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Brain-Machine Interface System Supporting Subjects with Cognitive Impairments via EEG Signals

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Abstract: A cognitive dysfunction can result from a multitude of factors, which can influence one's physical and mental fulfillment. It is therefore challenging for a human or animal to continue out their daily routines when they encounter issues with their upper or lower limbs due to impairment in the brain. Therefore in this article, thorough clarification about this for stimulating the brain signals is offered. The method called brain-machine interface (BMI) is proposed which uses EEG signals for utilizing brain impulses to develop an avenue for communication for individuals who are unfit to talk or paralyzed. We supply an innovative technique for recognizing emotions focused on the generic mixture dispersion framework to identify the emotion appearances by an immobile subject. The main advantage of this simulation is its imbalanced dispersion, which aids in the symmetric or asymmetric style of EEG signal gathering. The considerable amount of signal fluctuation in the EEG makes the recommended approach especially appropriate for precisely recognizing feelings. Happy, sad, neutral, and boredom are the basic feelings taken into consideration in this investigation, and a mean emotion recognition accuracy rate of 89% is obtained.

Keywords: *Brain-Machine Interface; EEG; emotion recognition; feature extraction*

1. Introduction

The latest technologies referred to as brain-machine interfaces (BMIs) convert brain impulses into predetermined instructions that allow users to converse with others or drive external devices. Regarding multiple neurological signals, EEG has been employed most extensively due to its non-invasive, high temporal resolution, lightweight, and reasonably priced [1]. The Brain-machine interface (BMI) is an instrument that establishes a computerized pathway for signals between the external hardware and the mind. BMI is commonly used in neuroprosthetic equipment to reconstruct communication pathways that have been disrupted as a consequence of sickness or harm to the nervous system. Clinical trial consequences showed that paralytic patients can manipulate a prosthetic limb that corresponds with the motor purpose transformed from brainwaves acquired by a BMI [2]. BMI technologies exhibit tremendous potential as a medicinal technique that could improve the lives of millions of people diagnosed with terrible brain conditions such as amyotrophic lateral sclerosis, spinal cord injury, and stroke. Nevertheless, the shortage of long-lasting implantable hardware remains one of the main challenges in the development of clinically feasible BMIs. The brain-recording devices in the embedded BMI microsystems utilize electricity to increase and synthesize acquired neurological signals. The amount of space and overall electrical consumption of these gadgets are severely constrained by their implant ability. High-channel-count capturing techniques must be used to track the electrical responses of the cortical neurons in numerous areas. To make sure that the entire system in general has a miniature form factor, the area of a chip per channel must be reasonable, which might allow for an incorporation of the electronic goods beneath the antenna configuration. Additionally, for remotely driven battery-less machines, the entire amount of dissipated capacity must be kept within a sensible range, indicating that electricity intake per channel must be brought to a minimum. Hundreds of lines can now be supported on just a single chip owing to recent improvements in integrated-circuit (IC) studies that have lowered chip space and power usage per recording channel [3].

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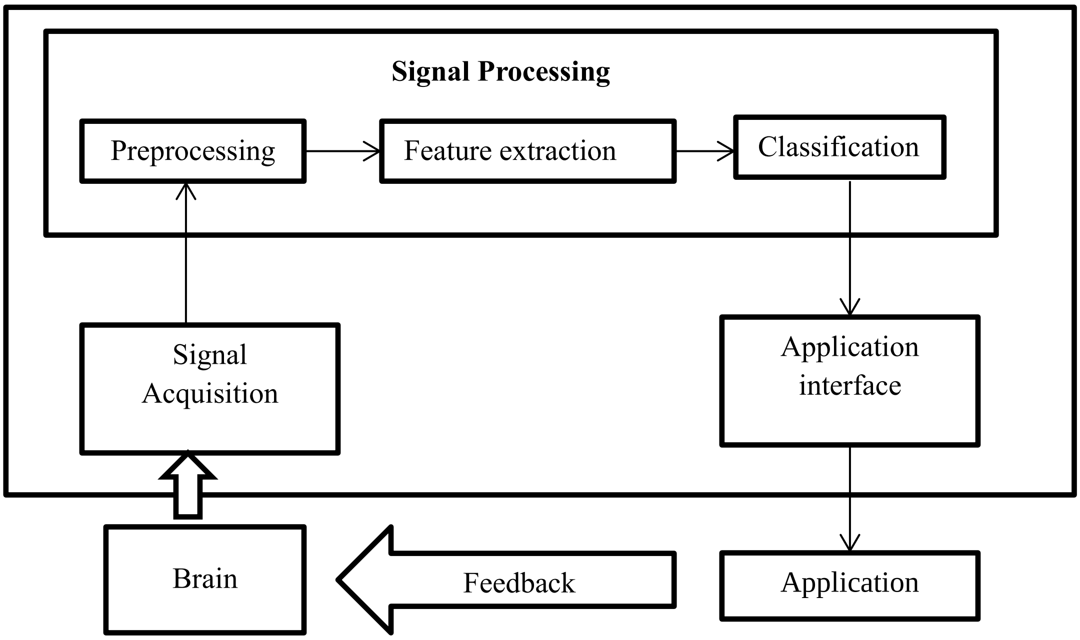

