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Review

Review of EEG-Based Biometrics in 5G-IoT: Current Trends and Future Prospects

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Abstract: The increasing integration of the Internet of Things (IoT) into daily life has led to significant changes in our social interactions. The advent of innovative IoT solutions, combined with the enhanced capabilities and expanded reach of 5G wireless networks, is altering the way humans interact with machines. Notably, the advancement of edge computing, underpinned by 5G networks within IoT frameworks, has markedly extended human sensory perception and interaction. A key biometric within these IoT applications is electroencephalography (EEG), recognized for its sensitivity, cost-effectiveness, and distinctiveness. Traditionally linked to brain–computer interface (BCI) applications, EEG is now finding applications in a wider array of fields, from neuroscience research to the emerging area of neuromarketing. The primary aim of this article is to offer a comprehensive review of the current challenges and future directions in EEG data acquisition, processing, and classification, with a particular focus on the increasing reliance on data-driven methods in the realm of 5G wireless network-supported EEG-enabled IoT solutions. Additionally, the article presents a case study on EEG-based emotion recognition, exemplifying EEG's role as a biometric tool in the IoT domain, propelled by 5G technology.

Keywords: IoT; 5G; EEG signal; wearable IoT devices; Internet of Things; seamlessly IoT devices; sensors

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1. Introduction

The capability to process, store, and transmit the immense volume of data produced by sensors, controllers, and various interconnected devices is essential for the optimal operation of the IoT. The IoT comprises a network of interlinked objects and devices that exchange data and communicate across diverse and decentralized networks, including both local area networks (LANs) and wide area networks (WANs) [1]. This interconnectedness facilitates an unprecedented level of automation, as devices, sensors, and connected entities provide crucial data that can be utilized to make informed decisions and improve efficiency [2].

The extensive amount of data produced by IoT devices presents a significant challenge, underscoring the need for adequate storage and organization to ensure effective use. Data analytics is fundamental in this context, as it allows for the identification of trends and patterns within these data. Utilizing these insights can lead to the automation of processes and more informed decision-making, thereby enhancing accuracy and diminishing the reliance on manual checks. A prominent instance of this was observed during the recent COVID-19 pandemic, where IoT devices were extensively utilized for monitoring purposes. These devices enabled the remote measurement of patients' temperatures through real-time data transmission over the internet, thus significantly aiding healthcare professionals in their response efforts [3].

According to a prediction by the International Telecommunication Union (ITU), the quantity of devices linked to internet protocol (IP) networks is expected to exceed three times the global population. By 2023, it is expected that machine-to-machine (M2M) connections will constitute almost half of all worldwide connected devices and connections. Furthermore, a significant surge in global mobile data traffic is forecasted over the next decade. An increasing share of this traffic is predicted to be allocated to machine-to-machine communications, signaling the imminent advent of an IoT revolution. Figure 1 presents a visual representation of the forecasted global mobile data traffic as projected by the International Telecommunication Union (ITU), illustrating the expected growth in exabytes per month from 2020 to 2030 [4].

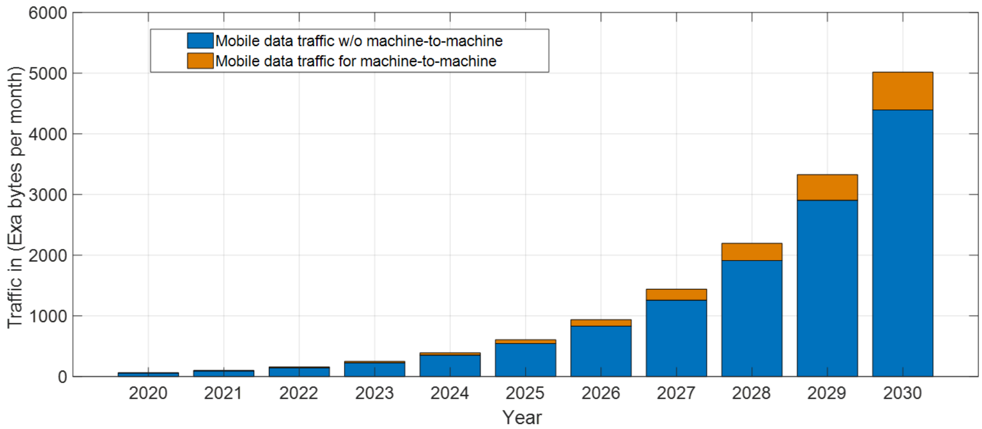

Figure 1. Global mobile data traffic forecast for the 2020 to 2030 period (ITU).

Fifth-generation (5G) networks are recognized as a key element of IoT systems, owing to their capability to provide the high speed and low latency essential for real-time communication between IoT devices and the internet. Furthermore, 5G technology facilitates the connection of up to one million devices per square kilometer, making it vital for extensive IoT deployments. Beyond scalability, 5G also enhances data rate efficiency, leading to reduced energy usage and longer battery lifespan in IoT sensors. These technological advancements amplify the future prospects of IoT, positioning 5G as a central force in realizing its utmost potential [5].

Moreover, 5G signals operate across three distinct frequency spectrums: millimeter waves, mid-band, and low-band, each with a specific bandwidth range. Millimeter waves deliver a downlink bitrate between 1 Gbps and 2 Gbps, operating at carrier frequencies ranging from 24 GHz to 72 GHz. Mid-band signals, on the other hand, offer downlink bitrates between 100 Mbps and 400 Mbps and utilize carrier frequencies between 2.4 GHz and 4.2 GHz. Lastly, the low-band spectrum functions within the same bandwidth range as 4G networks, providing the broadest coverage, albeit with a slower downlink bitrate [6,7].

The capacity of IoT solutions to collect, process at the edge, and transmit human biometric data via 5G networks is fundamental for the efficacy of the human–machine interface. This survey explores the diverse biometric authentication methods implemented in IoT frameworks, particularly emphasizing EEG biometric authentication. EEG data—known for their stability, universality, and distinctiveness—have broadened their applications from conventional brain–computer interface (BCI) solutions to encompass more varied fields, including neuroscience and neuromarketing. Figure 2 illustrates the primary emerging markets where EEG biometrics find applications within the context of the IoT [8].

BCI technology encompasses a broad spectrum of applications. A prominent example is BCI-controlled prosthetics, which enable individuals to use their thoughts to control devices aiding in daily activities. These devices range from wheelchairs to exoskeletons, designed to improve mobility for those with motor disabilities. Additionally, BCI technology shows promise in therapeutic domains. Current research is exploring the use of BCIs for monitoring, understanding, and potentially addressing neurological disorders like depression and anxiety. Another significant area of BCI applications is health monitoring. Analyzing brainwaves through BCIs can detect shifts in mental states, such as fatigue, alertness, or levels of intoxication [9–13].

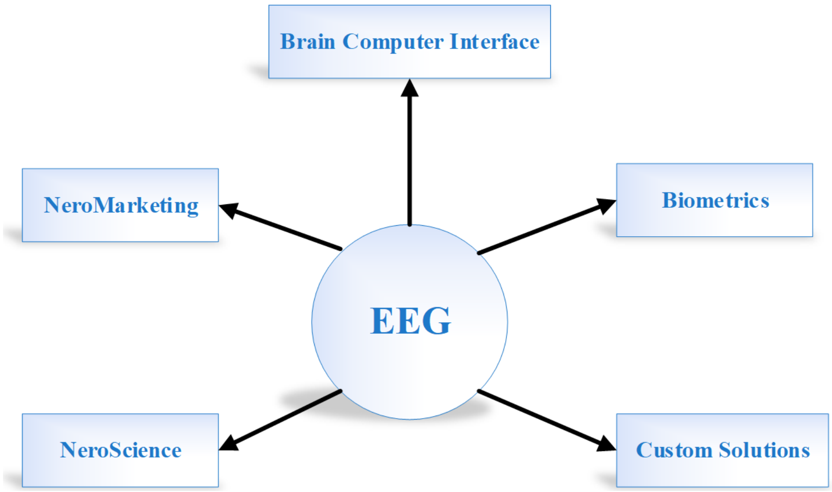

Figure 2. Various applications of EEG biometric signals in IoT solutions.

Technology can also function as an instrument for identifying individuals with certain neurological or psychological conditions. For example, EEG, a component of BCI, can be employed in the diagnosis of epilepsy and other neurological disorders, including Alzheimer's disease and autism spectrum disorder [14–17]. Additionally, it can aid in the diagnosis of mood disorders like depression and anxiety [18]. EEG can also help identify individuals who may be experiencing sleep problems, such as insomnia [19].

BCI systems utilizing EEG initially enabled the movement of a cursor on a computer screen or the selection between two images using brain signals. A key advantage of EEG signals is their rich content, reflecting a person's mental state, cognitive and motor functions, and a range of other neurological activities [9,20]. Therefore, EEG signals are particularly well-suited as input sources for BCI systems.

EEG can be employed for individual identification based on prior training. Researchers have explored the potential of using a person's EEG as a biometric identifier by analyzing the unique properties and patterns of their EEG signals [21]. Beyond its traditional uses, EEG has found applications in tailored scenarios like yoga classes, meditation sessions, immersive gaming experiences, and virtual reality platforms [22]. ts widespread use in understanding human brain functionality extends to gaining insights into human thoughts, needs, and emotions, particularly in marketing and strategic planning. EEG is increasingly being used to gauge customer reactions to marketing messages, advertisements, and product designs. In the realm of marketing, EEG provides valuable insights into customer perceptions, emotions, and responses to various stimuli. It can reveal hidden consumer preferences and guide the development of effective marketing strategies, messages, and product designs [23].

EEG fusion, a novel technological advancement, merges the capabilities of EEG, known for detecting brainwave patterns, with the IoT. This approach involves linking sensors and devices to the internet and leveraging these connections for the analysis and interpretation of brain signals. This technology is increasingly being used to create applications focused on monitoring, diagnosing, and treating mental illnesses, improving cognitive functions, and promoting overall health and wellness [24].

