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Research Trends Of EEG Biometrics: A Bibliometric Analysis

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Abstract
Biometric technology is gaining recognition as an important asset for development. While conventional biometric methods have mainly focused on identity verification, EEG person recognition methods present exciting avenues for research. The purpose of this paper is to explore existing EEG biometric techniques that utilize machine learning and Deep Learning approaches, while also suggesting potential directions for future research. This document offers a thorough overview of EEG biometrics, concentrating on the process of authenticating individuals using electroencephalogram (EEG) signals. The study is framed around several key research questions aimed at gaining a better understanding of the present state of EEG-based biometric systems. All in all, this document acts as an essential resource for both researchers and practitioners interested in EEG biometrics, providing insights into current techniques, existing challenges, and prospective future developments in the field.
Keyword: Biometrics, EEG, Bibliometric analysis, Author keyword co-occurrences, Vosviewer, Scopus Database, Web of science

1.Introduction

The incorporation of biometric technologies across different industries has transformed the methods used for identifying and authenticating individuals. Among the various biometric modalities available, electroencephalography (EEG) has surfaced as a distinctive and promising option due to its capacity to monitor the brain's electrical activity, which is uniquely characteristic to every person. This uniqueness positions EEG as an attractive substitute for conventional biometric methods, including fingerprinting, facial recognition, and iris scanning, especially in high-security and user authentication contexts. With the increasing demand for secure and efficient biometric systems, EEG's application in identity verification has garnered considerable interest. EEG-based biometrics utilize the individual-specific patterns of brain activity, which can be affected by cognitive states, emotions, and unique neural attributes. This adaptable quality of EEG signals not only boosts the security of biometric systems but also offers insights into users' mental states, rendering it a versatile asset for various fields, such as healthcare, security, and human-computer interaction. Recent technological advancements, particularly in deep learning and artificial intelligence, have accelerated the evolution of EEG-based biometric systems. These developments facilitate the extraction and evaluation of intricate features from EEG signals, enhancing the precision and dependability of identification processes. Additionally, the emergence of affordable and portable devices, such as those utilizing Raspberry Pi, has made it possible to deploy real-time EEG biometric systems in everyday settings. This survey strives to deliver a thorough overview of the prevailing trends, obstacles, and future possibilities within EEG-based biometrics. By exploring the latest research, technological progress, and practical implementations, this review aims to emphasize the potential of EEG as a strong biometric modality. Since 2020, the domain of EEG biometrics has experienced a notable surge in research activity, as illustrated in figure 1. Before this timeframe, there was comparatively limited awareness and attention directed toward EEG biometrics. However, in recent years, there has been a rising acknowledgment of the potential and use cases of EEG-based biometric systems. This growing interest can be linked to several elements, including advancements in EEG technology, the accessibility of extensive EEG datasets, and the refinement of advanced analysis methodologies, such as machine learning and deep learning techniques. The increasing volume of literature and research in EEG biometrics is illuminating its possible applications in areas like healthcare, security, human-computer interaction, and cognitive neuroscience. As a greater number of researchers recognize the functionalities and benefits of EEG biometrics, further progress, innovations, and actionable implementations are anticipated in the future.

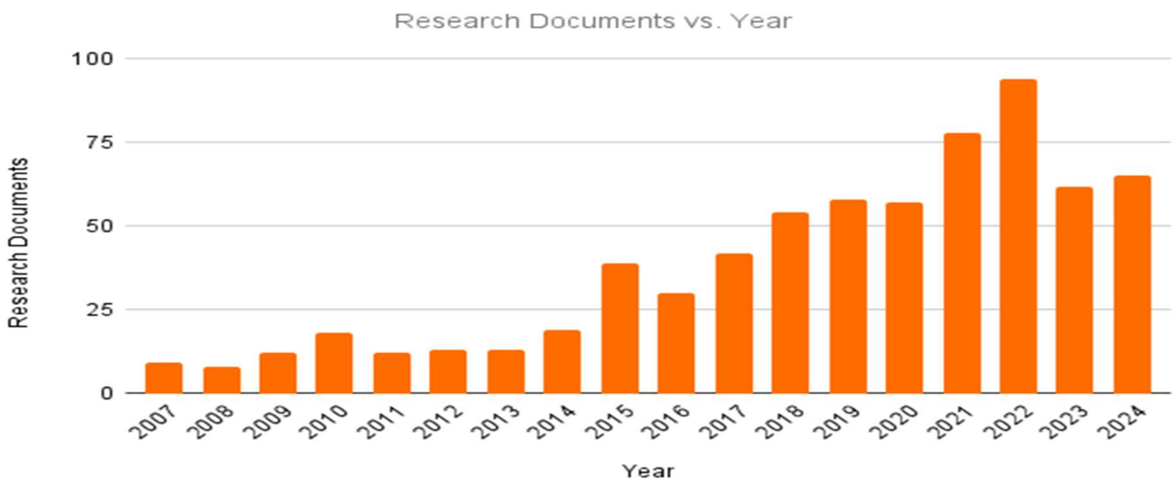


Figure 1:The Number Of Annual Publications On EEG Biometrics Indexed In Scopus 2007-2024

1.1 Motivation-

Extensive research has been conducted in the area of Biometrics. In the realm of EEG biometric approaches, a systematic review can assist researchers in assessing the accuracy, reliability, and effectiveness of the various techniques used for EEG-based identification and authentication. This knowledge is essential for making well-informed choices regarding the selection and implementation of suitable methods in real-world applications. Additionally, a systematic review helps in pinpointing the challenges and hindrances encountered in EEG biometrics research. By reviewing the existing literature, researchers can recognize recurring issues such as data variability, artifacts, and the limitations of current experimental setups. This insight can facilitate the creation of more efficient preprocessing, feature extraction, and classification methods to overcome these challenges.

