://doi.org/10.3390/math10193442

[29] Benomar, M.; Cao, S.; Vishwanath, M.; Vo, K.; Cao, H. Investigation of EEG-Based Biometric Identification Using State-of-the-Art Neural Architectures on a Real-Time Raspberry Pi-Based System. *Sensors* 2022, *22*, 9547. https://doi.org/10.3390/s22239547

[30] C. Freitas, P. Silva, G. Moreira, and E. Luz. "Rede Neural Convolucional e LSTM para Biometria Baseada em EEG no Modo de Identificação", in *Anais do XXII Simpósio Brasileiro de Computação Aplicada à Saúde*, Teresina, 2022, pp. 256-267, doi: https://doi.org/10.5753/sbcas.2022.222647.

[31] P. Arnau-Gonzalez, S. Katsigiannis, N. Ramzan, D. Tolson and M. Arevalillo-Herrez, "ES1D: A Deep Network for EEG-Based Subject Identification," *2017 IEEE 17th International Conference on Bioinformatics and Bioengineering (BIBE)*, Washington, DC, USA, 2017, pp. 81-85, doi: 10.1109/BIBE.2017.00-74.

[32] Kralikova, I.; Babusiak, B.; Smondrk, M. EEG-Based Person Identification during Escalating Cognitive Load. *Sensors* 2022, *22*, 7154. https://doi.org/10.3390/s22197154

[33] Xiang Zhang, Lina Yao, Salil S. Kanhere, Yunhao Liu, Tao Gu, and Kaixuan Chen. 2018. MindID: Person Identification from Brain Waves through Attention-based Recurrent Neural Network. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 2, 3, Article 149 (September 2018), 23 pages. https://doi.org/10.1145/3264959

[34] Zhu, Yuxuan et al. "RAMST-CNN: A Residual and Multiscale Spatio-Temporal Convolution Neural Network for Personal Identification with EEG." *IEICE Trans. Fundam. Electron. Commun. Comput. Sci.* 104-A (2021): 563-571.

[35] Y. Zhang, et al., "Affective EEG-based person identification using channel attention convolutional neural dense connection network," Secur. Commun. Netw., Vol. 2021, pp. 1–10, 2021. DOI:10.1155/2021/7568460.

[36] Chu, L., Qiu, R.C., Liu, H., Ling, Z., & Shi, X. Individual Recognition in Schizophrenia using Deep Learning Methods with Random Forest and Voting Classifiers: Insights from Resting State EEG Streams. (2017). *ArXiv, abs/1707.03467*.

[37] Alsumari, W.; Hussain, M.; Alshehri, L.; Aboalsamh, H.A. EEG-Based Person Identification and Authentication Using Deep Convolutional Neural Network. *Axioms* 2023, *12*, 74. https://doi.org/10.3390/axioms12010074

[38] Bidgoly, A.J., Bidgoly, H.J. & Arezoumand, Z. Towards a universal and privacy preserving EEG-based authentication system. Sci Rep 12, 2531 (2022). https://doi.org/10.1038/s41598-022-06527-7

[39] Lai, C.Q.; Ibrahim, H.; Suandi, S.A.; Abdullah, M.Z. Convolutional Neural Network for Closed-Set Identification from Resting State Electroencephalography. *Mathematics* 2022, *10*, 3442. https://doi.org/10.3390/math10193442

[40] Li, Y., Zhao, Y., Tan, T., Liu, N., Fang, Y. (2017). Personal Identification Based on Content-Independent EEG Signal Analysis. In: , et al. Biometric Recognition. CCBR 2017. Lecture Notes in Computer Science(), vol 10568. Springer, Cham. doi.org/10.1007/978-3-319-69923-3_58

[41] Amir Jalaly Bidgoly, Hamed Jalaly Bidgoly, Zeynab Arezoumand, "A survey on methods and challenges in EEG based authentication," Computers & Security, Volume 93, 2020, doi.org/10.1016/j.cose.2020.101788.

[42] Y. Di, X. An, F. He, S. Liu, Y. Ke and D. Ming, "Robustness Analysis of Identification Using Resting-State EEG Signals," in *IEEE Access*, vol. 7, pp. 42113-42122, 2019, doi: 10.1109/ACCESS.2019.2907644.

[43] Zaid Abdi Alkareem Alyasseri, Ahamad Tajudin Khader, Mohammed Azmi Al-Betar, Osama Ahmad Alomari, Person identification using EEG channel selection with hybrid flower pollination algorithm, Pattern Recognition, Volume 105, 2020, doi.org/10.1016/j.patcog.2020.107393.

[44] Yin, Zhong and Jianhua Zhang. "Cross-session classification of mental workload levels using EEG and an adaptive deep learning model." *Biomed. Signal Process. Control.* 33 (2017): 30-47.

[45] Rabie A. Ramadan, Athanasios V. Vasilakos, "Brain computer interface: control signals review," Neurocomputing, Volume 223, 2017, doi.org/10.1016/j.neucom.2016.10.024.

[46] Zeng Y, Wu Q, Yang K, Tong L, Yan B, Shu J, Yao D. EEG-Based Identity Authentication Framework Using Face Rapid Serial Visual Presentation with Optimized Channels. Sensors (Basel). 2018 Dec 20;19(1):6. doi: 10.3390/s19010006.