The biometric technology market is anticipated to expand from USD 21.5 billion in 2019 to USD 64.8 billion by 2025, demonstrating a compound annual growth rate (CAGR) of 22.0% during the forecast period [25]. The growth of this market is attributed to factors such as the rising demand for biometric security systems in sectors like banking, finance, and government, and there is an increased emphasis on access control and individual authentication in healthcare and retail. Furthermore, the use of mobile biometrics is escalating swiftly, establishing itself as a potent authentication method in virtually every mobile device and smartphone [26].

Regarding the IoT, human biometrics has emerged as a powerful technique that improves security and convenience in a variety of applications. Biometric authentication technologies such as fingerprint recognition, iris scanning, face recognition, and voice verification are being incorporated into IoT devices, allowing for safe and smooth interactions between people and connected devices [27]. When compared to traditional password-based or token-based authentication systems, these biometric-based solutions offer higher levels of accuracy and dependability. Furthermore, they provide a better user experience by eliminating the need to memorize difficult passwords or carry physical keys. IoT devices can precisely identify and verify individuals by employing biometrics, allowing for personalized experiences, secure access management, and efficient monitoring in sectors such as healthcare, smart homes, transportation, and security [28].

Incorporating EEG signals into biometric recognition systems represents a significant advancement in the field of identity authentication. While traditional biometric methods like fingerprint and facial recognition have been widely used, EEG-based biometrics offer unique advantages that, in some cases, surpass these conventional techniques. EEG-based biometric recognition utilizes the distinct and hard-to-replicate electrical activity of the brain, positioning it as a secure and innovative approach in identity verification. EEG captures the brain's electrical activity, offering deep and dynamic insights into an individual's cognitive processes. This uniqueness forms the cornerstone of its application in biometric recognition, enabling a more robust and personalized approach [29].

One of the key advantages of EEG-based biometrics is its ability to capture not only static physical attributes but also dynamic cognitive responses. This dynamic nature adds an additional layer of security, posing a challenge for malicious entities attempting to replicate or deceive the system [30].

In practice, EEG-based biometrics typically involve recording brainwave patterns through non-invasive electrodes. Advanced algorithms and machine learning techniques are then applied to analyze these patterns and extract distinctive features for individual identification. This method finds applications in secure access control, user authentication in computing systems, and forensic science. Despite its potential, EEG biometrics face challenges such as signal variability due to emotional or physiological states and the necessity for user cooperation. Future research is directed toward improving data acquisition methods, enhancing signal processing algorithms, and integrating EEG biometrics into practical, user-friendly systems [31].

Key attributes of EEG in biometrics include the inherent uniqueness of EEG patterns to individuals, shaped by their distinct neural pathways and brain activities. The dynamic nature of brain waves, which react to various stimuli, adds a layer of complexity, thereby enhancing security. Moreover, unlike fingerprints or iris patterns, EEG signals are difficult to mimic, reducing the likelihood of spoofing attacks. Standing at the forefront of secure authentication technology, EEG-based biometric recognition, with continued research and technological advancements, has the potential to revolutionize personal identification and security measures in the digital era [32,33].

In this review article, our primary focus is on the use of EEG signals for sensing human emotions among the various biometric signals and their associated features. This emphasis is due to the unique human ability to perceive and express emotions, a trait that is central to our survival, decision-making, and daily interactions. The following section will present a representative example of how EEG biometrics are integrated into IoT solutions.

The integration of IoT with 5G wireless networks marks a significant milestone, particularly in the field of EEG signal classification. This fusion introduces a range of advantages, deeply transforming the field of neuroscience. Additionally, it allows the potential to bring innovative changes in healthcare, human–computer interaction, and related domains. The convergence of IoT and 5G technology in the fields of biomedical research and neurotechnology represents a critical advancement, especially in enhancing EEG applications. EEG, known for its ability to record brain electrical activity, holds immense promise in diverse sectors such as medical diagnostics and BCI [8]. The integration of IoT and 5G into EEG systems signifies a substantial progression, opening up novel opportunities for enhanced data acquisition, processing, and utilization. The employment of IoT technology in EEG systems entails the utilization of sophisticated, interconnected devices designed for the acquisition and transmission of brainwave data. These devices, which include wearable EEG headbands or caps, are outfitted with numerous electrodes that capture the brain's electrical signals. The primary benefit of IoT-enabled EEG devices is their capacity to provide continuous monitoring and real-time data transmission, thereby enabling consistent evaluation and analysis [34].

The integration of IoT devices into EEG systems has transformed them into more lightweight and portable tools, significantly enhancing EEG accessibility beyond traditional clinical environments. This portability is particularly beneficial for remote patient monitoring and ambulatory EEG studies. IoT devices are capable of collecting extensive data sets, which are then transmitted to cloud-based platforms for storage and sophisticated analysis. This process is crucial for managing large data volumes and is essential in advanced research and analysis. Furthermore, the incorporation of 5G technology into EEG systems primarily addresses challenges associated with data transmission and processing [35]. Moreover, 5G networks provide significantly higher speeds compared to their earlier counterparts, a critical feature for transmitting the substantial data volumes produced by EEG devices, especially in detailed brain mapping. The minimal latency of 5G networks enables almost rapid data transmission, which is crucial for applications that require prompt responses or interventions, such as neurofeedback therapy or BCI. Additionally, 5G networks offer more reliable and stable connections, which are vital for continuous monitoring applications and ensuring the integrity of the transmitted EEG data [36,37].

The combination of IoT and 5G technologies within EEG systems opens up a diverse range of applications. In healthcare, it facilitates enhanced monitoring and management of neurological disorders, providing valuable insights into brain activity patterns that can inform treatment strategies. In research, it allows for more in-depth and detailed studies of brain functioning and neurophysiology. Furthermore, in the field of brain–computer interfaces, this integration sets the stage for the development of more sophisticated systems that offer faster and more accurate responses, potentially transforming the way humans interact with technology [38]. Overall, the integration of IoT and 5G technologies into EEG systems represents a significant advancement in neurotechnology. This merging is set to improve data collection, processing, and application, leading to deeper insights into the human brain and fostering innovative solutions in both healthcare and technology sectors. As these technologies continue to evolve, their impact on EEG research and applications is expected to expand, broadening our understanding and use of brain activity data [39,40].

The scope of the study was initially defined, encompassing key terms that are essential to the research, such as EEG, IoT, and 5G. This scope was instrumental in accurately identifying relevant aspects of the literature study. Academic databases like Elsevier, MDPI, IEEE Xplore, etc., were utilized. Keywords related to EEG, IoT, 5G, and their interrelated aspects were combined in the search strategy. The literature was thoroughly filtered based on criteria such as relevance, recency, and methodology. Priority was given to peer-reviewed articles and reliable sources, especially those focusing on the classification of EEG signals in the context of IoT and 5G integration. A thematic analysis was conducted on the chosen literature to extract and highlight key methodologies, challenges, and advancements, as reported in various studies. The primary goal was to develop a comprehensive understanding of how IoT and 5G technologies enhance EEG signal classification. Specific research questions were formulated to steer the study, including the investigation of the impact of 5G on real-time EEG monitoring and the exploration of the role of IoT in the development of interconnected EEG devices.

The diagram in Figure 3 presents a logical flow and interconnection of the various sections in the review paper, indicating how each section builds upon the previous ones and contributes to the overall narrative and understanding of integrating EEG with 5G and IoT technologies. Section 2 follows the introduction, delving into a specific application of EEG technology in the realm of emotion recognition. This section discusses the progress in EEG-based emotion recognition and relevant EEG databases. Section 3 provides an exploration of the fundamental properties of EEG signals, which is essential to understanding the subsequent sections on signal acquisition and processing. Section 4 addresses the common issues and noise factors in EEG data, which are crucial for ensuring accurate data interpretation in EEG studies. The acquisition of EEG signals is detailed in Section 5, where various methods for capturing EEG signals, such as different types of sensors (e.g., electrical geodesic, cup electrodes, dry electrodes, inductive sensors, ultrasound sensors), are presented. This section is foundational to understanding how EEG data are gathered before they are processed and analyzed, while subsequent pre-processing and feature extraction are detailed in Section 6, this section focuses on the techniques used for preparing EEG data for analysis, including filtering, segmentation, channel selection, feature extraction, and classification. This section might also delve into the methodologies, applications, challenges, and future directions in EEG signals. An architectural overview of the EEG biometric deployment in 5G-enabled IoT is presented in Section 7; this section explores the integration of EEG technology with modern IoT and 5G infrastructures, discussing aspects like EEG sensing networks, IoT cloud layers (mobile and edge computing, storage, application, intelligence, connectivity and integration, security, and authentication), and graphical user interfaces. Section 8 specifically delves into the architecture and infrastructure of 5G IoT, which is likely related to the deployment of EEG technology in these environments. Finally, challenges and opportunities for the seamless integration of wearable devices with IoT are described in Section 9, where the potential and difficulties associated with wearable EEG devices and their integration into daily life or medical applications are addressed. Section 10 wraps up the review paper, summarizing the findings, insights, and possible future directions in EEG and applied science.

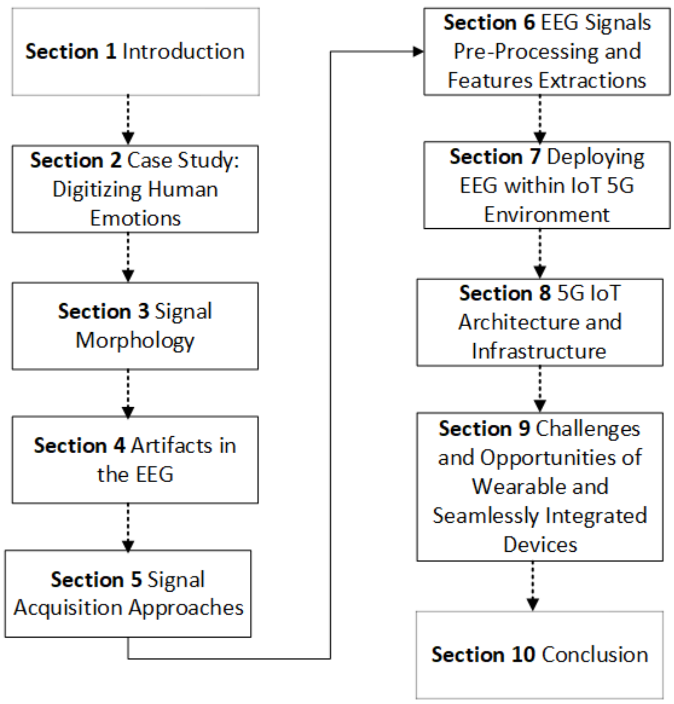

Figure 3. Review structure.