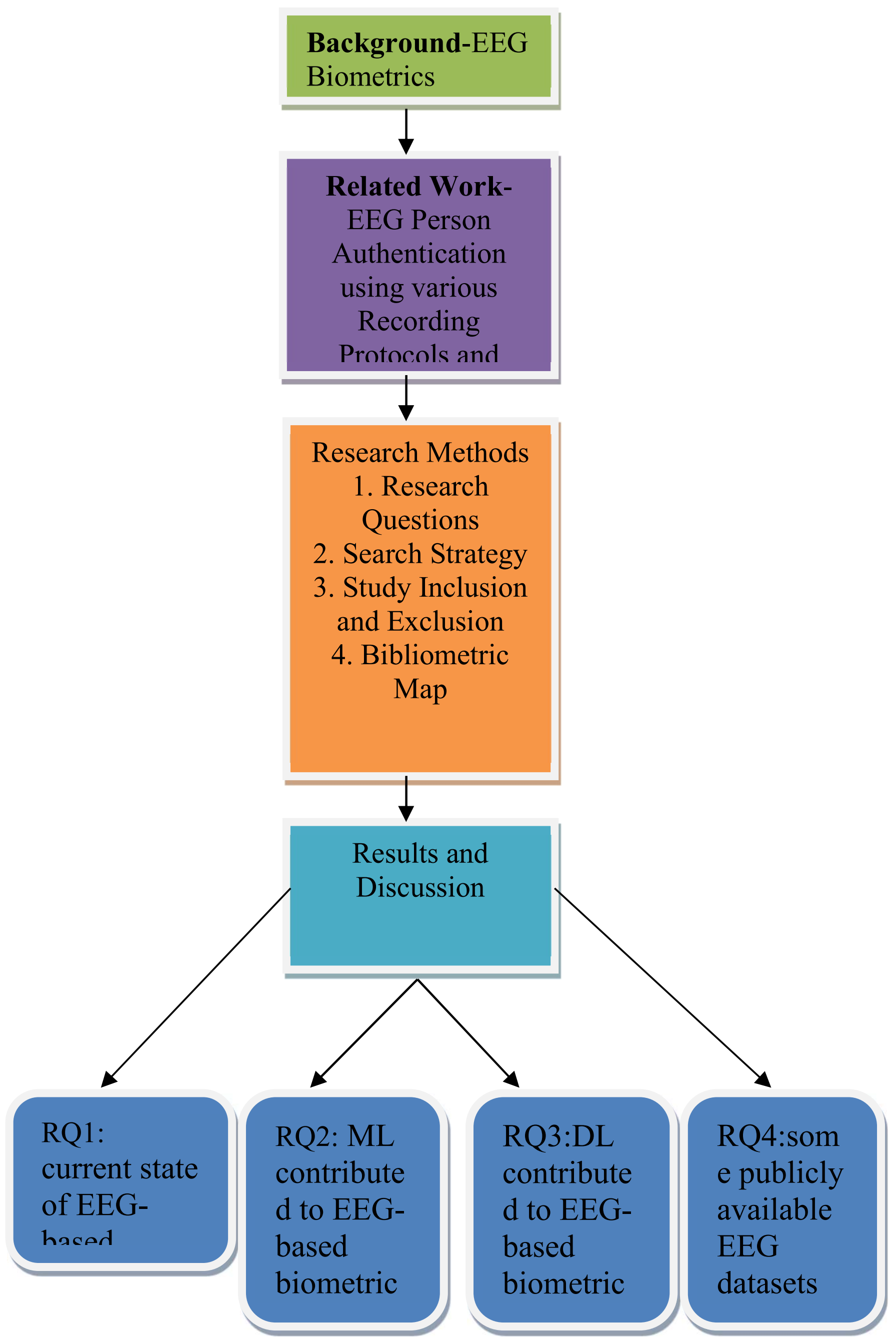


Figure 2: Workflow Of The Research Trends Of EEG Biometrics

2.EEG biometrics

2.1 Background of EEG-Electroencephalography (EEG) is a technique that measures the brain's electrical activity by placing electrodes on the scalp. The electrical patterns recorded represent the synchronized firing of neurons and typically appear as rhythmic voltage changes ranging between about 5 to 100 µV in magnitude and between 0.5 and 40 Hz in frequency. By examining the dominant frequencies and amplitudes of these EEG signals across different brain areas, it is possible to gain valuable insights into an individual's physical and mental state.

EEG brain waves are classified into five principal frequency bands:

- **Delta (1-4 Hz):** The slowest waves with the highest amplitude, commonly observed in infants and individuals in deep sleep.
- **Theta (4-8 Hz):** Frequently found in children, drowsy adults, and during memory recall, typically displaying amplitudes below 100 µV.
- **Alpha (8-12 Hz):** Prominent during relaxed, wakeful states with closed eyes. Its amplitude, often less than 50 µV, decreases with increased focus or when the eyes are opened.
- **Beta (12-25 Hz):** Associated with active thinking, focused attention, and concentration. Elevated beta activity may occur during exercise or when observing the actions of others, generally measuring below 30 µV.
- **Gamma (above 25 Hz):** Linked to various sensory processing tasks and known for the lowest amplitude levels.

Additionally, EEG signals embody certain unique personal traits, including distinctiveness, ease of capture, widespread applicability, and durability over time. These qualities make EEG signals particularly advantageous for use as a biometric identifier. A work flow diagram of eeg biometric shown in figure 2 and eeg based biometric using traits or various stimuli in table 1.

Unique characteristics:EEG signals are distinctive to each person, making them excellent for biometric identification.
Non-invasive: Recording EEG does not involve any invasive methods, ensuring a safe and comfortable experience for the user.
Difficult to spoof: It is challenging to counterfeit or mimic EEG signals, resulting in a highly secure biometric characteristic.

Applicable to a wide range of applications:EEG signals have a variety of applications, including in healthcare, security, and gaming, among others.
Continuous authentication:EEG signals are dynamic and can be captured in real-time, making them appropriate for ongoing authentication.
Resistance to environmental factors:EEG signals are less influenced by external factors like lighting, temperature, and humidity, ensuring their reliability in different conditions.
Internal insights:EEG signals can offer insights into a person's internal cognitive and emotional states, which can be beneficial for applications such as mental health assessments and brain-computer interfaces.
3.Related Work-In the existing literature, various researchers have suggested different authentication

systems that utilize EEG signals. These systems are typically executed using six unique protocols, as depicted in Figure 3, during the recording of EEG data from users aimed at establishing reliable person authentication systems.
The six protocols frequently employed in EEG-based authentication systems include:
1) Visual Evoked Potentials (VEP): EEG signals are recorded while users are shown visual stimuli, like an alternating checkerboard pattern displayed on a monitor. The EEG electrodes capture the user's response to these stimuli[12].
2) Resting-State (RS): EEG signals are recorded when the user is at rest and not engaged in any specific cognitive activities. The user is instructed to remain still with their eyes either open or closed throughout the recording[13].
3) P300 Wave: EEG signals are analyzed to detect the P300 component, which is an event-related potential linked to decision-making processes. This component arises when users come across unexpected stimuli or events[13].
4) Imagine Task (IT): EEG signals are recorded while the user is asked to visualize performing specific tasks, such as imagining speaking, writing mentally, or envisioning movements of fingers or hands.
5) Mind Task (MT): EEG signals are captured while the user engages in particular mental tasks, such as counting objects shown on a screen or solving math problems.
6) Eye Blinking/Music Listening: EEG signals are recorded during the user's eye blinks or while they listen to music. These actions can evoke unique patterns within the EEG signals.
These protocols facilitate the collection of EEG data in various conditions and tasks, which helps in creating reliable person authentication systems.

