Decoding Cognitive States and Emotions Using the Electroencephalogram

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Emotions are essential in human communication, social interaction, and decision-making. However, accurately classifying emotions is difficult with many applications in various domains such as psychology, psychiatry, neuroscience, and human-computer interaction. Emotion detection is one of the key challenges in current research, especially when emotional words are used. It is already known that positive and negative words have an impact on human behaviour and emotions, but very rare study that focus on emotions based on the words. In this study, we propose a novel approach for emotion classification based on electroencephalogram (EEG) data elicited by text stimuli, which are various English words. Text stimuli can evoke rich and diverse emotions, but they have been less explored than other modalities for emotion elicitation. In this study, EEG data of 25 participants were used, which were collected using a 128-channel EGI system. The collected data was pre-processed, and features were extracted using four methods: Convolutional Neural Network (CNN), Wavelet Transform (WT), Power Spectral Density (PSD), and the raw data itself was used as features. The results showed that CNN features achieved an average accuracy of 80%, followed by WT with 75%, PSD with 72%, and raw data with 65%. Our study shows the feasibility and effectiveness of using CNN, PSD, and WT with SVM for emotion classification based on EEG data and text stimuli. Lastly, a hybrid model was proposed based on the combination of CNN for feature extraction and SVM for classification.

Keywords: EEG, Text, Emotions, CNN, WT, PSD, Monte Carlo

Introduction:

Emotions play a vital role in human life and significantly influence cognitive processes such as reasoning, social interaction, intelligence, and perception. Affective computing aims to enhance the emotional intelligence of computers, thereby bridging the gap between technology and human emotions in Human–Computer Interaction (HCI) (George & George, 2022). HCI studies how people interact with computer systems by combining computer science, psychology, and other disciplines. Emotion recognition is an important part of HCI since it entails assessing a person's emotional state by observing their interactions with a computer. This can be accomplished using a variety of ways, including the analysis of facial expressions, speech patterns, and physiological reactions [1] [2] [3]. Emotion recognition systems have the potential to enhance human–machine interaction across diverse sectors, including gaming, industrial applications, military operations, and medical environments [4] [5].

Emotions can be identified in two primary ways: through external cues such as facial expressions and body language, and through internal signals such as physiological responses and breathing patterns. The latter technique relies on non-invasive sensors to record physiological processes like electrical impulses. Electrocardiogram (ECG), Electroencephalogram (EEG), and skin conductivity are often utilised methods in these models [6]. A strong tool for determining the electrical activity of the brain is the EEG, which is used to represent the electrical activity on a screen as wavy lines. EEG signals are divided into five frequency bands: delta waves (0.5–4 Hz), linked to deep sleep; theta (4–8 Hz), linked to light sleep; alpha (8–13 Hz), seen during relaxation with closed eyes; beta (13–30 Hz), linked to an attentive and awake state; and gamma (≥ 30 Hz), linked to advanced cognitive processing [7].

Positive emotions are generally linked to theta wave activity, while asymmetrical alpha waves in the frontal region indicate emotional valence. In EEG-based emotion analysis, the midline sagittal channel plays a particularly important role. Combining alpha, beta, and gamma wave patterns can further enhance emotion recognition, as emotional states are reflected in the non-stationary characteristics of EEG signals [8]. Asymmetry in the valence of emotions is associated with arousal, which is linked to activity in the frontal region. Positive emotions are more evenly distributed across frequency ranges, but negative emotions are more evident in the higher frequency band. The use of the mid-line power spectrum in EEG for emotion classification is made possible due to the associations between changes in emotional states like joy, sadness, or fear with the frequencies like theta, alpha, and beta waves in the central brain. The incorporation of a functional link network and local activation aids in understanding how certain brain regions respond to emotions and their connectivity, hence assisting in emotion detection using EEG data [9].

The purpose of this study is to categorise emotions using emotional text stimuli as input and identify changes in the human brain using EEG analysis. To accomplish this, this study investigates a few feature extraction techniques, including CNN, WT, and PSD, to determine the best features for emotion categorization. The most discriminative features for emotion classification are also determined using a T-test as a feature selection method. The average result of 100 iterations is reported in this study, which uses Monte Carlo cross-validation with 80% and 20% train and test split through random sampling to ensure trustworthy and robust results. The primary contribution of this article is to advance the understanding of human brain responses to different emotional words. This is accomplished by measuring brain activity using EEG and applying multiple analytical techniques, which are then compared to achieve the study's objectives.