2. Case Study: Digitizing Human Emotions

Emotions represent complex mental states resulting from electrochemical changes in the brain. While there is no universally accepted definition of emotions, they are commonly classified as either positive or negative. The exploration of emotions encompasses various disciplines, such as neuroscience, psychology, psychiatry, and medicine. Despite thorough research, the underlying mechanism through which thoughts and feelings translate into emotions is not yet fully understood. However, recent advancements in artificial intelligence and machine learning technologies have markedly propelled the field of emotion recognition research forward.

2.1. Progress in EEG-Based Emotion Recognition

Among various artificial intelligence approaches, deep learning has shown the most potential and has been extensively utilized in the study of human emotions [41–43]. Most deep learning models are trained on extensive datasets, containing labeled facial images [42,44,45], audio waves [46], and textual data [47,48]. These models utilize extracted features to classify emotions with a higher degree of accuracy than traditional methods. Furthermore, researchers are currently investigating multimodal approaches that integrate two or more types of inputs, such as visual and textual data, to achieve more precise representations of emotions [48,49]. Computer vision methods, such as gaze and body gesture tracking, have been proposed [49] to capture subconscious emotional indicators.

Emotion recognition employs a diverse array of methodologies to accomplish its goals. Initially, the focus was on analyzing facial expressions, which resulted in the creation of a highly efficient and subject-independent system for emotion detection. This process involves identifying specific facial features (like the eyes, eyebrows, and mouth) and comparing these features against a predefined set of emotions [44,45,50]. For example, aspects such as the shape of the eyes, the movement of the eyebrows, and the curvature of the mouth can be employed to identify emotions like happiness, sadness, anger, or surprise [51]. After identifying these facial features, a computer vision algorithm can be applied to recognize the facial expression and categorize it into one of the predetermined emotions.

Initially, facial expression recognition exhibited low efficiency, but with technological advancements, including high-definition (HD) cameras, and the implementation of deep learning and machine learning algorithms, there has been significant improvement in efficiency. In certain instances, the accuracy of recognition has surpassed 95% [42,44,50,52,53]. A primary advantage of using facial expressions for emotion recognition is their subject-independent nature, as they tend to be relatively consistent across different individuals. However, relying solely on facial expressions for emotion detection presents a significant challenge due to their potential to be feigned. For example, an individual might force a smile despite feeling sad or depressed, or display tears of joy, which could be challenging for systems based solely on facial expressions to accurately discern. Moreover, these systems necessitate a continuous HD camera focused on the subject's face to monitor facial expressions consistently, enabling the analysis and extraction of human emotions.

In addition to facial expressions, other vital signs have been employed for emotion recognition, including speech [54], human posture, and functional magnetic resonance imaging (fMRI) [55]. Conversely, with notable advancements in portable, user-friendly EEG headsets, brain signals have become increasingly common for emotion recognition in both single and multimodal systems [45,56,57]. While EEG signals are utilized in this domain, there is a notable variation in the features extracted, as evidenced in prior studies [58]. Techniques for emotion recognition often employ both time-based and frequency-based features.

Regarding the number of channels and their optimization for use in neural networks for recognition, researchers have investigated 62 different channels on the human scalp, as delineated in the 10–20 system illustrated in Figure 4. These 62 channels, cataloged in an online database, have been employed in numerous studies using various training techniques, predominantly the support vector machine (SVM) method [13,59–61]. The channels are distributed with 27 on the left side of the scalp, 27 on the right side, and the remaining 8 along the midline of the scalp. Most research in this field concentrates on the EEG signal itself rather than on brain mapping activities [60,62]. Although the brain map activity, a virtual representation of the EEG signal, is not currently used for emotion detection, it presents potential for future applications involving convolutional neural networks.

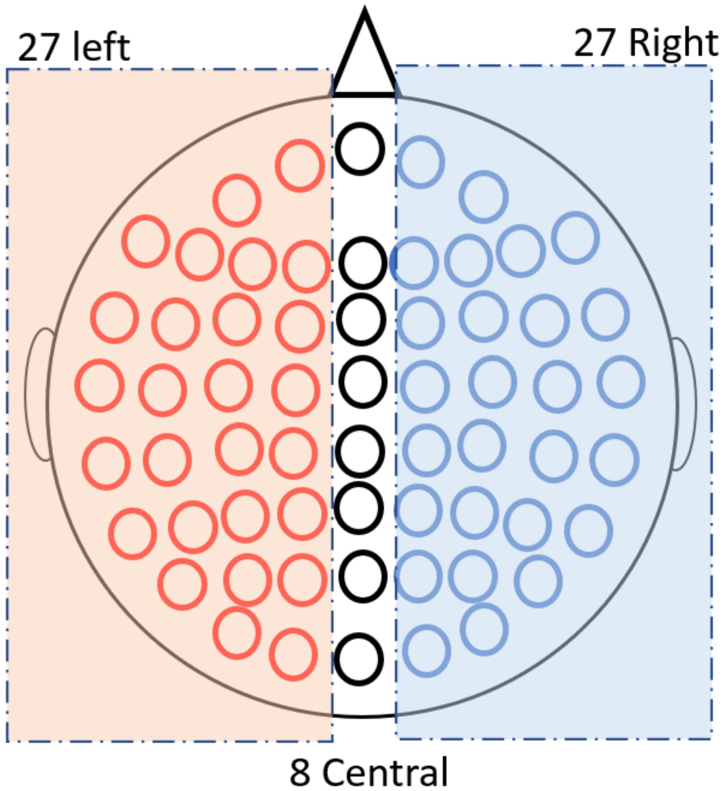

Figure 4. The optimal locations for all 62 EEG electrodes on the human scalp [41].

Researchers are employing a variety of features extracted from EEG signals, including those from the time domain [63], frequency domain [53], and mixed domain features [64]. Multimodal systems may integrate EEG signals with one or more other types of input signals. These additional inputs can include skin conductance, facial expressions, eye movement, muscle activity, or other vital signs, used in conjunction with EEG to create a comprehensive multimodal system. Among these inputs, facial expressions are frequently used in conjunction with EEG in emotion recognition systems due to their high accuracy relative to other signals [42,45,52,56]. The effectiveness of these systems in detecting different emotions varies, with accuracies ranging from 83% to 89.6%. The highest accuracy, 89.6%, was achieved by Aguiñaga, Adrian R. in 2021 [45] using 15 EEG channels. This system utilized signal processing to extract wavelet features from the EEG signals, recognizing a four-class emotions model: happiness (high arousal–high valence (HA-HV)), anger (high arousal–low valence (HA-LV)), and sadness (low arousal–low valence (LA-LV)). EEG signals have also been incorporated into a multimodal system along with galvanic skin conductance and blood volume pressure, using 15 EEG channels [65]. The accuracy of this system was approximately 75% for three different emotional states. Table 1 presents a comparison of various EEG-based emotion recognition techniques.

Table 1. Comparison between various EEG-based emotion recognition methods.

Ref.	Channels	Accuracy	Subject	Database	Detection
[41]	62	N/A	Dependent	Seed	Positive Neutral Negative
[42]	14	77.6–78.96%	Dependent	DEAP	Valence Arousal Dominance
[43]	12	81.5–86.87%	Independent	12 subjects	High Low Valence Arousal
[66]	14	87.25%	Dependent	19 subjects	Happiness and Sadness Fear and Anger Surprise and Disgust
[44]	32	96.28–96.62%	Dependent	DEAP	High Low Valence Arousal
[45]	62	83.33%	Independent	Seed	Neutral sadness and fear happiness
[46]	32	N/A	Dependent	MAHNOB	High Low Valence Arousal
[47]	10	58.47–60.90%	Independent	N/A	High Low Valence Arousal

Moreover, the integration of EEG with the IoT has the potential to develop applications designed to enhance cognitive performance, improve physical and mental well-being, and aid in comprehending the human brain and its functions. For example, technology that utilizes EEG sensors and IoT-connected devices could be used to detect and interpret signals associated with emotions. This would enable users to gain a deeper understanding of, and potentially exert greater control over, their conscious and subconscious behaviors. Additionally, this technology could be applied to create applications aimed at boosting memory, concentration, and creativity by analyzing and interpreting cognitive processes [1,24,67].

Numerous studies and surveys have concentrated on classifying emotions and developing physical systems to achieve the highest possible accuracy [68]. These activities comprehend the application of various machine learning techniques and the investigation of different methods for feature extraction and frequency range analysis [69]. Additionally, some research has been directed toward optimizing the selection of channels for emotion recognition processes [70] and monitoring other health conditions [71]. Furthermore, general daily movements and actions were analyzed and mapped using EEG signals in [72]. However, relatively few studies have focused on the implementation of secure EEG biometric data transfer between servers and clients within the framework of IoT solutions over 5G wireless networks [67,73–75].

2.2. EEG Databases for Emotion Recognition

In the classification of human emotions through EEG signal recordings, it is a standard practice to use musical videos or short clips to evoke a range of emotional responses from participants. The duration of these clips can range from a few seconds to six minutes, where participants may display their emotions in diverse ways. Despite the growing interest in exploring the influence of emotions on brain signals, there remains a notable lack of readily available databases for such studies. Table 2 presents a summary of five publicly available datasets.