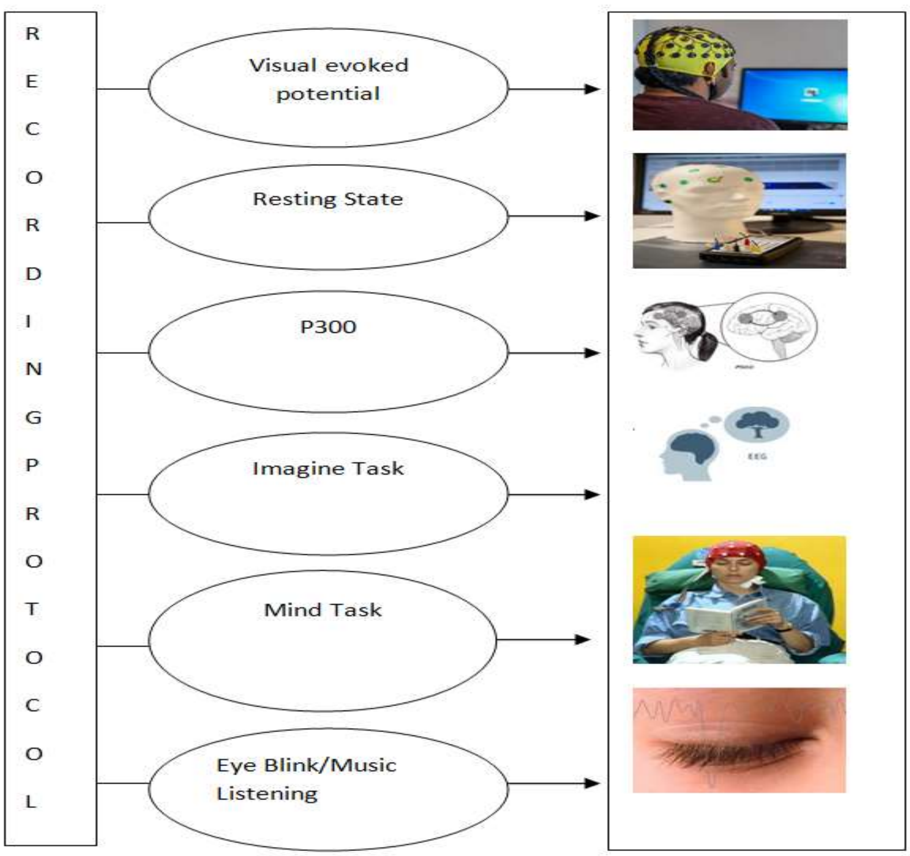


Figure 3:EEG Recording Protocols

Table 1-EEG Based Biometric Using Traits Or Various Stimuli

S. no	Author & year	Trait/sensor/stimuli	Database /subjects	Device/Channel	Features/ Algorithm	Accuracy
1	Abo-Zahhad et al.[14]	Eye(EOG)+ EEG	40 subjects	Neurosky Mindwave	LDA or Mahalanobis DA	93.72
2	Merrill et al.[15]	Tasks +EEG	7 subjects	OpenBCI-8channel	XGBoost tool	99.82
3	Wu et al.[16]	i)self- or ii)non-self-face rapid serial visual presentation +EEG	45 subjects (15 users and 30 imposters)	16 channels	hierarchical discriminant component analysis (HDCA)	i)91.31 ii)91.61
4	Rahman et al.[17]	EEG+ KINECT face	Eeg-14 subject EUROCOM Kinect face dataset-52 subjects	15 channels	KNN	100
5	Campisi et al.[18]	EEG+RS(resting state)	48subjects neurophysiology laboratory of the IRCCS	64	ARmodel +polynomial regression	96.08
6	Choi et al.[19]	EEG+RS(resting state)	17 subjects	31 channels	-	88.4
7	Puengdang et al.[20]	EEG+VEP	20 subjects	6 channels	LSTM of SSVEP and ERP features+d	91.44%

					eep learning	
8	Hu et al.[21]	EEG+motor imagery[MI]	BCI competition 2003	64 channel	Mlbpn Traindx algorithm	-
9	Zhang et al.[22]	EEG+GAIT	7 subjects	EPOC+ Emotiv headset-14	RNN	99.57
10	Smithaet al.[23]	EEG+VOICE	8 subjects	Emotiv Epoc neuroheadset	LDA	72.2
11	Kumaret al[24]	Envisioned speech+EEG	23 subjects	Emotiv EPOC+-14	RF	85.20
12	Kaur et al.[25]	Music+EEG	60 subjects	Emotiv Epoc+ 14 sensors +2 references	HMM and SVM classifiers	97.50 % and 93.83 %
13	Saini et al.[26]	Signature+EEG	70subjects	Emotiv Epoc+ 14 sensors +2 references	Feature-PHOG HMM	98.24%.
14	Zahhad et al.[27]	EEG+EOG +Eyeblinking	31 subjects	Neurosky Mindwave headset	LDA	-
15	Barra et al.[28]	EEG+ECG	EEG Motor Movement/Imagery Dataset (EEGMI)(109 subjects)& PTB Diagnostic ECG Database (PTB)(290 subjects)	ECG(12LEADS)&EEG(64 CHANNEL)	ECG(peak detection method)EEG(power spectral density)	-
16	Krishna et al.[29]	AR/VR+eye tracking+EEG	i)EEG-MI from physionet	64 channels	i)svm+rbf ii)RF	-

17	T. Salturk et al. [30]	EEG+VEP	ii) EMVIC 2012 competition DEAP 32 subjects	32 channels	CNN	89.06

2.2 EEG Biometrics Stages-

The interest in utilizing electroencephalogram (EEG) signals for cognitive-based biometric systems has been on the rise, leading to advancements in brain biometrics. These signals possess unique characteristics, universal applicability, and inherent resilience, presenting a promising option for thwarting spoofing attacks[31]. EEG signals serve as visual representations of the brain's electrical activities, which are recorded through electrodes positioned at various locations on the scalp. The process of implementing biometrics with EEG entails preprocessing the EEG data, from which features are subsequently extracted and used to train a model specific to the individual.

2.2.1 Pre-processing-Signals recorded at the scalp often lack fine spatial resolution and are susceptible to various types of noise. Moreover, EEG measurements may be influenced by a range of physiological and non-physiological artifacts. To address these limitations, numerous preprocessing approaches are employed. Such approaches include applying filters, re-referencing procedures, segmenting the data, removing noisy channels and trials, and utilizing independent component analysis (ICA) for EEG decomposition. Appropriate band-pass filtering can substantially reduce artifacts arising from multiple sources within the EEG data [32]. Re-referencing techniques, which involve linear transformations of the EEG signals, help mitigate noise introduced by reference electrodes. Extracting time-locked data segments aligned with specific experimental events enables investigation of task- or stimulus-related changes in the EEG. Discarding artifact-contaminated trials or channels preserves data quality and accuracy. As EEG signals recorded at the scalp represent a combination of neural sources—while artifacts are independent from one another—ICA serves as a powerful and effective tool for isolating artifacts from the underlying EEG signals [33].

2.2.2 Feature Extraction

To capture various aspects of brain activity, multiple types of characteristics can be extracted from EEG signals. Among the commonly used characteristics are[34]:

Time-domain features: These features in the time domain illustrate different aspects of the EEG signal. Examples include mean amplitude, root mean square (RMS), variance, skewness, and kurtosis.

Frequency domain Features: These components provide insights into the frequency characteristics of the EEG signal. They are obtained through techniques such as the Fourier transform or wavelet transform, with examples including peak frequency, spectral entropy, and power spectral density (PSD).

Statistical Features:-These statistical features explain the statistical properties of the EEG signal. They may encompass statistics like mean, median, standard deviation, and correlations between different EEG channels[34].