The rest of the paper is organized as follows. The following section reviews recent advances in emotion recognition based on EEG signals. Section reports a brief overview of the emotions and emotion detection using the EEG signal, while the section provides the details about the experimental setup, subjects, protocols, and data collection. Subsequently, the paper discusses various feature extraction and classification techniques along with their implementation. The results are presented in the following section, and the paper concludes with final remarks in the last section.

Related Work:

Due to the nature of emotions, most of the research on emotion recognition employs experimental data [10]. Studies by [11] and [12] have shown that emotional signals can take various forms, including speech (audio) [13], text [14], facial expressions [15], or a combination of multiple modalities [16].

The number of datasets for identifying face emotions is large. These datasets include the facial expressions of participants that were collected in still images or quick facial videos.

Authors have commonly employed audio-visual stimuli, such as movie clips, to elicit emotions for detection [17]. However, some studies have also used still images [18], lab-based tasks to induce emotions [19], or posed emotional expressions.

There has been a lot of interest in functional connection research employing EEG in the context of emotion recognition [20]; [21]; [22]. EEG-based functional connectivity is used to examine the brain regions involved in each task. Functional connections are analyzed by identifying common patterns in activation maps or time series data. EEG-based functional connectivity has been employed in various research to look at the brain areas involved in emotion perception tasks. Participants in the study by [23] watched video clips to generate neutral, positive, or negative emotions, and the feelings were then classified using the EEG signals. The goal of the study was to investigate the functional connectivity patterns in the brain using EEG-based functional connectivity. The classification results revealed a high degree of accuracy in classifying various emotional states.

Researchers in a study [24] employed the IAPS dataset to elicit positive or negative valence, and electrode caps were used to record the EEG signals. The classification of emotions was accomplished using an SVM classifier and a feature extraction approach created using Hjorth parameters. The outcomes showed that the IAPS images' evoking emotions could be classified precisely using the Hjorth parameters and SVM classifier. Additionally, artificial environments were developed [25] that evoked positive or negative valence using IAPS images, and they used an SVM classifier to classify the EEG-derived attributes. The goal of the study was to determine whether it was possible to use EEG data to identify emotions elicited by visual stimuli in virtual environments. The results mentioned that the SVM classifier is good enough for accurate classification of emotions evoked by virtual environments.

In another study [26], joyful sentiments are found using video clips to classify happy emotions with EEG recorded data. The purpose of the study is to see whether it is possible to identify various pleasant emotions with EEG. The participant assessments are done by [27] to classify the feelings as "encouragement," "playfulness," and "harmony. However, emotion recognition is only possible with a dataset of video stimuli.

IAPS images are used to generate joyful or sad feelings, and electrodes are utilised to collect the EEG data [28]. As a feature extraction method, discrete wavelet transforms (DWT) are used. Twenty-two subjects have participated in the experiment. The goal of the study is to find how EEG signals and DWT can identify emotions that are elicited by visual stimuli. The outcomes demonstrate that the SVM classifier is competent to distinguish between the emotions elicited by the IAPS images.

EEG signals are used in another study [29] to examine the impact of both positive and negative emotions. Music is utilised to elicit the associated emotions in groups of positive and negative participants, who are randomly assigned to 28 individuals. The study's goal is to find out how emotions affect false memory. The findings indicated that happy emotions significantly affected false memory and that the positive group's brain is more active than the negative group. The datasets used for speech-based emotion recognition can be divided into three categories: induced, mimicked, and natural. The most used datasets are simulated datasets, which often consist of recordings from specific individuals. While the vocabulary in these recordings is linguistically neutral, it is expressed with a range of intended emotions [30]. Even while there are numerous separate, easily standardisable simulated datasets for a wide range of emotions available in many languages, they might not always precisely match emotions felt. As opposed to synthetic datasets, induced speech recognition datasets more closely mimic actual human emotions. In the study, the datasets are created by recording a participant's chat with an anchor, who guides the language to induce an emotional response. However, the scope of emotions that can be elicited may be limited.