Fig. 1. Brain-Machine Interface Architecture

Based on a recent investigation, individuals who have impairments may benefit from BMI. When it pertains to talking to citizens, these individuals who have forfeited all control over their gaits might depend solely on their cognitive talents; BMI architecture in Figure 1 proves beneficial in this context. Furthermore, BMI could help those who suffer from autism. BMI makes sense for both those with mental illnesses and disabled individuals. Human emotions may have an important impact on how judgments are reached. Feelings are essential for both communication and the precise representation of behaviors. Applications of emotion categorization in healthcare encompass neurology and psychology. An automatic sentiment recognition system has the potential to evaluate neurological disorders. Since the mind is the neurological system's core section, an EEG may precisely represent what an individual is feeling. The biggest advantage of EEG is that it delivers a rapid and persistent signal of the brain's operations. Also, measurements of EEG signals can be both inexpensive and with little risk of side effects [4].

A summary of the several elements that together make up the essay can be read below. In the second portion, a summary of the principal previous research is presented. The final section explores the proposed Brain-Machine interface and wraps the schemes, achievements basis, procedural fields derived from graphs, and data analysis. In the fourth section, BMI is examined to determine signal recognition using different graphs and examples. These BMI and EEG signals are dealt with in Section 5, which addresses the conclusion.

2. Related Works

Katona et. al [5] An electrophysiological measurement instrument termed an electroencephalograph can record real-time neuronal electric activity. The electroencephalogram, or EEG, is a complex, multi-component periodic curve that can be employed as a lead signal. There are two approaches to recording the electroencephalogram: invasive and non-invasive. For the first technique, a channel is drilled into the skull to inject a small number of micron-diameter microelectrodes into the brain cells. This procedure is frequently relied on in animal inquiries, but in the case of people, the non-invasive approach is implemented, by installing low-resistance metal macro electrodes on the skull.

Rak, R. J. et. al [6] At the start, the main concentration of the investigation was on neuroprosthetic technologies. Its major mission was to aid individuals in restoring their mobility and affected senses like eyesight and speech. In neuroprosthetics, robotic devices are put to work to substitute specific human organs/senses. On many occasions, the brain has to "develop" how to sense signals supplied by the limb or produce signals necessary to regulate the prosthesis, right through the entire neurological system. However, those electrical signals do not need to be yielded immediately to the head or originate straight from the brain (central nervous system), but instead pass through peripheral nerves. Although the BMI permits immediate communication from the brain to the machine, it is usually thought that in the arena of neuroprosthetics, a relationship can be implemented: the nervous system (any portion of it) to the machine.

Bird, J. J. et. al [7] Fisher's Discriminant Analysis was implemented by the most widely available state-of-the-art technique for categorizing emotional EEG information from a low-resolution image, an inexpensive EEG setup that yielded a precision of 95 percent. The study aimed to stop participants from blinking and from being clenched nevertheless an earlier investigation revealed that EMG information regarding these habits aided in categorization since, for instance, blink frequencies are an attribute in memory. Therefore, the brand-new research that will be discussed in the article will examine sentiment classification in EEG data when unintentional activities are neither supported nor rejected. As a result, this research, like an earlier investigation that utilized music videos, targets film categories that have sound recordings (music and/or spoken) to generate sentiments.