Time-frequency features:-These features analyze the changes in the spectral content of the EEG signal over time to capture both temporal and frequency information. Commonly utilized techniques for time-frequency analysis include wavelet scalograms, continuous wavelet transformations, and spectrograms.

Topographical characteristics: These features assess the spatial distribution of EEG activity across various areas of the scalp. They can be determined through operations involving variables such as electrode asymmetry, inter-channel coherence, or power maps and spectral features of the scalp.

Nonlinear features: These features illustrate the complexity and nonlinear dynamics of the EEG signal. They can be derived from metrics such as phase synchronization, approximation entropy, or fractal dimension.

Connectivity features: These features reflect the functional connectivity between different regions of the brain based on the EEG signal. They may include measures such as coherence, phase synchronization, or cross-correlation.

These features can offer valuable insights into different dimensions of brain activity and can be employed for various applications, including brain-computer interfaces, assessments of cognitive states, or the diagnosis of neurological disorders[35]. The selection of features is determined by the specific needs of the research or application.

2.2.3 Classification-

A variety of authentication systems have been suggested in academic research, utilizing six essential protocols to capture signals from the human brain and develop effective authentication systems, as illustrated in Figure 2. These protocols form the groundwork for creating EEG-based authentication systems, enabling researchers to record and interpret brain signals in different scenarios. EEG classification is the method of assigning or categorizing EEG signals into distinct classes or categories according to their features or patterns. This process entails creating machine learning or pattern recognition models capable of accurately classifying EEG signals and differentiating between various brain states, activities, or conditions. Several methods and techniques are employed for EEG classification, including [36]:

Supervised learning: This approach involves training a machine learning model on EEG data that already includes known class labels, ensuring that each data instance is linked to a specific category. Commonly utilized supervised learning techniques for EEG classification include Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks (ANN) [37].

Unsupervised learning: Conversely, the unsupervised approach seeks to uncover inherent patterns or clusters within the EEG data in the absence of predefined class labels. By applying clustering algorithms such as k-means or hierarchical clustering, it becomes possible to group similar EEG patterns together without prior knowledge of their categories [38].

Deep learning: Deep learning methods, notably Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated significant success in EEG classification tasks [39]. While CNNs effectively capture spatial features in EEG recordings, RNNs excel at modeling the temporal dependencies present in sequential signals.

Transfer learning: Furthermore, transfer learning applies knowledge acquired from models initially trained on extensive datasets to a targeted EEG classification scenario, thereby enhancing performance with minimal task-specific data. By adjusting these pre-trained models on a smaller annotated EEG dataset, it is achievable to reach improved classification performance even with a limited number of labeled samples [40].

Ensemble methods: Ensemble techniques merge multiple classifiers to enhance overall classification accuracy. Methods such as bagging, boosting, or stacking can be used to integrate predictions from multiple classifiers trained on various subsets of the EEG data [41]. The selection of a classification method is influenced by the particular EEG classification task, the quantity of available labeled data, the computational resources, and the intended performance. Applications of EEG classification span diverse fields, including brain-computer interfaces, individual identification, sleep analysis, emotion recognition, epilepsy diagnosis, and mental state evaluation.

3.Research methods

3.1.Research Questions

The analysis is organized around several key research questions focused on understanding the present landscape of EEG biometrics:

1. RQ1: What is the present condition of EEG-based biometric systems?

2. RQ2: In what ways has machine learning (ML) influenced the advancement of EEG-based biometrics?

3. RQ3: What is the impact of deep learning (DL) in improving EEG-based biometric systems?

4. RQ4: Which publicly accessible EEG datasets are available for biometric research?

3.2 Search Strategy

To compile a thorough and sound collection of pertinent articles that have significantly contributed to EEG biometrics, the following search criteria were utilized. The search keywords and phrases were derived from the formulated research questions. We also included synonyms and alternative terms. We extracted synonym keywords from relevant literature on EEG biometric subjects. The search keywords are listed as follows: “EEG based Biometrics,” “EEG biometrics,” “EEG based person Identification,” “EEG biometrics utilizing machine learning and deep learning.” Boolean operators like "OR" and "AND" were employed to gather data. Search parameters were generated based on the research question, which served as keywords. Identifiers from related studies were also taken into account. The search results reflected outcomes based on combinations of keywords and Boolean operators, such as ("human brain" AND "EEG biometrics using machine learning and deep learning") OR ("EEG biometrics") OR ("identification" OR "recognition" OR "deep learning" OR "feature extraction"). A systematic review process was subsequently conducted to evaluate the contributions of neural networks to EEG biometrics, using numerical assessments to uncover new patterns, methods, and techniques within the field of EEG person identification. Table 2 presents details on the number of articles retrieved from the respective indexed databases, and a Prisma flow is illustrated in Figure 4.

Table 2- Number Of Articles Downloaded From The Respective Indexed Databases

S.no	Digital Libraries	Search summary	Included Article	Percentage
1	Elsevier	458	229	31.32
2	Science Direct	551	100	13.67
3	Emerald	41	41	5.60
4	Taylor & Francis	204	50	6.83
5	IEEE	312	100	13.67
6	Wiley	95	20	2.73
7	Clarivate Analytics	141	141	19.28
8	ACM	1301	50	6.83

	Total		731	100

3.2.1 Electronic Sources

Well-known digital libraries have been utilized to find research papers—these libraries include IEEE Xplore, Science Direct, Scopus, Emrold, and Google Scholar. These platforms serve as the main resource for publications within the field of computer science.

3.2.2 Reference Management

By employing a range of search terms, including both primary keywords and their synonyms, we were able to locate a substantial number of studies from the specified electronic sources. We used Mendeley as our reference management solution to compile and organize all retrieved materials. This approach made it straightforward to add or remove studies as necessary.

3.2.3 Search Process

Our initial efforts involved searching various digital libraries for relevant publications, including journal articles, conference proceedings, and book chapters. This comprehensive search yielded more than 1,500 studies. With the support of Mendeley, we effectively managed PDFs and corresponding citation data, streamlining the reading and reviewing process. Afterward, we conducted a screening procedure to exclude any studies that did not align with our research objectives.

3.3 Inclusion and Exclusion criteria

In a systematic literature review, predetermined inclusion and exclusion criteria are utilized to decide which articles will be part of the review. These criteria assist in ensuring that the chosen articles are pertinent to the research question and adhere to specific quality benchmarks. The data shown in table 3 below presents the inclusion and exclusion criteria applied in this systematic literature review.