Table 2. Comparison among EEG datasets in terms of participants, clips, channels, emotions, and frequencies.

Dataset	Participants	Clips	EEG Channels	Emotions	Sampling Frequency
DEAP	32	40	32	Valence Arousal Dominance	512 Hz–down sampled to 128 Hz
SEED-IV	15	15	62	Valence Arousal Dominance	200 Hz–down
DREAMER	23	18	14	Valence Arousal Dominance	N/A
AMIGOS	40 Short Experiment 37 Long Experiment	16 Short 4 Long	14	Valence Arousal Dominance	N/A
MAHNOB HCI	30	Exp 1: 20 clips Exp 2: 28 images	32	Valence Arousal	256 Hz
MPED	23	28	62	Joy Funny Neutral Sad Fear Disgust Anger	1000 Hz

Most of these databases are aimed at identifying emotions across three primary dimensions: valence, arousal, and dominance. Arousal reflects the spectrum from passive disinterest to stimulated enthusiasm, whereas valence covers the spectrum from tense unhappiness to joyfulness. The dominance dimension comprehends feelings, ranging from vulnerability to a sense of empowerment, as represented in the illustration provided in Figure 5.

The self-assessment manikin (SAM) is the most widely used standard for reporting emotions in studies [76–78]. This method involves presenting manikins to users, who then describe their emotional state according to a linear scale on each emotional axis, as illustrated in Figure 5. A significant limitation of the databases currently using SAM is that participants are required to represent their feelings throughout an entire video or experimental trial with a single value. However, it is more realistic to consider that a participant's emotions may vary during the course of the experiment.

The DEAP database [79] includes 32 recordings from 32 subjects engaging in various emotional processing tasks, making it a popular resource in research. Each participant viewed 40 one-minute-long videos that acted as emotional stimuli. During each of the two experimental sessions, a two-minute baseline recording was conducted. A total of 32 electrodes, positioned according to the international 10–20 system, captured physiological data, including EEG and GSR, at a sampling rate of 512 Hz, which was then downsampled to 128 Hz for analysis. The data were divided into training and testing sets to facilitate research. Additionally, the database includes extra information, such as measurements of the left pinky finger's body temperature and GSR, along with observations of facial expressions, eye movements, mouth shapes, and lip expressions [80].

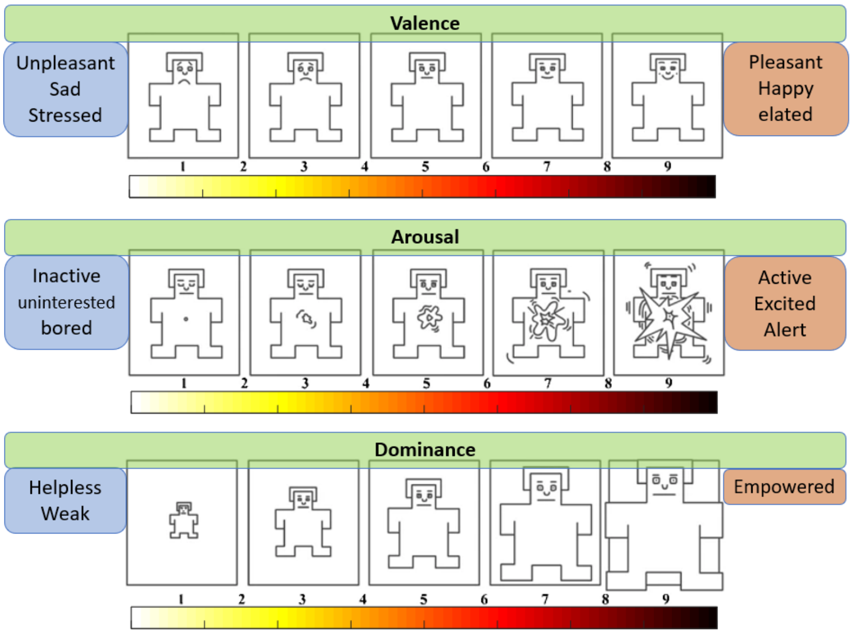

Figure 5. Three emotion-scaling axes superimposed on the standard self-assessment manikin system (SAM).

The SEED IV EEG database is an extensive collection featuring EEG recordings from 15 subjects who engaged in 24 distinct mental activities or tasks. These recordings were captured using the Neuroscan SynAmps 2 amplifier, coupled with a 62-channel high-resolution EEG cap. Each participant underwent three sessions. The EEG data include responses to a range of auditory, visual, and somatosensory stimuli, and also include eye movement information [67,81].

The Dreamer EEG database features EEG recordings from 14 channels of 23 healthy adults, aged 22–33. These participants were exposed to 18 different video clips, during which their brain's electrical activity was recorded using an EMOTIV EPOC headset. The data were initially collected at a sampling rate of 256 Hz and subsequently downsampled to 128 Hz for analysis [82].

The AMIGOS dataset serves as a significant resource for investigating the effects of visual media on group dynamics, emotional states, and mood. It is particularly useful for exploring how emotions (like positivity and arousal) manifest in brain activity and for studying the neural mechanisms influencing individual and group behaviors. This dataset involves physiological recordings from multiple body sites, including EEG, electrocardiography (ECG), and galvanic skin response (GSR). These recordings are beneficial for research in emotion regulation, attention, and affective neuroscience. The data were collected through two separate experiments. In the first experiment, EEG signals were recorded from 40 participants as they watched 16 short video clips, each less than 250 s in duration. The second experiment involved EEG recordings from 37 participants, who were also part of the first experiment, as they viewed four longer video clips, each exceeding 14 min. In both experiments, the same 14 channels from the EPOC headset were utilized for recordings [83].

The MAHNOB-HCI database is highly suitable for researchers exploring the impact of visual media on human emotions. It comprises EEG recordings from 27 healthy subjects, including both males and females, who took part in two distinct experiments. In the first experiment, the participants watched 20 short video clips, while in the second experiment, they were exposed to a combination of images and videos (28 images and 14 videos). The EEG data were gathered using 32 channels, and additional psychophysiological data, such as facial expressions and heart rate (HR), were simultaneously recorded. This database offers an extensive range of data for studying the neural mechanisms that underlie emotional responses to visual stimuli [84].

The MPED database includes EEG recordings from 23 participants who viewed 28 distinct videos. These recordings were captured using a total of 62 channels, incorporating EEG artifact rejection techniques. A sampling frequency of 1000 Hz was employed. Alongside the EEG data, other physiological measurements, such as respiration, galvanic skin response (GSR), and electrocardiography (ECG) data were concurrently collected for each participant during their viewing of the stimulus videos [85].

All datasets in Table 2 employ a scale from 1 to 9, as shown in Figure 5, except for the AMIGOS and DREAMER databases, which use a linear scale from 1 to 5.

3. Signal Morphology

The morphology of EEG signals is shaped by the brain activity at the time of waveform capture, which depends on the active section of the brain. The anatomy of the human brain comprises three primary lobes, as illustrated in Figure 6. The cerebrum, being the largest and most significant part, is split into two hemispheres, each containing four lobes: the frontal, parietal, temporal, and occipital lobes. The frontal lobe manages planning and complex voluntary movements, personality, judgment, decision-making, and cognitive functions, like language, abstract thinking, and problem-solving. The parietal lobe processes somatosensory information, such as touch and coordinate movements [86], while the temporal lobe handles auditory information and is integral for memory and speech. The occipital lobe, the smallest of the lobes, is tasked with vision, including color and spatial perception. The brain stem oversees basic life functions like breathing, blood pressure, and swallowing, and the cerebellum controls balance and fine movement coordination, including activities like walking and speaking [87]. EEG waveforms exhibit distinct shapes that are indicative of various types of brain activities. The EEG signal is represented as a time series of voltage values corresponding to electrical activity detected by electrodes, measured in microvolts (μV), and is typically sampled at regular intervals ranging from 128 Hz to 1024 Hz. Common EEG signals have a frequency range of up to 45 Hz, and EEG frequencies are usually standardized as delta, theta, alpha, beta, and gamma waves [72]. However, in certain cases, the EEG frequency range can extend beyond 200 Hz. These frequencies offer insights into the functioning of different brain areas and are instrumental in diagnosing and treating various neurological and psychiatric conditions. They are also employed to monitor brain activity during various states like sitting, sleeping, and meditating [73].

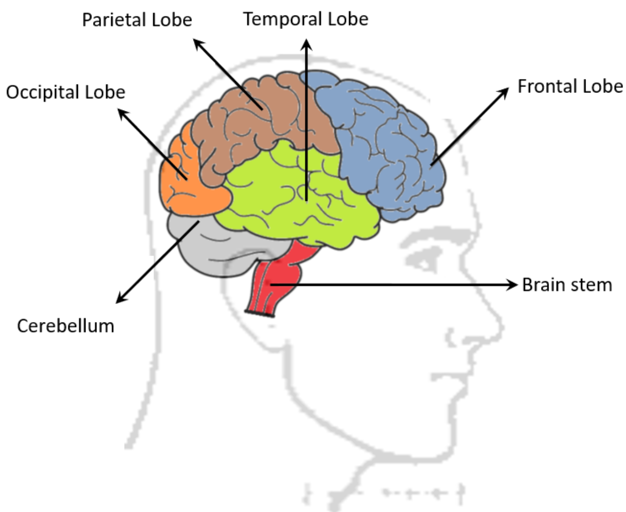

Figure 6. Brain anatomy with the primary lobes highlighted.

4. Artifacts in the EEG

As previously noted, EEG signals have potential use in biometric identification [21]. The raw EEG signals can be altered by various neurological and psychological conditions. Numerous factors influence EEG signals, including aging, certain medications or drugs, diseases, sleep deprivation, physical activity, mental states, eye or muscle movements, substance use, metabolic conditions, hydration levels, environmental factors, and even the type and placement of the EEG electrodes.