Carella, T. et. al [8] We have been mystified by human emotions for hundreds of years. Emotions have become better recognized and explored by every generation thanks to advances in neuroscience, psychology, society, and even technology. Brain-computer interfaces (BCIs) are a non-invasive technology capable of obtaining electroencephalography (EEG) signals connected to emotional inputs. The signals that brain-computer interfaces (BCIs) acquire may help us comprehend more fully emotional reactions. Nevertheless, how we might effectively and extensively interpret emotion is still a mystery.

Uma, M. et. al [9] Simultaneous brain-computer interfaces function in an externally driven mode. The user has an appointed amount of time to generate particular emotions. The command process is started by the system. The brain behavior is continuously examined when functioning in an asynchronous mode. The particular mental work that is employed as the command signal and is user-initiated can be freely started by the user. The premise of universal BCI is that a classification function that should work for all users can be found by accumulating EEG data from a small number of users. Thus, each user's BCI is the same. Individual BCI takes into consideration the reality that no two persons are alike, both psychologically and biologically.

Sargent, G. et. al [10] The group of specialists utilized the 256-channel device to acquire signals appointed by a human being witnessing an array of graphics that produced a psychological reaction. The five primary sentiments that investigators intend to discover are joy, sorrow, distaste, anxiety, surprise, and neutrality. An alternate group of researchers deployed a 14-channel system to manage an autonomous arm solely via mental directions. Their proposed system's limitation is that it can only classify two distinct ideas at a time. Investigators made an effort to apply brain implants to accomplish a task similar to the one previously addressed. Their goal is to have anyone join words on a screen via a passive EEG headgear, which is accessible online. Their objective is to have the person input communications into the headset, allowing a means of communication for those who aren't likely to be able to do so otherwise. According to latent dynamic contingent random fields, investigators observed a 42.55% classification accuracy (LDCRF).

Chen, X. et. al [11] EEGs are an often utilized technique for detecting brain activity. However, motor picture categorizing is a difficult task because of an inadequate signal-to-noise ratio. Consequently, enhancing the ability of classifiers involves understanding how to choose the most discriminative features. The majority of pertinent research was discovered to be connected to the use of BMIs in EEG diagnosis. As mentioned earlier, the crucial basis for the development of BMIs was the grouping of motor visuals. Numerous attempts have been made to organize EEG signals for motor imagery-BMI. For instance, demonstrated a new multiclass EEG classifier targeted to boost the classification accuracy in EEG-driven BCIs involving multiple cognitive duties. Furthermore, EEGs have become extensively employed in the examination of problems connected with mental diseases alongside artificial intelligence. In this regard, a classifier comprised of quantitative EEG data was constructed and evaluated to aid in differential diagnosis between participants struggling with illnesses like Parkinson's and Alzheimer's.

Atkinson et. al [12] A prevalent physiological message that is extensively utilized to analyze human emotions is the EEG, etc. Compared to other physiological signals, EEG is a noninvasive method with good temporal and sufficient spatial resolution, so EEG could have an essential part in picking up feelings that originate in the brain at greater spatial and temporal resolution. Individuals possess distinct arbitrary sensations as responses to similar stimuli, which render it harder to pinpoint emotions. As an outcome, sentiments can be divided into two taxonomy approaches discreet and dimensional. Technologies that use sentiment recognition may gather nonverbal messages from human subjects and then utilize those signals to contextualize activities by considering the fundamental feelings that were collected. Individuals can detect emotions from voice (voice modulation and conversation) with a precision of about 60% or from facial and body movements with an effectiveness of 78–90%.

3. Methods and Materials

Employing an EEG acquiring device, the subject's brain signals are gathered. The collected signals are then preprocessed to mitigate vibration, and the amplitude instructions are gathered and normalized into different levels based on rhythm. This makes it possible for the lowering of dimensionality, information characteristic collection, and classification for emotion recognition. Five distinctive rhythms can be exploited to evaluate the brain signals considered in the EEG data: delta (δ), theta (θ), alpha (α), mu (μ), beta (β), and gamma (γ). Each rhythm has a discrete frequency spectrum that corresponds to a certain aspect of neural activity. Table 1 demonstrates each rhythm's range and influence.