Table 3-Inclusion and Exclusion criteria

S.no	Inclusion	Exclusion
1	Research studies that discuss EEG biometrics	Paper with unidentified references
2	Research studies that involve EEG as new security traits in biometric field	Papers focusing on other biometric traits than EEG biometrics
3	Studies that combine EEG with other biometric traits	Duplicated research paper
4	Studies that uses EEG biometrics and involve Machine learning and deep learning	Paper published before 2007

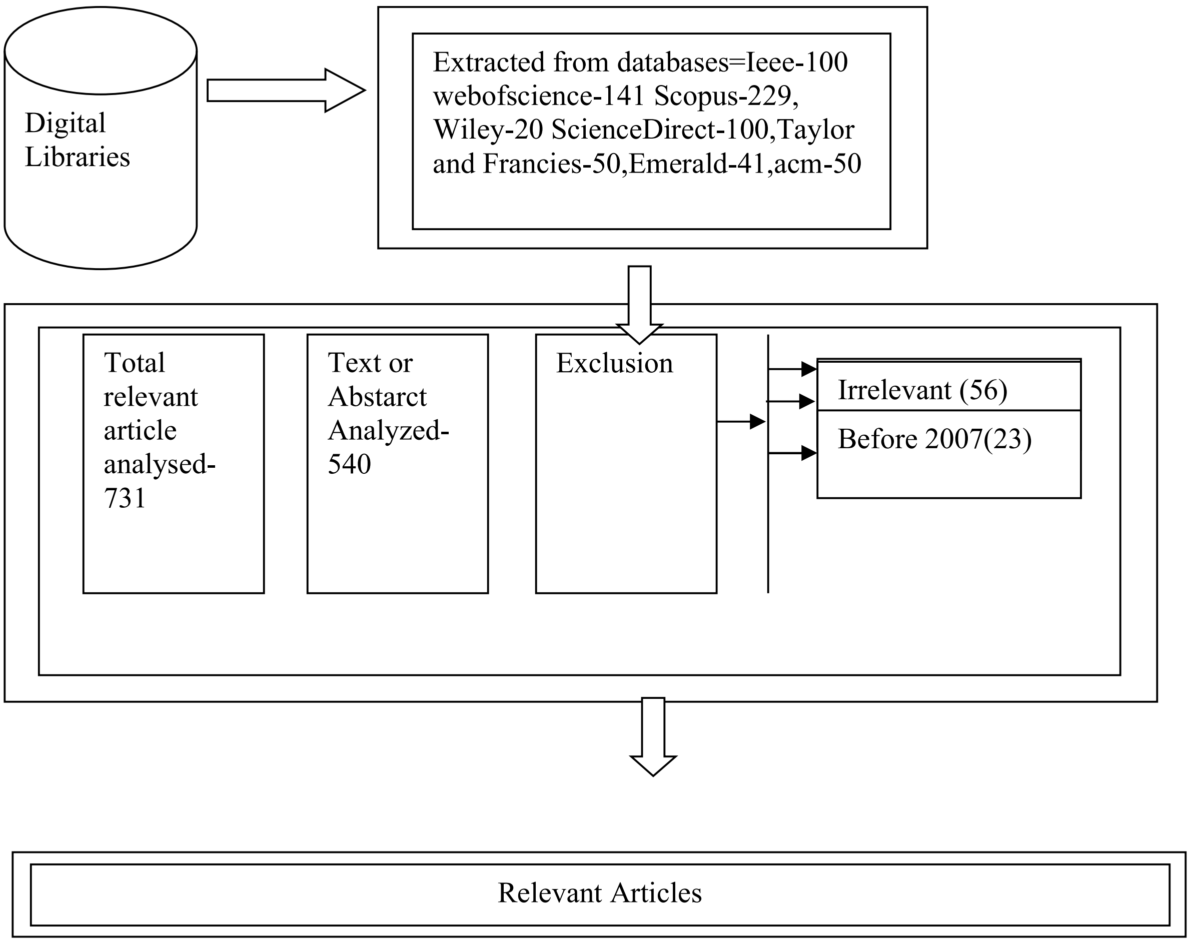


Figure 4:Prisma Flow Diagram.

3.4Co-occurance analysis of Bibliometric maps

The VOS viewer software was utilized to examine a collection of 143 articles from the Web of Science and 229 articles from the Scopus database, concentrating on author keywords, citations, and bibliographic information. VOS viewer is a tool designed to produce bibliometric maps and visual representations. Through this application, we created maps that illustrated author keywords and their co-occurrence patterns shown in figure 5 and 6. The strength of the connections between items was represented by positive numerical values, indicating their significance. Co-occurrence analysis was instrumental in identifying and examining the presence of keywords within the publications, uncovering research themes, trends, and clusters of interconnected concepts. By integrating co-occurrence analysis with author keyword analysis, we gained insights into the thematic relationships between authors and keywords. The visualization methods applied overlay techniques to depict clusters and the strength of links between keywords, providing a thorough overview of the frequency of occurrences and relationships. In summary, VOSviewer enabled an in-depth analysis of the dataset, assisting in the investigation of research topics, author contributions, and thematic interconnections[42].