EEG is a valuable tool used in diagnosing a range of diseases. For instance, seizures and epilepsy can be identified by analyzing brain activity patterns in EEG recordings [17]. Other neurological diseases, particularly those leading to dementia, can also be detected through EEGs. Structural brain changes, such as tumors, are often reflected in EEG signal alterations. Furthermore, EEG modifications can be helpful in diagnosing and monitoring certain sleep-related disorders, including narcolepsy [13,15,74,75].

EEG signals are also capable of mirroring an individual's emotions. Distinct brainwave patterns are produced when a person experiences specific emotions such as happiness, sadness, anger, fear, or surprise. Both positive and negative emotions induce changes in EEG activity. For example, sudden emotions like surprise or fear are associated with high-frequency beta activity, indicative of alertness and arousal [48,88–90]. Additionally, EEG signals show increased delta and theta activities, which are related to deep relaxation and enhanced mental receptivity. In conclusion, various emotions significantly influence EEG signals [69,72].

Muscle movements can significantly influence EEG recordings, often leading to artifacts in the signal. The most common artifact observed in EEG due to muscle activity is the muscle jerk or spike, which is an electrical impulse generated by muscle contractions or relaxations and captured in the EEG recording. Other muscle-related artifacts include movements of the eyes and face, blinking, chewing, and jaw movements. Moreover, muscle movements can modify the characteristics of EEG waveforms, causing them to appear wider, shallower, or to display spikes. These movements can also introduce artifacts into other parts of the EEG recording, such as the baseline and transitions between waveforms [91–93]. Noise is another element that can impact the EEG signal, leading to interference, distortion, and additional artifacts in the recording. This can complicate the signal analysis process, potentially resulting in inaccurate conclusions. To counteract the effects of noise, various methods are employed, including signal averaging, artifact detection and rejection, signal filtering, multiband or wavelet-based filtering, and the application of robust statistical techniques. These approaches are instrumental in minimizing noise and enhancing the EEG signal's quality for more reliable analysis [94,95]. The choice of electrodes can also affect the outcome of an EEG recording. Electrodes differ in size, shape, and material, which can influence the EEG signal's quality. Some electrodes, for example, may be better suited for capturing a broader frequency range. The material of the electrode affects its impedance, directly impacting signal quality. The shape of electrodes can be tailored to optimize signal detection from specific scalp locations. Additionally, the conductive gel or paste used to create a connection between the electrode and the skin also influences the signal. Variations in viscosity among different brands or types of conducting gels or pastes can affect the signal quality [41,96,97].

5. Signal Acquisition Approaches

An EEG sensor is an instrument that captures brain signals using electrodes placed on the scalp, which detect and record the brain's electrical activity. Various types of EEG sensors are employed in data acquisition, including the following.

5.1. Electrical Geodesic Sensors

These sensors are specifically designed to measure electrical activity on the scalp and are widely used in EEG studies for their ability to monitor activity across the entire scalp [98]. Electrical geodesic sensors utilize a geodesic sensor net to provide even coverage and reliable scalp contact. Typically, these sensors incorporate a large number of electrodes, enhancing the resolution and accuracy of the EEG data. They find extensive application in fields like cognitive neuroscience and clinical diagnostics, proving especially effective in high-density EEG recordings.

5.2. Cup Electrodes

Comprising small cups made of silver or gold plating, these electrodes are positioned on the scalp to record electrical activity from specific or multiple areas [99]. The choice of materials, such as silver or gold, is crucial for their high conductivity and biocompatibility. Setting up these electrodes involves using conductive paste or gel, and their placement is critical for targeted brain region monitoring. While they offer high signal quality, the setup can be cumbersome, and there might be discomfort involved for the subject, especially in long-term recordings.

5.3. Dry Electrodes

These are adhesive sensors that do not require conductive gel. They can be applied directly to the skin and provide a high signal-to-noise ratio [95]. The advancement in materials and technology enables these electrodes to function without conductive gel, often using micro-needle arrays or novel conductive materials. Their ease of use, comfort, and minimal preparation make them increasingly popular in portable EEG devices, suitable for long-term monitoring in telemedicine and consumer-based health applications.

5.4. Inductive Sensors

These sensors detect changes in the electromagnetic field caused by brain electrical activity, capturing comprehensive brainwave patterns. They are typically used in research settings [100]. Operating on the principle of electromagnetic field detection, these sensors are adept at capturing specific types of brainwave patterns. While their non-contact, non-invasive nature is a significant advantage, there are limitations to the kinds of signals they can detect. They are most beneficial in studies that require non-contact methods of brain activity monitoring.

5.5. Ultrasound Sensors

Employing ultrasound waves, these sensors measure the brain's electrical activity and are often used in medical settings to detect seizure activity. Ultrasound sensors work by using sound waves to detect changes in brain activity, a method known as echoencephalography. They are particularly useful in medical diagnostics for detecting abnormalities in brain activity, such as seizures, and in monitoring cerebral blood flow. Recent advancements in ultrasound technology have improved the efficacy and applications of these sensors in neurological research and diagnostics.

6. EEG Signal Pre-Processing and Feature Extraction

6.1. EEG Signal Pre-Processing

6.1.1. EEG Signal Filtering

EEG signals exhibit a measurable power spectral density across various frequency bands. Typically, the frequency content of EEG signals spans from 0.5 Hz to around 70 Hz. The frequency bands of EEG signals are standardized, as detailed in Table 3.

Elevated signal power in the delta band is often associated with brain activity during deep sleep. Recent research has demonstrated that the frequency bands most relevant for emotion recognition, based on various publications, are the theta, alpha, and beta bands [88,101,102]. To focus on these specific bands, a second-order band-pass filter is employed to exclude unwanted frequencies.

Table 3. EEG frequency bands.

Signal Band	Frequency Range
Delta	<3 Hz
Theta	4–7 Hz
Alpha	8–12 Hz
Beta	13–30 Hz
Gamma	>30 Hz

6.1.2. EEG Signals Segmentation

The brain produces signals rich in information, not limited to emotions. These signals are too complex to be analyzed in their entirety. To enhance the effectiveness of detection techniques, a method known as window-based segmentation is utilized. This approach breaks down the signals into smaller, more manageable segments for analysis. This segmentation helps in reducing noise and simplifying the detection process. The duration of the segmentation window can vary, typically ranging from 0.5 s [89] to 60 s [103], depending on the specific requirements of the study or research.

6.1.3. EEG Channels Selection

Optimizing the number of EEG channels used for recognition is crucial to enhancing recognition performance. This involves experimenting with various combinations of EEG channels, conducting tests, and selecting the combination that provides the best results. Additionally, the impact of different algorithms and methods of feature extraction and selection on performance can be evaluated to further refine recognition accuracy.

The placement of sensors on the scalp is vital for minimizing artifacts. Some studies utilize all available sensors in a dataset, regardless of the number [79], while others focus on optimizing the channels to reduce noise and increase system efficiency [104].

6.2. EEG Signals Feature Extraction

Nonlinear features are commonly used in emotion recognition research utilizing EEG signals. When using datasets like DEAP, the correlation between electrode voltage and reported emotions is often weak, as indicated by statistical analysis [79]. Therefore, incorporating nonlinear features is essential in EEG-based emotion recognition systems. After determining the appropriate frequency band and the number and placement of sensors, the most frequently used feature is power spectral density. In some studies, power density is employed to create a topographical representation of brain signals, considering specific sensor numbers and frequency ranges within a selected window size, as illustrated in the heat map in Figure 7.

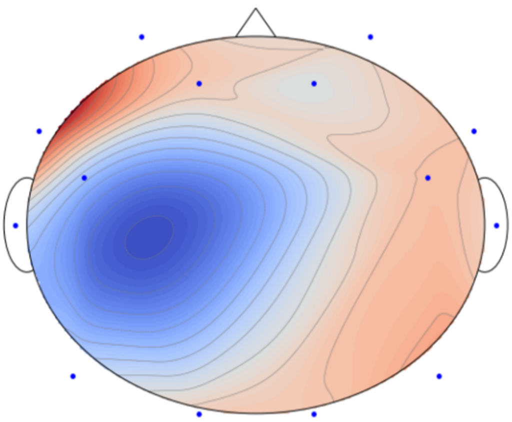

Figure 7. EEG topography heat brain image.

Generally, EEG features can be classified into three categories: time domain, frequency domain, and time–frequency domain features. Time domain features including various statistical measures such as the mean, standard deviation, range, skewness, kurtosis, as well as Hjorth parameters including activity, mobility, and complexity [105–107]. These standard statistical features are described below:

- Mean:

$$\text{Mean}(x) = \frac{1}{n}\sum_{t=1}^{n} x(t) \tag{1}$$

- Standard Deviation:

$$\text{Std}(x) = \frac{1}{n}\sum_{t=1}^{n} (x(t) - \text{Mean}(x)) \tag{2}$$

- Range:

$$\text{Range}(x) = \max(x) - \min(x) \tag{3}$$

- Skewness:

$$\text{Skewness}(x) = \text{Mean}((x - \text{Mean}(x))^3) \tag{4}$$

- Kurtosis:

$$\text{Kurtosis}(x) = \frac{\text{Mean}((x - \text{Mean}(x))^4)}{Std(x)^4} \tag{5}$$

- Hjorth parameter-activity:

$$\text{Activity}(x) = \text{Std}(x)^2 \tag{6}$$

- Hjorth parameter-mobility:

$$\text{Mobility}(x) = \sqrt{\frac{(\text{Std}(\frac{dx}{dt}))^2}{(\text{Std}(x))^2}} \tag{7}$$

- Hjorth parameter-complexity:

$$\text{Complexity}(x) = \sqrt{\frac{\text{Mobility}(\frac{dx}{dt})}{\text{Mobility}(x)}} \tag{8}$$

In this context, $x(t)$ denotes the raw EEG signal comprising n samples. The described features are commonly known as statistical features. Frequency domain features, on the other hand, are derived from the frequency components extracted from the original signal. The key frequency features include power, power ratio, and power spectral density, which can be summarized as follows:

- Power spectral density:

$$\text{PSD}(x) = \lim_{T\to\infty} \frac{1}{2T}\int_{-T}^{T} \left| s(t)e^{-j2\pi xt}dt \right|^2 \tag{9}$$

- Power:

$$\text{Power }(k) = \int_{-\infty}^{\infty} PSD(x)\,dx \tag{10}$$

- Power Ratio:

$$\text{Power Ratio }(x) = \frac{\text{Power}}{\text{Power Sum}} \tag{11}$$

where

$$\text{Power Sum} = \sum_{k=1}^{5} \text{Power} \quad (12)$$

The final category of features includes those derived from both the time and frequency domains. Although fewer in number, these features are frequently utilized in numerous studies [13,64,94,103]. The principal time–frequency domain feature is the wavelet energy of the signals. Additionally, a feature known as wavelet entropy is notable in this domain. These two features can be characterized as follows:

- Wavelet Energy:

$$\text{ENG}(x) = \sum_{t=1}^{n} (x(t))^2 \quad (13)$$

- Wavelet Entropy:

$$\text{ENT}(x) = -\sum_{t=1}^{n} (x(t))^2 \log\left((x(t))^2\right) \quad (14)$$

6.3. EEG Signals Classification

The core of EEG signal processing is encapsulated in the classification stage, where extracted features are utilized to train machine learning algorithms for pattern recognition. This stage is crucial for categorizing EEG signals into distinct classes based on their characteristics, aiming to interpret the underlying brain activities or states.

6.3.1. Methodologies in EEG Signal Classification

The classification of EEG signals typically involves advanced algorithms and methods. Techniques such as support vector machines (SVMs), neural networks, and k-nearest neighbor (k-NN) are commonly employed. These classifiers are selected for their proficiency in handling the high-dimensional nature of EEG data and their effectiveness in addressing non-linear relationships within these data [108].

6.3.2. Applications in Medical Diagnoses and Brain–Computer Interfaces (BCIs)

EEG signal classification is vital in medical diagnosis, especially for identifying neurological disorders like epilepsy, Alzheimer's disease, and sleep disorders. In the realm of BCI, EEG classification plays a key role in interpreting user intentions from brain activity, facilitating the control of external devices or communication, especially in scenarios involving severe motor disabilities [109].

6.3.3. Challenges in EEG Signal Classification

A major challenge in EEG classification is the high variability of EEG signals among individuals, compounded by the presence of artifacts and noise. This variability can markedly affect the accuracy of classification algorithms. Overcoming this challenge requires sophisticated preprocessing and feature extraction techniques to ensure the use of the most relevant and noise-free features for classification [110].

6.3.4. Future Directions in EEG Classification Research

Ongoing research in EEG signal classification is moving toward developing more robust, adaptive algorithms capable of managing the inherent complexities and variabilities of EEG data. This includes the exploration of deep learning and artificial intelligence techniques, which have shown potential in autonomously extracting and learning features from EEG signals [111].

In summary, EEG signal classification is a complex and multifaceted field of research with profound implications in medical and technological spheres. Despite existing challenges, continual advancements in computational methods and an enriched understanding of EEG data are driving progress in this area.

7. Deploying EEG within IoT 5G Environment

The integration of EEG technology within the IoT 5G framework offers the potential to seamlessly incorporate real-time brain activity and behavioral data into existing digital health networks. Utilizing advancements in wearable and mobile computing technology, EEG in the 5G era can facilitate real-time monitoring of a patient's brain waves. This integration allows for immediate access to a vast array of personal digital health data and insights [71,112]. Furthermore, the advancements in low-power 5G networks, coupled with energy-efficient 'Always-On' 5G-enabled devices, are poised to meet the emerging demands for cost-effective and long-term EEG monitoring. These technological innovations have the potential to reduce operational costs for healthcare providers and enhance patient outcomes by enabling remote access and monitoring of EEG data from any internet-connected location [113]. In summary, the advent of the IoT 5G era indicates a transformative phase in the monitoring, analysis, and application of EEG data, heralding new opportunities in digital health and personalized medicine. IoT-based EEG monitoring systems are typically comprised of three interconnected components: the EEG sensing network, the IoT cloud, and the graphical user interface (GUI). This structure is depicted in the representative example shown in Figure 8.

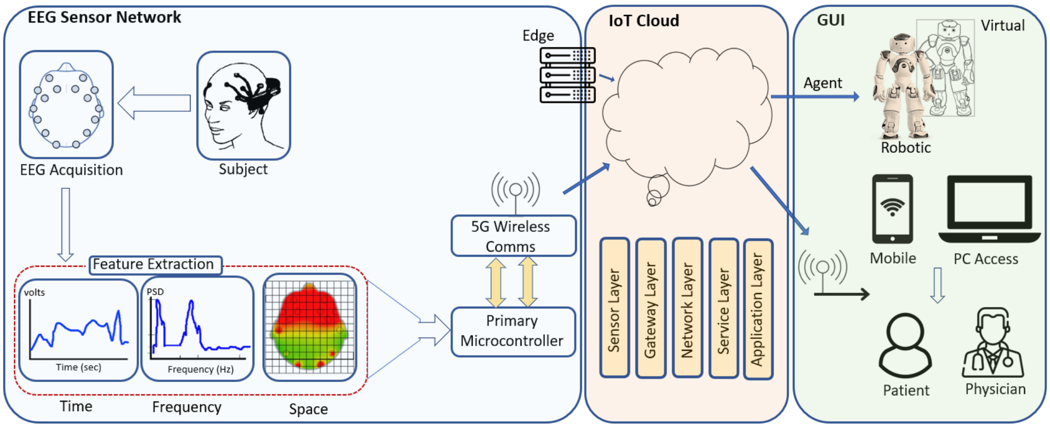

Figure 8. An example of an IoT-based EEG monitoring system.

7.1. EEG Sensing Network

The primary objective of the sensing network is to gather data and extract pertinent features. In the example illustrated in Figure 8, a headset is employed for capturing raw EEG data. The data are then processed to extract features from various dimensions, including time, frequency, and electrode location, to discern the emotional state of the subject. Feature extraction can be conducted either at the sensing node or on the IoT edge processor. Once the raw EEG signal data are successfully transmitted through the medium, they are forwarded to the IoT cloud. Generally, the EEG sensing network involves steps such as EEG signal acquisition, pre-processing, and feature extraction [70]. This process includes selecting an appropriate EEG sensor, determining the optimal sensor placement, establishing the data sampling rate, and signal quantization. The collected EEG signals are preprocessed to eliminate artifacts and normalized using baseline data. Signal processing techniques like principal component analysis (PCA) and wavelet transforms are then applied to extract features from the EEG signals [114].

Following the transmission of EEG data to the cloud, the next steps typically involve data storage and analysis, integral to delivering a personalized EEG monitoring service. Utilizing Bluetooth technology, the sensor data can be linked to various devices such as mobile phones, laptops, or computers. Subsequently, a secure data packet is created, facilitating the transfer of data to a cloud-based platform backed by a high-performance computing center. Within the IoT cloud, the signals undergo analysis, and the derived real-time information is relayed back to the initial device or directed to the owner's mobile phone, wearable device, or laptop, based on the user's preferred device selection [24,44].

To enhance the classification accuracy of the signal and the individual's physical state, advanced EEG signal processing algorithms are employed. Moreover, the analyzed EEG data can be archived or utilized for further processing in applications like detecting sleep state disorders, emotion recognition, and various other aspects pertinent to optimizing human well-being. Beyond analysis, the cloud can also offer additional services, including user behavior monitoring and general health and lifestyle management [115].

Various wireless networking options are available for transmitting raw EEG signal data from devices to the cloud for processing and analysis. As detailed in Table 4, Wi-Fi employs radio waves to connect devices over short to medium distances, ensuring high data transfer rates without data loss. Bluetooth, utilizing low-energy radio frequency, facilitates connections over short distances of up to 30 feet but typically has lower data transfer rates compared to Wi-Fi. Zigbee technology, also using low-energy radio frequency, connects devices over distances up to 230 feet. It is often chosen for applications needing lower data transfer rates, and its minimal power requirements make it suitable for battery-operated devices.

Table 4. Comparison of typical EEG sensing networks: Wi-Fi, Bluetooth, and Zigbee.

Standards/Methods	**Wi-Fi-Based EEG Sensing Network**	**Bluetooth-Based EEG Sensing Network**	**ZigBee-Based EEG Sensing Network**
Protocol	TCP or UDP	Bluetooth	ZigBee Protocol
Coverage	150 Feet indoor	30 Feet indoor	230 Feet indoor
Data rates	2.4 GHz	2 MHz	2.4 GHz
Power consumption	High	Low	Low

7.2. IoT Cloud

The data gathered from the EEG sensing network are transmitted to the IoT cloud for long-term storage and further analysis. This cloud can be hosted on a remote server or a public cloud platform, such as Amazon Web Services. It offers remote access to users, enabling data analysis, monitoring, and remote control capabilities. The cloud platform facilitates resource sharing, making it a compelling choice for EEG authentication [116]. IIoT enhances device-to-device communication by enabling secure data sharing over the internet. Cloud technology in IoT also supports scalability in data storage and management from thousands of devices. It adds value to the data collected from IoT by enabling users and organizations to identify trends and insights, while also minimizing costs. Additionally, the cloud provides a more rapid response to large data volumes and improves the management of the IoT environment. To effectively handle EEG signal data, an IoT cloud must incorporate six essential levels [80,117,118].

7.2.1. Mobile and Edge Computing Layer

This layer is tasked with collecting, processing, and forwarding data from connected devices and sensors. In the realm of EEG signals, this could include sensors that gather and store data at a patient's location and subsequently transmit it to the cloud.

7.2.2. Storage Layer

This layer handles the storage of data received from sensors and devices. The data can be stored in various databases and file systems, including structured query language (SQL), not only SQL (NoSQL), Big Data, and others.