Table 1. Different brain rhythms are represented by the EEG units

Rhythm	Frequency	Range Location	Reason
Delta (δ)	(1-5) Hz	Posterior portion	Deep sleep
Theta (θ)	(5-8) Hz	Midline, chronological	Sleepiness and contemplation
Alpha (α)	(9-14)Hz	Posterior, occipital	Relaxing, locked eyes
Mu(μ)	(9-13)Hz	Central	Contra lateral Motor acts
Beta (β)	(14-31)Hz	Posterior, central	Attention and intellectual
Gamma (γ)	(31-101+)Hz		Cognitive roles

Feature vectors based on Mel-frequency Cepstrum Coefficients (MFCC), MFCC-LPC (Linear Prediction Coefficients), and MFCC-LPC-SDC (Shifted Delta Coefficients) are employed to efficiently identify emotions. Precision and Recall, two classification performance metrics, are employed to evaluate the established model. Figure 2 offers a quick overview of the process.

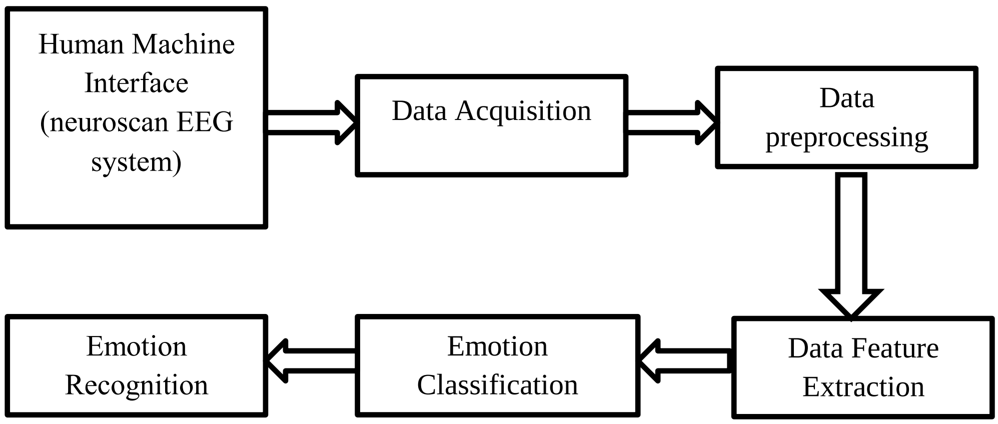

Fig. 2. Block diagram for EEG signal-based emotion detection

3.1 Distribution of Generalized Mixture Model

Maximum posterior estimate models should be taken into consideration to obtain reliable characteristic extraction from the EEG signals that were obtained from the brain. Consequently, to divide the brain signals into distinct feelings, a Generalized Mixture Distribution Model (GMDM) is employed in the current research in partnership with a mix of compression and Skew GMM. In the instance of asymmetric distributions, GMDM shows that the shortening can be implemented to both ends, the right or left side, or both.

3.2 GMM's probability density function

The equation that follows symbolizes the GMM's probability density function (PDF):

$$g(a) = \frac{1}{\sqrt{2\pi\tau}} e^{-\frac{1}{2}\left(\frac{a-\vartheta}{\tau}\right)^2}; \quad -\infty < a < \infty \tag{1}$$