[47] Kaur, B., Singh, D. & Roy, P.P. "A Novel framework of EEG-based user identification by analyzing music-listening behavior." Multimed Tools Appl 76, 25581–25602 (2017). https://doi.org/10.1007/s11042-016-4232-2

[48] A.S. Al-Fahoum, A.A. Al-Fraihat " Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains." ISRN Neurosci., 2014 (2014), pp. 1-7, 10.1155/2014/730218

[49] S. Yang and F. Deravi, "On the Usability of Electroencephalographic Signals for Biometric Recognition: A Survey," in *IEEE Transactions on Human-Machine Systems*, vol. 47, no. 6, pp. 958-969, Dec. 2017, doi: 10.1109/THMS.2017.2682115.

[50] S. Yang and F. Deravi, "Wavelet-Based EEG Preprocessing for Biometric Applications," *2013 Fourth International Conference on Emerging Security Technologies*, Cambridge, UK, 2013, pp. 43-46, doi: 10.1109/EST.2013.14

[51] S. Yang and F. Deravi, "Novel HHT-Based Features for Biometric Identification Using EEG Signals," *2014 22nd International Conference on Pattern Recognition*, Stockholm, Sweden, 2014, pp. 1922-1927, doi: 10.1109/ICPR.2014.336.

[52] A. Craik, Y. He, J.L. Contreras-Vidal, "Deep learning for electroencephalogram (EEG) classification tasks: a review." J. Neural Eng., 16 (3) (2019), Article 031001

[53] H. Cecotti, M. P. Eckstein and B. Giesbrecht, "Single-Trial Classification of Event-Related Potentials in Rapid Serial Visual Presentation Tasks Using Supervised Spatial Filtering," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 25, no. 11, pp. 2030-2042, Nov. 2014, doi: 10.1109/TNNLS.2014.2302898.

[54] Honglak Lee, Roger Grosse, Rajesh Ranganath, and Andrew Y. Ng. 2009. Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. In Proceedings of the 26th Annual International Conference on Machine Learning (ICML '09). Association for Computing Machinery, New York, NY, USA, 609–616. https://doi.org/10.1145/1553374.1553453

[55] Chuang, J., Nguyen, H., Wang, C., Johnson, B. (2013). I Think, Therefore I Am: Usability and Security of Authentication Using Brainwaves. In: Adams, A.A., Brenner, M., Smith, M. (eds) Financial Cryptography and Data Security. FC 2013. Lecture Notes in Computer Science, vol 7862. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-41320-9_1

[56] Javad Sohankar, Koosha Sadeghi, Ayan Banerjee, and Sandeep K.S. Gupta. 2015. E-BIAS: A Pervasive EEG-Based Identification and Authentication System. In Proceedings of the 11th ACM Symposium on QoS and Security for Wireless and Mobile Networks (Q2SWinet '15). Association for Computing Machinery, New York, NY, USA, 165–172. https://doi.org/10.1145/2815317.2815341

[57] Q. Gui, Z. Jin and W. Xu, "Exploring EEG-based biometrics for user identification and authentication," *2014 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*, Philadelphia, PA, USA, 2014, pp. 1-6, doi: 10.1109/SPMB.2014.7002950.

[58] P. Kidmose, D. Looney, M. Ungstrup, M. L. Rank and D. P. Mandic, "A Study of Evoked Potentials From Ear-EEG," in *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 10, pp. 2824-2830, Oct. 2013, doi: 10.1109/TBME.2013.2264956.

[59] Das, B.B., Ram, S.K., Pati, B., Panigrahi, C.R., Babu, K.S., Mohapatra, R.K. (2021). SVM and Ensemble-SVM in EEG-Based Person Identification. In: Panigrahi, C.R., Pati, B., Mohapatra, P., Buyya, R., Li, KC. (eds) Progress in Advanced Computing and Intelligent Engineering. Advances in Intelligent Systems and Computing, vol 1199. Springer, Singapore. https://doi.org/10.1007/978-981-15-6353-9_13

[60] Qiong Gui, Maria V. Ruiz-Blondet, Sarah Laszlo, and Zhanpeng Jin. 2019. A Survey on Brain Biometrics. ACM Comput. Surv. 51, 6, Article 112 (November 2019), 38 pages. https://doi.org/10.1145/3230632

[61] Q. Gui, W. Yang, Z. Jin, M. V. Ruiz-Blondet and S. Laszlo, "A residual feature-based replay attack detection approach for brainprint biometric systems," *2016 IEEE International Workshop on Information Forensics and Security (WIFS)*, Abu Dhabi, United Arab Emirates, 2016, pp. 1-6, doi: 10.1109/WIFS.2016.7823907.

[62] P. Campisi and D. L. Rocca, "Brain waves for automatic biometric-based user recognition," in *IEEE Transactions on Information Forensics and Security*, vol. 9, no. 5, pp. 782-800, May 2014, doi: 10.1109/TIFS.2014.2308640.

[63] M. D. Pozo-Banos, J. B. Alonso, J. R. Ticay-Rivas, and C. M. Travieso. 2014. Electroencephalogram subject identification: A review. Expert Systems Applications 41, 15 (Nov. 2014), 6537–6554.

[64] Lahti, David C. "The limits of artificial stimuli in behavioral research: the umwelt gamble." Ethology 121.6 (2015): 529-537.

[65] Teplan, Michal. "Fundamentals of EEG measurement." Measurement science review 2.2 (2002): 1-11.