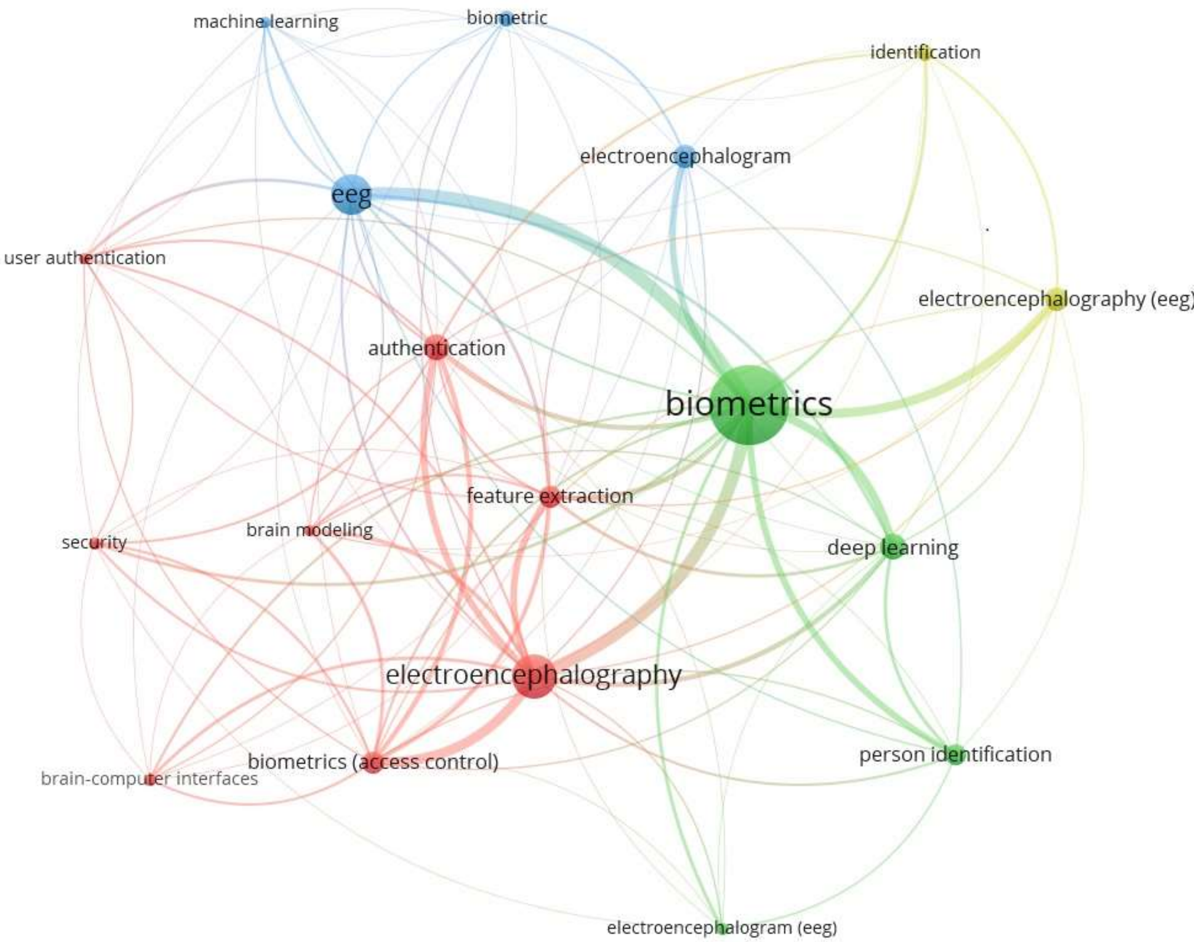


Figure 5:Bibliometric Map (Web of Science Articles)Created Based on Author Keywords Co-Occurrence. Minimum Occurrence Of A keyword Are Set To One

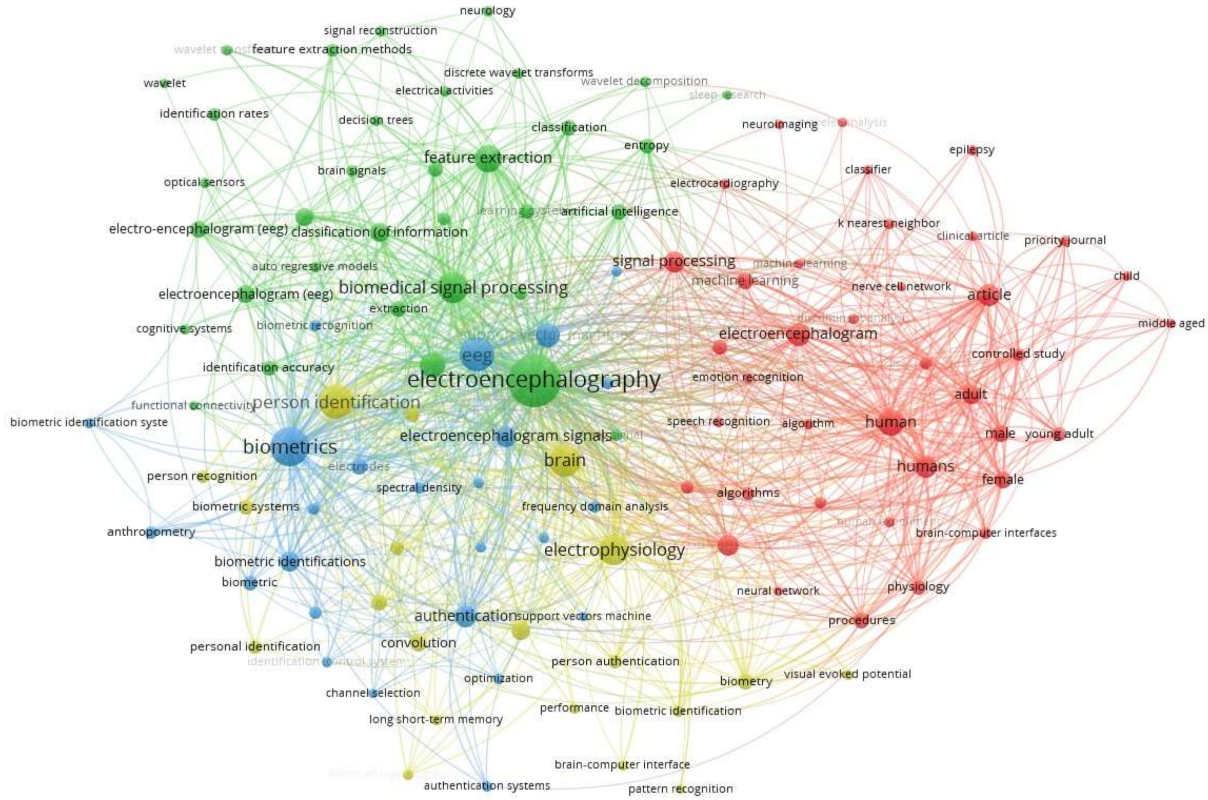
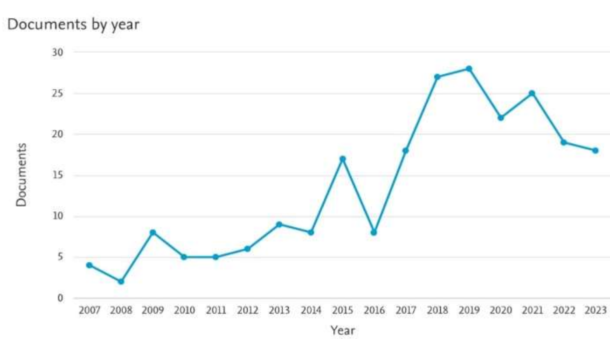
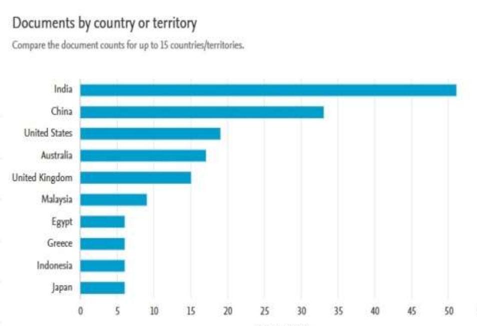


Figure 6:Bibliometric Map (scopus Articles)Created Based on Author Keywords Co-Occurrence. Minimum Occurrence Of A keyword Are Set To One.





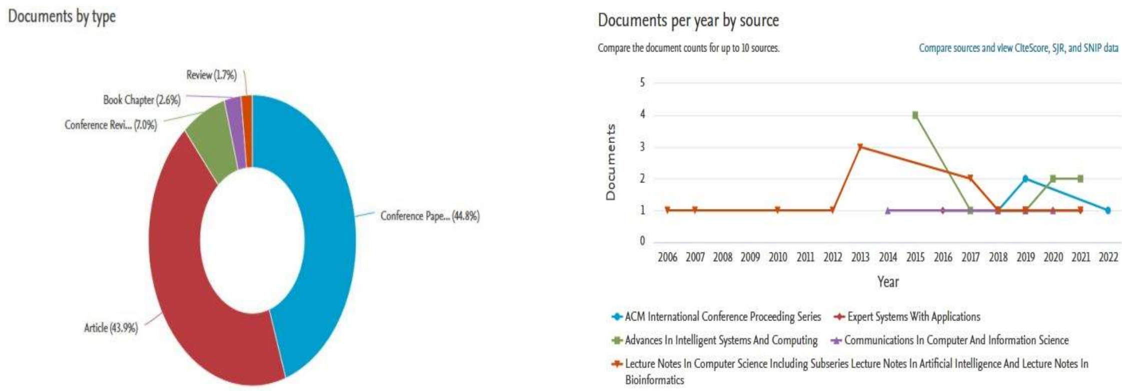


Figure:7 Document Analysis Over The Period From 2007-2023. (a) Number Of Research Documents Published Per Year (b) Large Counts Of Documents Published By Countries (c)Type Of Research Documents (d) Research Documents Published Per Year By Reputed Sources.