Here, $-\infty < a < \infty, 0 < \tau$

The distribution is reduced to either left or right or both ways in equation (1) for the reason that the A value spans exceed certain upper truncation sites A_N while below some lower truncation points A_M. The probability density function (PDF) is defined as follows:

$$h(a) = \frac{a(a)}{\int_{A_N}^{A_M} g(a)da}, -\infty \leq a < \infty \tag{2}$$

$$B = \int_{-\infty}^{A_M} \frac{e^{-\frac{1}{2}\left(\frac{a-\vartheta}{\tau}\right)^2}}{\sqrt{2\pi\tau}} da \tag{3}$$

$$C = \int_{-\infty}^{A_N} \frac{e^{-\frac{1}{2}\left(\frac{a-\vartheta}{\tau}\right)^2}}{\sqrt{2\pi\tau}} da \tag{4}$$

$$h(a) = \frac{\frac{1}{\sqrt{2\pi\tau}} e^{-\frac{1}{2}\left(\frac{a-\vartheta}{\tau}\right)^2}}{\int_{-\infty}^{A_N} \frac{e^{-\frac{1}{2}\left(\frac{a-\vartheta}{\tau}\right)^2}}{\sqrt{2\pi\tau}} da - \int_{-\infty}^{A_M} \frac{e^{-\frac{1}{2}\left(\frac{a-\vartheta}{\tau}\right)^2}}{\sqrt{2\pi\tau}} da} \tag{5}$$

In this instance, A_N represents the more significant truncation spots, and A_M the less significant ones.

Updating β

We derive $\beta(\epsilon; \epsilon^{(m)})$ in regard to β to zero. This means, [13]

$$\int_{-\infty}^{\beta\left(\frac{z-\vartheta}{\tau}\right)} \frac{e^{-\frac{1}{2}\left(\frac{u-\vartheta}{\tau}\right)^2}}{\sqrt{2\pi}} du. \left[\frac{e^{-\frac{1}{2}\left[\frac{\beta\left(\left(\frac{z-\vartheta}{\tau}\right)-\vartheta\right)}{\tau}\right]^2}}{\sqrt{2\pi}} \left(\frac{z-\vartheta}{\tau}\right) \right] . u_j\left(z_t, \epsilon^{(m)}\right) = 0 \tag{6}$$

Now to determine the updated equation for β

$$\frac{\partial}{\partial \beta}[\log g(z)] = \left[0 - 0 + 0 + \frac{1}{\int_{-\infty}^{\beta\left(\frac{z-\vartheta}{\tau}\right)} e^{-\frac{1}{2}\left(\frac{z-\vartheta}{\tau}\right)^2} du} + \int_{-\infty}^{\beta\left(\frac{z-\vartheta}{\tau}\right)} 0 + e^{\frac{-\frac{1}{2}\left[\frac{\beta\left(\frac{z-\vartheta}{\tau}\right)-\vartheta}{\tau}\right]^2}{\tau^2}} . \frac{d}{d\beta}\left[\beta\left(\frac{z-\vartheta}{\tau}\right)\right] - 0 \right] . u_j\left(z_t, \epsilon^{(m)}\right) \tag{7}$$

Currently the above equation indicates that

$$\sum_{t=1}^{O} u_j\left(z_t, \epsilon^{(m)}\right) \left[\log\left(\frac{z-\vartheta}{\tau}\right) + \frac{[(\beta+\tau)\vartheta - \beta z]^2}{2\tau^4}\right] = \sum_{t=1}^{O} u_j\left(z_t, \epsilon^{(m)}\right) \left[-\log\left(\frac{1}{\int_{-\infty}^{\beta\left(\frac{z-\vartheta}{\tau}\right)} e^{-\frac{1}{2}\left(\frac{z-\vartheta}{\tau}\right)^2} du}\right)\right] \tag{8}$$

The updated equation for β

$$\beta^{(m+1)} = \frac{\sqrt{2\tau^{2(m)}}}{\vartheta^{(m)} - z} \left[\log\left(\int_{-\infty}^{\beta^{(m)}\left(\frac{z-\vartheta^{(m)}}{\tau^{(m)}}\right)} e^{-\frac{1}{2}\left(\frac{u-\vartheta^{(m)}}{\tau^{(m)}}\right)^2} du \right) - \log\left(\frac{z-\vartheta^{(m)}}{\tau^{(m)}}\right) \right]^{\frac{1}{2}} - \frac{\tau^{(m)}\vartheta^{(m)}}{\vartheta^{(m)} - z} \tag{9}$$

4. Implementation and Results

In this research, two separate studies were carried out: a virtual experiment and a conventional investigation. The first experiment's information was employed as guidance for this study. Six 20 to 33-year-old sound individuals from the local research unit attended the trials. The recipients of the experiment were given instructions not to do anything or blink while they were sat in a comfortable chair.