7.2.3. Application Layer

This layer is responsible for delivering application-specific services and functions. It processes the data collected from devices by extracting, analyzing, and visualizing key insights.

7.2.4. Intelligence Layer

This layer provides insights useful for making health monitoring decisions. It might incorporate data mining, machine learning, predictive analytics, and other related analytical techniques.

7.2.5. Connectivity and Integration Layer

This layer ensures the connection of diverse IoT devices and systems, such as sensors, gateways, and data sources, to the cloud. It involves the use of application programming interfaces (APIs), electronic data interchange (EDI), file transfer protocol (FTP), and other related technologies.

7.2.6. Security and Authentication Layer

This layer guarantees the security and integrity of the data stored in the cloud, encompassing identity and access management, encryption, digital signatures, and other security protocols. Given the sensitive nature of EEG data, maintaining stringent security measures is crucial.

7.3. Graphical User Interface (GUI)

The GUI is utilized for the visualization of EEG signal, feature extraction, and authentication outcomes. It enables users to monitor the authentication system's performance in real-time, observing any changes in accuracy. The GUI also allows for the adjustment of authentication parameters to enhance system performance [119]. It includes a web page and various user interfaces like virtual keyboards, mice, and touchscreens. Moreover, the GUI offers functionalities for data storage, analysis, and sharing, displaying alarm alerts, patient information, trend analyses, and diagnostic data [120].

In a specific implementation [121], a BCI system was established to control a surrogate humanoid robot or virtual agents, as depicted in Figure 8. This setup allowed the robot to simulate empathy and interact with the subject based on pre-defined behavioral models [90].

8. 5G IoT Architecture and Infrastructure

8.1. 5G Architecture

Fifth-generation (5G) networks are increasingly adopted for their high-speed connectivity and low latency. This fifth-generation technology employs a high-bandwidth spectrum with wider channels to facilitate faster data transfers. It also enhances spectrum efficiency, supporting seamless connections for numerous users. Additionally, 5G technologies lead to more reliable wireless connections and increased data transfer speeds, making them ideal for connecting a multitude of devices to the Internet and advancing IoT applications [122].

The 5G architecture comprises three primary components: the radio access network, the core network, and the transport network. The radio access network, functioning as a cellular network, connects devices via radio waves. This network includes base stations or towers for wireless coverage, alongside transmitters, receivers, and antennas. The core network connects the radio access network components to the internet, handling tasks like IP address allocation, authentication, and VoIP (voice over internet protocol). The transport network, consisting of wires and fiber-optic cables, is fundamental in facilitating data transfer within the 5G network, ensuring high-speed access and network scalability [123].

As illustrated in Figure 9, the 5G architecture is structured into five layers. The sensor layer, the first layer, is made up of wireless sensing devices that collect data, including physical and environmental parameters, and EEG brain signals in this research context. These sensors, both active and passive, can detect various parameters like temperature, pressure, and light. The gateway layer, the second layer, functions as the access layer, encompassing the radio access network (RAN), which interfaces between the user equipment and the core network of the mobile service provider [124]. The third layer, the network layer, includes the core and transport networks, acting as the backbone connecting multiple access points. The fourth layer, the service layer, is responsible for providing active services to users and applications, managing service access, and bridging the gap between network and application layers to meet user expectations. Lastly, the application layer, the fifth layer, enables user access to services and applications provided by the service layer, offering the user interface and experience for these applications [125].

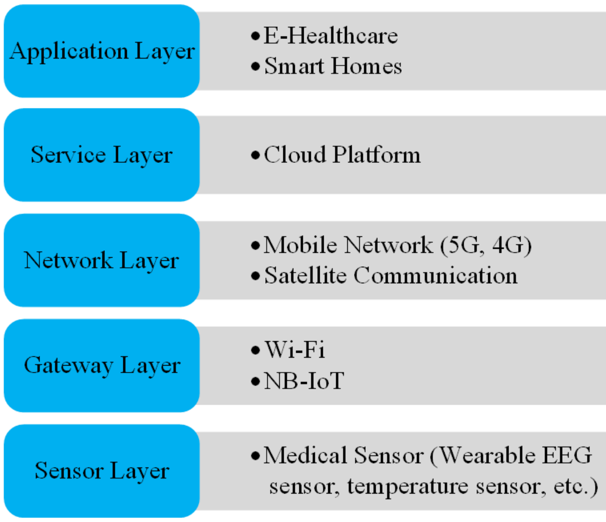

Figure 9. Architecture of 5G IoT.

8.2. 5G Infrastructure

Fifth-generation (5G) technology holds the potential to revolutionize EEG biometric authentication in health and IoT services. This network offers a reliable and secure channel for transmitting EEG data, crucial for authentication and related services. Furthermore, 5G enables efficient computation of EEG biometric data through its distributed computing capabilities. Additionally, the advanced signal processing capabilities of 5G, including artificial intelligence, can significantly enhance the accuracy of biometric authentication. The consistent and reliable data transmission capabilities of the 5G network are also particularly beneficial for real-time health monitoring and diagnostic applications using wearable and implantable sensors. With its extensive frequency range reaching up to 100 GHz, 5G networks are equipped to achieve substantially faster speeds and more efficient data transmission compared to the existing LTE networks [126].

Fifth-generation (5G) technology is engineered to accommodate a greater number of users simultaneously, optimizing the use of limited spectrum resources. It aims to achieve peak speeds of up to 20 Gbps in millimeter wave networks and up to 1 Gbps in lower-band frequencies. A primary goal of 5G is to consistently provide sufficient spectra to support high-bandwidth applications, while also maintaining broad coverage. Moreover, 5G technology offers faster response times and reduced latency compared to current technologies [37]. Wireless 5G networks comprise the new-generation radio access network (NG-RAN) and the 5G core network (5GC), as illustrated in Figure 10.

The NG-RAN architecture for 5G encompasses both ng-eNBs (next-generation evolved Node B) and gNBs (gigabit network base stations) [127]. This architecture integrates the existing LTE radio access network (eNodeB) with new 5G next-generation radio access network nodes, including gNBs, to support both 4G and 5G services. This integration results in improvements in speed, latency, and coverage. The Xn interface plays a crucial role in facilitating the transfer of control and user plane traffic between these nodes and is commonly used for inter-eNB connections, forming a key component of the 5G RAN architecture. With advancements in 5G technology, EEG and biometric data can now be collected, processed, and analyzed remotely, enabling non-intrusive and portable authentication in various EEG deployment scenarios [128].

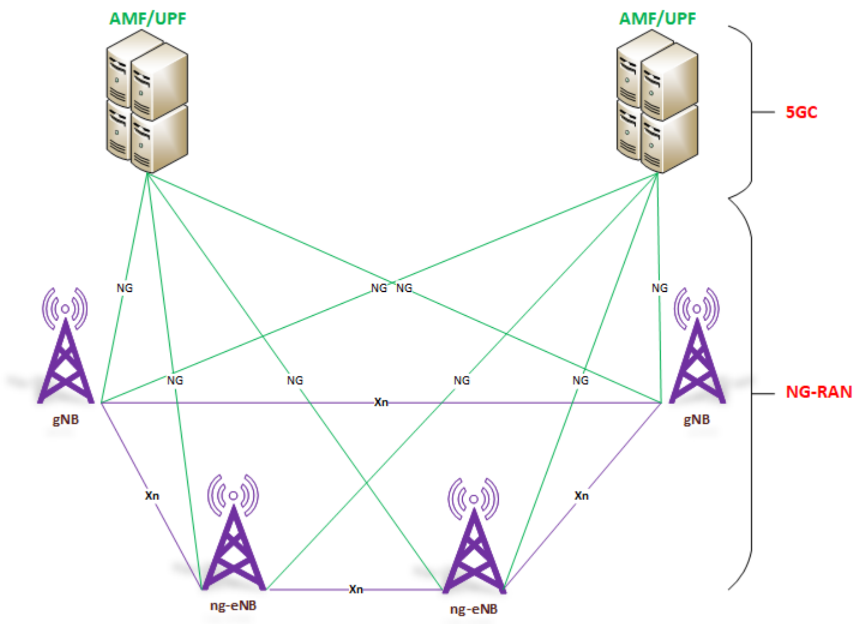

Figure 10. NG radio access network.

The rise of EEG-enabled IoT deployments offers new opportunities for organizations and individuals to monitor and respond to brain activities in real time. Smart wearables and EEG sensors are increasingly used for biofeedback and performance metrics, enabling the measurement of attention and autonomic nervous system (ANS) responses, crucial in the diagnosis and management of conditions such as autism and epilepsy [129].

EEG-enabled IoT deployments have a vast array of potential applications. When combined with AI, these devices can provide predictive analytics applicable in multiple industries, including mental health and augmentative robotics. An EEG-enabled IoT platform can offer invaluable insights into user behavior and needs, leading to informed decision-making and improved strategies for growth and efficiency. Real-time collection and analysis of EEG data in biomedical applications can be significantly enhanced by such platforms. The incorporation of nanomaterials in electrodes and EEG sensors allows for the capture of a wider range of neurological signals, providing more detailed information than traditional electrodes. This use of nanomaterials also facilitates the miniaturization of EEG systems, making them smaller, more portable, and suitable for non-invasive EEG scans outside conventional settings, thus increasing accessibility for general healthcare. This miniaturization empowers individuals to conduct EEG tests at home, reducing reliance on costly hospital equipment [24,70].

Big data also plays a crucial role in providing insights into personalized healthcare services, consumer behavior, operational efficiency, feedback from healthcare settings, and disease management patterns [117]. Big data analytics tools can analyze patient data and individual genomic profiles, enhancing the understanding of diseases and identifying trends and patterns. The use of big data analytics enables the creation of predictive models for disease patterns and risk prediction in specific populations, contributing to precise diagnoses, effective treatments, and improved health outcomes. The application of big data analysis in healthcare also involves developing algorithms for early detection and disease prevention, streamlining costs and communication, and providing personalized recommendations for decision-making [18].