4.Results and Discussion

This section discusses various research questions that were formulated at the outset to examine research in this field. The findings are then structured into separate subsections to offer meaningful interpretations.

RQ1: current state of art in EEG-based biometrics

In the first phase, a categorized approach was utilized to discover similar articles on EEG Biometrics and biometrics by examining paper titles and relevant keywords before finalizing a conclusive search strategy. The search for related studies was conducted for the years 2007 to 2024 across several sources, including Scopus, Web of Science, Springer, Wiley, ACM, IEEE, and Emerald. Figure 1 illustrates the number of relevant articles related to our research obtained from different databases. Document analysis spanning the years 2007 to 2024 reveals the annual publication of research documents, the substantial number of documents published by various countries, the types of research documents, and the yearly publication rates from reputable sources, as depicted in Figure 7. The current landscape of EEG-based biometrics indicates significant progress in identity verification through the utilization of the brain's distinctive and challenging-to-reproduce electrical activity. EEG (Electroencephalography) biometrics verify identities by capturing brainwave patterns with non-invasive devices. These signals are unique to each person, shaped by their neural pathways, providing a high level of security and resistance to spoofing attempts.

Key Features and Applications:

1. EEG authentication enhances security by capturing both static and dynamic responses, in contrast to conventional biometric methods like fingerprinting and iris recognition.

2. Applications: Research is underway to explore EEG biometrics for secure access control, user verification in computer systems, and applications in forensic science. They are also being integrated into wearable devices and IoT technology for real-time authentication and monitoring.

Challenges:

• Signal Variability: Changes in emotions or physiological states can lead to variations in brainwave patterns, which may compromise reliability in practical settings.

• The use of EEG may face restrictions due to the necessity for active engagement, such as using the device.

• To effectively analyze vast amounts of EEG data, strong algorithms and proper infrastructure are essential.

Advancements in Technology:

• The integration of 5G with IoT enhances EEG systems by enabling real-time monitoring and secure data transmission. Wearable EEG devices, like smart hats, are extending their applications beyond the clinical environment.

• Cutting-edge machine learning techniques are utilized to identify distinctive features in EEG data, increasing precision and reliability.

EEG biometrics hold significant potential as they evolve, aiming to address existing challenges and seamlessly adapt to various sectors, including healthcare, cybersecurity, and smart devices. Ongoing research and innovation in this area are essential for making these systems more practical and user-friendly.

RQ2: How has machine learning (ML) contributed to the development of EEG-based biometrics?

To address the issue of closed set recognition, also referred to as closed set identification, this problem arises in the fields of pattern recognition and machine learning, where the objective is to classify an input into one of the predetermined classes. In closed set recognition, the potential classes are fixed and predefined, and the aim is to accurately identify the correct class label for a given input.

In closed set recognition, the classifier is trained using a labeled dataset that includes examples from all classes. During the training stage, the classifier learns the distinctive patterns and features associated with each class. Subsequently, in the testing stage, the trained classifier is employed to categorize new, unseen inputs into one of the established classes.

The difficulty in closed set recognition lies in crafting a classifier that can effectively differentiate between various classes and generalize properly to new data. The classifier must manage variations and uncertainties in the input data while keeping the error rate low. Common evaluation metrics used to measure the effectiveness of closed set recognition algorithms include accuracy, precision, recall, and F1 score.

Closed set recognition is frequently applied in a range of domains, such as face recognition, fingerprint recognition, speech recognition, and object detection. It is often compared to open set recognition, where the input may either belong to a known class or to an unknown class that is absent from the training dataset.

Several well-known algorithms for closed set recognition include:

k-Nearest Neighbor (k-NN): The k-Nearest Neighbors (k-NN) method determines the category for an unknown sample by examining the labels of its k most similar points in the dataset. First, it computes how close the new point is to all existing labeled examples, typically using a distance metric. Then it selects the k examples with the smallest distances. The class assigned to the new sample corresponds to the most common label found among those k closest neighbors.

Support Vector Machines (SVM):A Support Vector Machine (SVM) is a highly effective supervised learning algorithm that defines one or more hyperplanes in a high-dimensional feature space to separate data points belonging to different classes. Its primary goal is to maximize the margin, which is the distance between the support vectors—those closest points from each class that lie near the decision boundary. Through the use of various kernel functions, SVMs can proficiently manage both linear and nonlinear classification tasks.

Decision Trees: Decision trees systematically divide the input feature space based on various features, forming a model that resembles a tree. Each internal node in the tree corresponds to a decision made according to a specific feature, while each leaf node indicates a class label. Decision trees can manage both categorical and continuous input features and tend to perform effectively across a diverse array of challenges.

Random Forests: Random Forests are an ensemble-based technique that integrates multiple decision trees to produce predictions. Each tree is trained on a unique subset of the training data and a randomly chosen set of features. To predict a target class, the forest aggregates the outputs of all its trees, relying on majority voting for the final decision. Compared to relying on a single decision tree, Random Forests typically yield improved accuracy and more robust generalization.

Neural Networks: Neural networks, which include Multilayer Perceptrons (MLP), are models that draw inspiration from biological neural systems. They are composed of nodes (neurons) that are interconnected and structured in layers. By modifying the weights and biases of these connections through a process known as back propagation, neural networks can learn intricate non-linear relationships between input features and output labels. Their flexibility allows for application across a diverse array of classification tasks.

Long Short-Term Memory (LSTM) networks are a specialized kind of recurrent neural network (RNN) designed to effectively handle and interpret sequences of data. They are frequently utilized in applications such as speech recognition, natural language processing, and time series analysis. In the context of closed set recognition, LSTM networks can model temporal dependencies and capture long-term relationships within the data, facilitating accurate classifications.

HMM: Hidden Markov Models (HMMs) are probabilistic frameworks often employed in the analysis of sequential data and pattern recognition. HMMs can represent the hidden states and the transitions between them based on the observable data. When addressing the closed set recognition challenge, HMMs can be used to analyze the sequence of observations and determine the most probable sequence of hidden states, which can subsequently assist in classification.

Transfer Learning: Transfer learning refers to the strategy of applying knowledge acquired from one task or domain to another related task or domain. This method can be particularly useful in closed set recognition, where a pre-trained model on a larger dataset or a related task is utilized and then refined on a smaller closed set recognition dataset. This approach allows the benefits of the knowledge gained from the initial training to be harnessed, improving the effectiveness on the target closed set recognition issue.

These methods provide various strategies for tackling the closed set recognition challenge, each possessing its unique advantages and disadvantages. The selection of an appropriate algorithm hinges on the specific nature of the problem, the data at hand, and the performance goals intended.