Experiment 1 (offline): In this study, 40 tasks total—20 for happiness and 20 for sad emotional expressions—were utilized to gather data. The sequence of the two psychological states' look was unforeseeable. A fixation mark was first displayed in the central portion of the GUI at the beginning of every session to catch the subjects' notice. An image of a joyous or sorrowful face showed up in the GUI's center after two seconds. The subjects had been told to focus on the visual for eight seconds. A couple of trials were preceded by a 10-second pause. Utilizing this dataset, we were able to discover what frequency ranges worked best for every individual. We then utilized this knowledge to generate an SVM classifier, which was later integrated into the BCI technique in the online Experiment 2.

Experiment 2 (online): There were 40 samples total, 20 of which were positive and 20 of which incorporated sad gestures. Each attempt subsequently followed an equivalent protocol to that of Experiment I. Although, the BCI algorithm determined or established, its mental state that follows an 8-second presentation of facial movements. A happy or weeping face (which was used as the trigger in this trial) and loud applause would appear for four seconds if the result of detection was valid; otherwise, there would be zero feedback. Functionality assessment: The ratio of accurate estimates to the total amount of trials offered was utilized to derive the online accuracy in this study. Furthermore, we investigated the subject-oriented online precision intervals compared to those of the wide frequency band (5-60 Hz), theta (θ: 5-8 Hz), alpha (α: 9-14 Hz), beta (β: 15-31 Hz), and gamma (γ: 32-49 Hz). Here, the information from Experiment 1 was employed for preparing an SVM classifier and a CSP geographical filter for every frequency range and customer, whilst the data from Experiment 2 were employed for testing. The predicted accuracy of the locked frequency bands was achieved in this way.

4.1 Outcomes of Experiment 1:

Table 2 offers an outline of the twelve frequency ranges relying on the 10-fold cross-validation for the three topics. We observed the precision fluctuated greatly with the wavelengths and that distinct individuals were not always responsive best to the same spectrum of frequencies. For the internet-based examination, we discovered four categories of frequencies with the greatest consistency (Experiment 2).

Table 2. 10-fold cross-validation based accuracy for each frequency band and each subject in Experiment 1

Frequency band range (Hz)	**Accuracy based on 10-fold cross-validation (%)**		
	Subject 1	**Subject 2**	**Subject 3**
5-9	53.6	51	56
9-13	61	66	61
13-17	73.6	63.6	53.6
17-21	68.6	58.6	58.6
21-25	53.6	53.6	66

4.2 Outcomes of Experiment 2

For six issues, the average online precision was 71%, 66%, 76%, 81%, 83.6%, and 73.6%, in that proportion. The online precision determined by fixed frequency ranges and subject-specific frequency channels is summed up in Table 3. Subject-related frequency ranges delivered an elevated average proficiency rate of 75.28%, by Table 2's outcomes while standardized frequency channels yielded maximum test accuracies of 62.64%, 63.47%, 59.94%, 64.94%, and 69.55. As revealed by Table 3, subject-oriented frequency ranges manufactured a median test reliability that was more effective at 74.17%, whereas all participants' average test preciseness for fixed frequency bands was 50.42%, 61.25%, 57.92%, 62.92%, and 58.33% for theta, alpha, beta, gamma, and the entire frequency band range, respectively. A paired t-test was carried out employing the exact scores provided in Table 3. Between the subject-specific bands of frequency and the rest of the constant frequency bands, there existed significant variation in the correctness rates (all with a $p<0.06$) [14].

Table 3. The online correctness dependent on subject-relevant bands and the fixed frequency band efficiency

Subjects	Accuracy based on distinct frequency bands (%)		
	Theta	Alpha	Beta
Subject 1	51	51	56
Subject 2	51	66	61
Subject 3	56	63.6	53.6
Subject 4	48.6	58.6	58.6
Subject 5	53.6	53.6	66

ANNs have been considered for usage in brain-machine interfaces relying on EEG. An array of factors, such as reliability, precision, recollection, and tactical cost, are utilized for evaluating these methods compared to standard methods.