Nanomaterials are also advancing the development of smart textiles for measuring EEG signals. These nanotech-enabled fabrics can capture brain signals accurately, even from a distance, improving the ease and reliability of EEG recordings.

However, challenges remain, including the accuracy and reliability of EEG-based data, privacy and data security concerns, integration with traditional systems, cultural and contextual considerations, and regulatory compliance.

Despite these challenges, EEG-enabled IoT deployments hold vast potential and present a dynamic area for further research and innovation. Addressing these challenges can unlock a myriad of possibilities, including relationship building, health monitoring, predictive analytics, and beyond.

In terms of security measures for EEG data in IoT systems, encryption, authentication, and authorization are essential. Encryption protects data by converting it into an unreadable format, accessible only to authorized individuals [80]. Authentication verifies the identity of users seeking access, while authorization grants access post-authentication. Privacy-enhancing technologies (like anonymization and pseudonymization) protect user anonymity, supplemented by auditing and data backup measures to ensure data security [37].

9. Challenges and Opportunities of Wearable and Seamlessly Integrated Devices

The utilization of wearable IoT devices can expose users to potential risks, like cyberattacks, data theft, and malicious tracking. To ensure data privacy and security, it is essential to deploy advanced security measures, such as robust authentication protocols, encryption, and sophisticated data encryption algorithms [130]. Moreover, users need to be informed about basic security practices, including the importance of regularly updating passwords and exercising caution when dealing with suspicious links or messages. As the IoT market expands, wearable systems are expected to become increasingly significant. Addressing the critical challenges for their successful integration into the IoT ecosystem is paramount. These challenges encompass energy efficiency, data management and aggregation, device interoperability, user privacy and security, and scalability [131]. With the growing number of connected devices, managing these challenges becomes more complex, necessitating solutions tailored to IoT applications. Service providers should also focus on network security and reliability to ensure smooth user interactions [132].

Additionally, there is a need to make IoT systems more affordable to enhance accessibility and service quality. The emergence of 5G networks and cloud computing offers researchers a platform to develop cost-effective and efficient IoT solutions, focusing on power consumption and reduced latency. Wearable devices should support standardized, interoperable applications, calling for the development of open libraries and APIs, such as communication protocols for risk evaluation in low-power wireless systems [133]. These steps are vital for integrating and ensuring the functionality of various devices, crucial for delivering comprehensive and reliable user-centric services. This strategy allows for intricate customization and boosts user satisfaction through effective data analysis and processing.

Recent advancements in wearable technology and the IoT have brought EEG into everyday applications through wearable and seamlessly integrated devices. This integration offers new opportunities for real-time monitoring and understanding of brain activity, with significant implications in healthcare, wellness, and lifestyle sectors. However, incorporating EEG into these devices presents several challenges. One primary challenge is designing wearable EEG devices that are comfortable and capable of capturing reliable signals. Accurate placement of EEG electrodes on the scalp is crucial for optimal signal quality [134,135]. Developments in materials science and nanotechnology are leading to more user-friendly and efficient electrodes. Nanomaterials, for instance, enhance electrode conductivity and flexibility, improving signal acquisition. Additionally, the miniaturization of EEG sensors facilitates their integration into wearable devices like headbands, helmets, or clothing, making EEG monitoring more accessible and convenient [136].

Processing and analyzing data from wearable EEG devices is another challenge. EEG signals are complex and often noisy, necessitating advanced signal processing techniques for extracting meaningful information. Real-time analysis requires low-latency processing, which can be addressed by edge computing. This approach, leveraging the processing capabilities of wearable devices and IoT connectivity, allows local data processing and analysis, reducing reliance on cloud-based solutions and minimizing latency. Privacy and security are critical when handling EEG data from wearable and integrated devices, as the data contain sensitive information about the individuals' brain activity and cognitive states. Robust data encryption, authentication, and authorization mechanisms are essential to protect data privacy and integrity. Strict access control measures should be implemented to ensure that only authorized individuals access and manipulate EEG data [137,138].

Interoperability and standardization are vital for the seamless integration and compatibility between different EEG devices and platforms. Standardized protocols, communication interfaces, and data formats are necessary for the exchange and sharing of EEG data across various devices and systems. Open libraries and APIs can foster collaboration and innovation, leading to diverse applications and services utilizing EEG data. Despite these challenges, the use of EEG in wearable and integrated devices offers significant opportunities. Continuous monitoring of brain activity through wearable EEG devices can provide valuable insights into mental health, performance, and emotional well-being [139]. Real-time EEG data analysis can detect early signs of neurological or psychological conditions, leading to timely interventions and improved treatment outcomes [140]. Furthermore, EEG-enabled devices can enhance human–machine interactions and augment various applications. Brain–computer interfaces (BCIs), for example, enable individuals to control external devices or interact with virtual environments using their brain signals, potentially revolutionizing assistive technology, gaming, and rehabilitation, especially for individuals with limited mobility or communication abilities [141].

In neuromarketing, wearable EEG devices offer valuable insights into consumer behavior, preferences, and emotional responses. Analyzing brain activity during shopping or exposure to advertisements can provide companies with a deeper understanding of consumer engagement, informing data-driven marketing strategies. Moreover, EEG integration with wearable devices facilitates personalized and adaptive interventions across various fields. Wearable EEG devices can continuously monitor brain activity and mental states, providing real-time feedback and interventions to optimize performance, enhance learning, and improve well-being [142]. For instance, in educational settings, wearable EEG devices can identify patterns of attention and cognitive load, enabling tailored learning experiences to individual needs. In sports and fitness, EEG-enabled wearables can analyze mental states during training and competitions, aiding athletes in optimizing performance and preventing injuries. The integration of EEG with other sensor modalities in wearable devices can enhance health monitoring and intervention [143]. Combining EEG with heart rate sensors, accelerometers, or sleep trackers offers a comprehensive view of an individual's physiological and mental states, leading to personalized healthcare solutions like stress management tools, sleep optimization systems, and tailored mental health interventions [144].

With 5G technology, the integration of EEG with wearable and seamlessly integrated devices becomes even more potent. Furthermore, 5G networks provide higher bandwidth, reduced latency, and increased device density, enabling efficient real-time communication and data exchange between wearable devices, edge servers, and cloud platforms [145]. This enables the rapid transmission and timely analysis of EEG data for improved healthcare outcomes. Moreover, 5G's edge computing capabilities allow for local processing and analysis of EEG data, enhancing privacy and security. Realizing the full potential of EEG in wearable and integrated devices requires collaboration between researchers, engineers, and healthcare professionals. Further research is needed to improve EEG measurement accuracy and reliability, develop advanced signal processing algorithms, and explore novel EEG applications. Establishing a privacy and integration policy is crucial to ethically use EEG data, protect privacy, and address risks associated with integrating EEG into wearable devices [146].

The integration of EEG with wearable and integrated devices holds significant promise in healthcare, wellness, and lifestyle applications. Wearable EEG devices could revolutionize brain monitoring, diagnosis, and treatment of neurological and psychological conditions. They also have the potential to enhance human–machine interactions, offer personalized interventions, and yield insights into consumer behavior. However, challenges related to signal quality, data processing, privacy, and standardization need addressing to fully utilize EEG in wearable and integrated devices [147]. With ongoing research, technological progress, and interdisciplinary collaboration, EEG-enabled wearables could significantly change how we understand and interact with our brain activity, leading to enhanced well-being and quality of life.

10. Conclusions

This survey delves into the various aspects and challenges of using EEG signals in human biometric authentication systems, particularly within the 5G and IoT environments. EEG-enabled IoT solutions hold the promise of transforming how brain activity is measured and monitored. Advances in sensor technology are increasingly contributing to the diagnosis and monitoring of neurological disorders, offering insights into everyday brain functions. Furthermore, these solutions can aid in developing preventative measures for mental health, providing information on cognitive patterns and behavioral responses that affect well-being. Looking ahead, EEG-enabled IoT solutions might be used to detect early changes in brain activity that precede symptoms of neurological or psychological conditions, offering valuable insights for healthcare professionals to enhance patient treatment.

The objective of this survey is to elucidate the effective implementation of EEG biometric authentication systems within the 5G IoT architecture and infrastructure. It explores factors influencing the use of EEG signals in biometric authentication systems, including signal morphology and specific considerations for deploying EEG in 5G IoT environments. The survey also addresses common methods for EEG signal acquisition, with a focus on wearable and integrated devices, which are prominent in both IoT research and industry. Additionally, it reviews commonly used EEG databases for raw signal data, preprocessing and feature extraction techniques, the 5G IoT architecture, and the opportunities and challenges involved in EEG deployment.

Overall, integrating EEG technology into the IoT landscape opens up numerous possibilities in healthcare, wellness, and lifestyle applications. This integration can significantly improve the efficacy of EEG technology in various healthcare contexts. However, addressing security concerns is essential when employing this technology. Developers and manufacturers must ensure product security, proper data handling, and encryption, along with implementing robust authentication measures. Users should also be cautious in handling and storing their EEG devices, remaining vigilant against potential threats posed by malicious actors. With careful consideration and preventive strategies, the risks associated with EEG-enabled IoT solutions can be effectively managed, unlocking their full potential.

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Abbreviations

The following abbreviations are used in this manuscript:

IoT	Internet of Things
EEG	electroencephalography
BCI	brain–computer interfacing
LANs	local area networks
IP	internet protocol
fMRI	functional magnetic resonance imaging
SVM	support vector machine
HA-HV	high arousal–high valence
HA-LV	high arousal–low valence
SAM	self-assessment Manikin
HR	heart rate
GSR	galvanic skin response
µV	microvolts
PCA	principal component analysis
APIs	application programming interfaces
EDI	electronic data interchange
FTP	file transfer protocol
RAN	radio access network
NG-RAN	new-generation radio access network
ng-eNBs	next-generation evolved node B
gNBs	gigabit network base station
ANS	autonomic nervous system

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