RQ3: What role does deep learning (DL) play in enhancing EEG-based biometric systems?

Deep learning methods have transformed EEG recognition by utilizing neural networks to extract intricate features and develop hierarchical representations directly from unprocessed EEG data. Several deep learning techniques frequently employed in EEG recognition include the following:

Convolutional Neural Networks (CNNs):CNNs have been largely used in image analysis and are also applicable to EEG evaluation. They identify local spatial features in EEG signals through their convolutional layers and derive significant characteristics. CNNs have achieved success in tasks such as emotion detection, sleep stage categorization, and seizure identification.

Recurrent Neural Networks (RNNs):RNNs are tailored for handling sequential data, which makes them ideal for examining time-series EEG signals. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are widely recognized types of RNNs utilized in EEG recognition. RNNs are designed to grasp temporal relationships and can represent long-term dependencies in the EEG data, facilitating tasks such as mental state assessment and brain-computer interfaces.

Autoencoders: Autoencoders serve as unsupervised deep learning frameworks that can identify compact representations of input data. They can be utilized for dimensionality reduction and feature extraction in EEG recognition. Training an autoencoder on an extensive unlabeled EEG dataset allows for the acquisition of meaningful latent representations that can be leveraged for classification purposes.

Generative Adversarial Networks (GANs):GANs consist of a discriminator network generator and a generator that are trained in opposition to one another. GANs have been employed in EEG recognition to produce synthetic EEG signals, enhance training datasets, and boost the generalization ability of classifiers.

Deep Belief Networks (DBNs): Deep Belief Networks (DBNs) are deep, layered architectures composed of multiple Restricted Boltzmann Machines (RBMs). They excel at extracting hierarchical feature representations from EEG signals and have been effectively used in applications like sleep stage classification and evaluating mental workload.

Attention Mechanisms: Attention mechanisms function to emphasize particular regions or time intervals of the EEG data that offer the most relevant information for the classification objective. They have been incorporated into deep learning models to enhance both the interpretability and effectiveness of EEG recognition systems.

These deep learning techniques have shown encouraging outcomes in various EEG recognition tasks, offering precise and robust models for applications like emotion detection, cognitive workload assessment, motor imagery classification, and epileptic seizure identification. Nonetheless, it is crucial to acknowledge that the efficacy of deep learning models in EEG recognition is largely dependent on having ample labeled data, suitable model architecture, hyperparameter optimization, and computational resources.

RQ4: What publicly available EEG datasets exist for biometric research?

Datasets of EEG biometrics are essential for progress in research, as they offer standard data for creating and evaluating biometric systems described in table 4. These datasets present a variety of thoroughly documented EEG signals, facilitating advancements in EEG-based authentication systems. Notable datasets consist of:

Table 4- Most Relevent EEG Dataset Used In Research

S.no	Dataset Name	Description	Link
1	**EEG Motor Movement/Imagery Dataset**	Includes more than 1500 EEG recordings, each lasting one to two minutes, from 109 participants engaged in various motor tasks.	PhysioNet(EEG Motor Movement/Imagery Dataset, n.d.)
2	**Grasp and Lift EEG Challenge**	EEG data from subjects performing grasp and lift tasks, aimed at detecting hand movement events.	GitHub Repository(GitHub - Alexandrebarachant/Grasp-and-Lift-EEG-Challenge: Code and Documentation for the Winning Sollution to the Grasp-and-Lift EEG Detection Challenge, n.d.)
3	**TUH EEG Seizure Corpus**	A large dataset with over 30,000 EEG recordings from patients with seizures, useful for seizure detection and prediction.	TUH EEG Seizure Corpus(TUH EEG Seizure Corpus Dataset | Papers With Code, n.d.)
4	**CHB-MIT Scalp EEG Database**	Contains long-term EEG records from pediatric patients with epilepsy, useful for automated seizure detection.	PhysioNet(Automated Epileptic Seizure Detection in Pediatric Subjects of CHB-MIT EEG Database—A Survey - PMC , n.d.)
5	**Bonn EEG Database**	EEG recordings from healthy subjects and patients with epilepsy, useful for various EEG analysis tasks.	Bonn EEG Database(EEG Datasets for Seizure Detection and Prediction— A Review - PMC , n.d.)

6	**DEAP Dataset**	A dataset for analyzing emotions through physiological signals, which incorporates EEG and peripheral data collected from 32 individuals.	DEAP Dataset(EEG Brainwave Dataset: Feeling Emotions , n.d.)
7	**BIOMEX-DB**	A multimodal collection of synchronously captured EEG, voice, and video data from 51 participants, designed for biometric applications.	BIOMEX-DB((PDF) BIOMEX-DB: A Cognitive Audiovisual Dataset for Unimodal and Multimodal Biometric Systems, n.d.)
8	**M3CV Database**	A comprehensive database with multiple subjects, sessions, and tasks dedicated to EEG-based biometrics, featuring data from 106 individuals.	M3CV Database(M3CV: A Multi-Subject, Multi-Session, and Multi-Task Database for EEG-Based Biometrics Challenge - ScienceDirect, n.d.)
9	**Mental Imagery Dataset**	A large dataset with over 60,000 examples of motor imageries recorded from participants, useful for BCI applications.	Mental Imagery Dataset(A Large Electroencephalographic Motor Imagery Dataset for Electroencephalographic Brain Computer Interfaces | Scientific Data, n.d.)
10	**EEG Brainwave Dataset: Feeling Emotions**	EEG data capturing emotional experiences, useful for emotion recognition and biometric applications.	Kaggle Dataset(EEG Brainwave Dataset: Feeling Emotions , n.d.)

Discussion

The study of EEG biometrics, which depends on brainwave signals for personal identification, marks anexciting intersection of neuroscience, biometric technologies, and machine learning. This analysis examines the present trends, challenges, and future possibilities in the field through a bibliometric review. EEG biometrics utilize the distinct electrical activity produced by the brain for individual verification. Recent progress in machine learning and deep learning techniques has improved the capability to process and evaluate EEG signals, resulting in more precise and effective recognition systems. The future of EEG biometrics appears promising, propelled by technological innovations and interdisciplinary collaboration. Improved algorithms to handle signal variability will provide enhanced stability and dependability, broadening their use in dynamic, real-world scenarios. Compact, affordable EEG devices will promote widespread usage beyond clinical and research settings. Personalized AI applications will enhance recognition accuracy by adjusting to individual-specific patterns over time. In addition to security, EEG biometrics have the potential to transform healthcare through neurological monitoring, tailored education, and brain-computer interface technologies. International cooperation and standardization of protocols will help address ethical issues, promote interoperability, and position EEG biometrics as a groundbreaking technology across various fields. This bibliometric review emphasizes the advancements made in EEG-based identification, while also outlining the existing challenges. By tackling these problems and engaging in innovative research avenues, EEG biometrics can transition from specialized research to broad practical usage, influencing the future of secure and intelligent systems. This detailed overview acts as a foundational reference for further investigation, offering both a glimpse into the current landscape and a guide for advancing this transformative technology.

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