4.3 Exactness

Reliability in the grouping of cognitive emotional reactions is characterized by the use of accurate categorization to the overall amount of incidences. The preciseness of the present system as well as the suggested system is demonstrated in Figure 4.1. It was recently advised that the provided ANN be utilized for classifying cognitive sentimental feelings based on its reliability. The strategy suggested has a preciseness rate of 98%, whereas the DNN, CNN, and LSTM have precision rates of 94%, 91%, and 93.5%, respectively. This demonstrates that the approach suggested is more correct than the one adopted. The correct values can be seen in Table 4.

Table 4. Comparison of accuracy with various methods

Methods	**Accuracy (%)**
CNN	91
LSTM	93.6
DNN	94
ANN	98

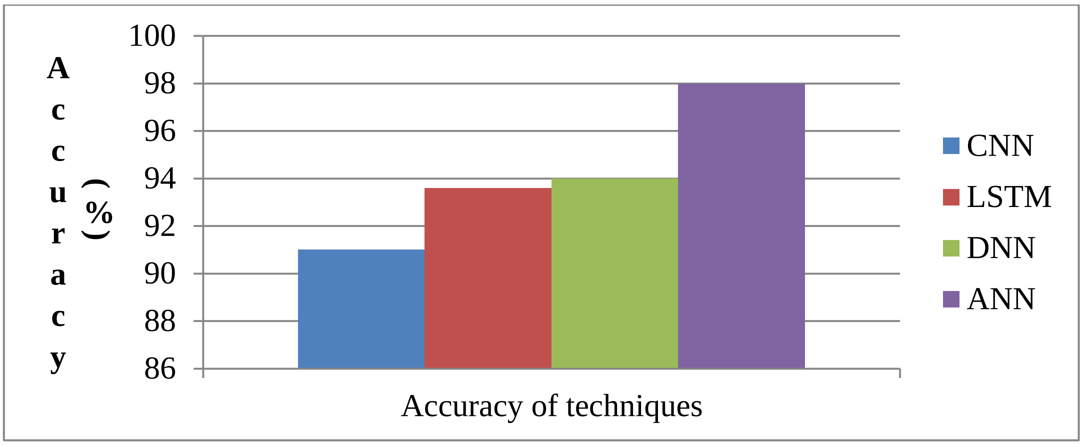

Fig. 4.1. Accuracy comparison with different methods

4.4 Precision

A framework for categorizing is implemented to recognize only the necessary information elements to group cognitive sentimental thoughts. The correctness of the intended and current methods is demonstrated in Figure 4.2. It has been recommended that the introduced ANN accuracy be employed for categorizing cognitive sentimental thoughts. Whereas the exactness of the offered methodology is 97.3%, that of DNN, CNN, and LSTM is 96.5%, 92%, and 94.7%, respectively. This indicates that the suggested approach is more accurate than the one currently used. The precision values are shown in Table 5.

Table 5. Precision

Techniques	Precision (%)
CNN	92
LSTM	94.7
DNN	96.5
ANN	97.3

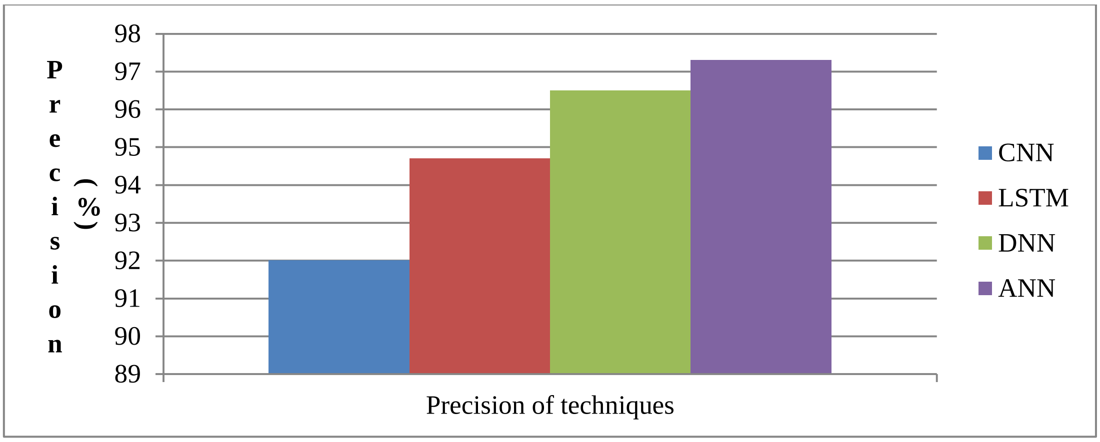

Fig. 4.2. Comparison of Precision from Various Techniques

4.5 Recall

The aggregate of the true positives fewer the false negatives is the quantitative estimate for recall. The capacity of a model to determine every noteworthy event in a collection of data may be utilized by cognitive sentimental emotions. Figure 4.3 illustrates the reminders for the requested and actual systems. The planned ANN recall has been considered for use in cognitive sentimental emotion. DNN has a recall of 96.5%, CNN has an accuracy of 90%, and LSTM has a precision of 91.2%. The planned technique has a yield of 95%. This shows the suggested method has a greater recall rate than the current method. The recall ratings are shown in Table 6.

Table 6. Memory

Techniques	Memory (%)
CNN	90
LSTM	91.2
DNN	96.5
ANN	97.3

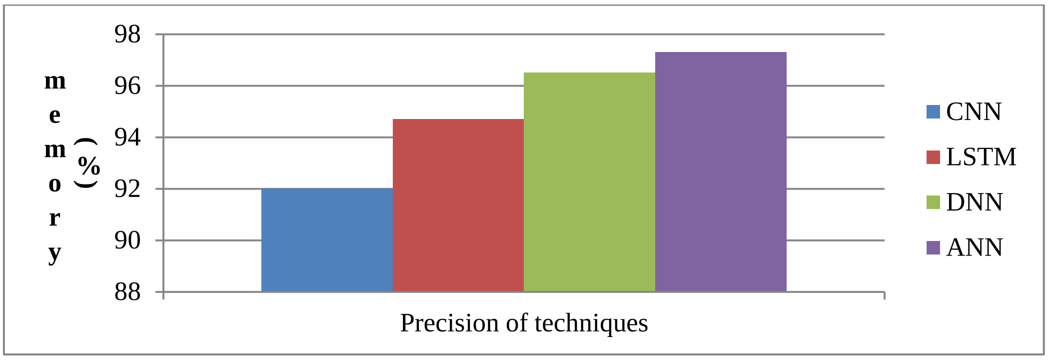

Fig. 4.3. Clear illustration of memory using this bar diagram

4.6 F1 measure

Blending accuracy and recall, the F1 score is an index that analyzes a categorization model or system's overall efficiency. It is commonly utilized to evaluate how effectively an object can identify and categorize emotive cognitive sentiments. The F1 statistic is the harmonic median of remember and reliability, which is the final result when you combine the two metrics to get a single value. The F1 metric for the suggested and current systems is shown in Figure 4. It has been offered to use the suggested ANN's F1 measure for cognitive sentimental sensation [15].

5. Conclusion

Understanding one's feelings based on ongoing EEG waves is an essential stage in real-time sense of emotion. In this work, we presented an original BCI methodology to organize the two distinct psychological states of sorrowful and pleasure. With regard to the conventional approach that depends on predetermined spectrum bands, our suggested method chose significant substances within subject-specific wavelength ranges. Our methodology and BMI system have been proven in two separate studies involving six people each. The outcomes of the data evaluation revealed that our methodology, which centered on subject-specific frequency ranges, performed more precisely than the one that was based on predefined frequency bands. In the present investigation, the usage of each individual and ensemble algorithms for classification to assess the participant's mental state at that specific time was evaluated using windowed data from four points on the scalp. The techniques proved that a low-resolution EEG headband that is now widely accessible might be leveraged to assess a participant's mental health. EEG-based BMIs has showed viability for numerous functions, such as the classification of emotive and mental sentiments. While the discipline is still in its early years, EEG-based BMIs have numerous fascinating new approaches and promise advancements.

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