The identification of emotions using brain waves is substantially different from traditional methods. Most people can tell someone's feelings merely by looking at them or listening to them. However, in a natural environment, people are unable to interpret brain signals. Most brain signal databases employ EEG recordings. One reason for this preference is that EEG systems are generally more affordable and easier to use compared to other brain signal recording technologies [31]. Nevertheless, researchers have also employed magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI) to detect emotions and localize the associated brain regions. Emotions are often extracted from brain signals using auditory (like music), visual (like still photos) [64], or audio-visual (like movie clips, music videos) stimuli [6]. For most brain signal recordings, participants must stay still. Theoretically, portable EEG sensors might be used to record brain signals for emotion recognition in a natural setting.

Research has also been done on categorising emotions using a range of different modalities. In one study [32], for instance, facial expressions and EEG data are combined, whereas in another study [33], speech and facial films are combined. Text can also be used to identify emotions. These datasets frequently contain phrases (and/or small paragraphs) with labels annotated (sometimes by third parties). The fact that most of the research uses audio-visual stimuli to generate emotions, such as movie clips or photos, is a frequent shortcoming of the existing literature on emotion recognition. Textual stimuli, however, can also cause readers to have emotional reactions and may have various emotional repercussions. In addition to stimulating readers' diverse cognitive and emotional memories, text can transmit more nuanced and complex emotions than visuals or videos. To better understand how text stimuli can be used to identify emotions, more research is required.

Objectives and novelty:

In neuroscience, emotion detection is an important study that refers to the scientific methods used to identify, measure, and decode human emotions from brain activity and physiological signals. It combines neuroscience, psychology, machine learning, and signal processing. EEG is one of the best methods to measure brain activity. In existing studies, emotion detection is done as discussed in the literature review, but according to our knowledge in this study, emotional words are presented for the first time as stimuli to measure the brain signals for various emotional words. Moreover, a novel hybrid model is proposed based on deep learning for better discrimination of emotional states against the words.

Background:

Emotions:

Emotions, which are subjective mental states, encompass a wide range of feelings such as joy, sadness, anxiety, and anger. A subjective experience, a physiological reaction, and a behavioural or verbal response are the three fundamental elements of emotions, according to Don Hockenbury and Sandra E. Hockenbury's book "Discovering Psychology" [34].

Figure 1. The six dimensions of well-being are visualized as described by [35]

Subjective experience refers to the conscious awareness of an emotion. It reflects an individual's personal perception of their emotional state, which can vary significantly depending on the person and the context. For instance, while viewing a horror film, one individual can feel scared, while another might feel excited. The physical changes that take place in reaction to an emotion are known as a physiological response. Blood pressure, respiration rate, heart rhythm, and muscle tension may all vary because of the modifications. For instance, a person's heart rate might increase when they're angry, whereas it might decrease when they're joyful. Behaviour or verbal response refers to how someone acts or communicates in response to an emotion. This can include elements like tone of voice, body language, and facial expressions. For instance, when someone is joyful or sad, they could cry or smile, respectively. These three elements combine to provide the overall emotional experience. They can all be utilised to comprehend and recognise various emotions in ourselves and others. They are all necessary for the manifestation of emotions.

Emotional Well-Being:

One of the most important aspects of general well-being is emotional well-being, commonly referred to as emotional health. Having positive feelings, a high level of life satisfaction, happiness, and the capacity to control unpleasant emotions are the usual definitions [36]. According to Loven et al. [37], six factors can be used to quantify emotional well-being: the physical, social, mental, emotional, material, and professional dimensions. A balance of negative and positive emotions can also be categorized as low levels of stress and emotional resilience. Figure 1 illustrates the six aspects of well-being that are commonly used to describe emotional well-being.

EEG Signal Acquisition:

A measure of physiological arousal produced by the human body is the Galvanic Skin Response (GSR) [26] signals, which exponentially rise with increased neuronal activity.

Table 1. Letters to identify the lobe position

Ser	Lobes	Electrodes
1	P	Parietal Lobe
2	T	Temporal Lobe
3	F	Frontal Lobe
4	C	Central Lobe
5	O	Occipital Lobe

Synaptic excitations, which stimulate the dendrites of neurons and produce a difference in electrical potentials, are the reason for this rise in activity. The authors in [38] showed that to detect these low-voltage events, EEG sensors must stimulate a significant number of neurons. Brain electrical activity can be recorded using both invasive and non-invasive techniques. Non-invasive methods do not require surgical implantation of devices, whereas invasive techniques do. Electroencephalography (EEG), which records brain waves, is a widely used non-invasive approach. The EEG is a tool used to assess electrical activity in the brain. According to the authors in [39], electrodes are applied to the scalp surface using conductive gel, amplifying and digitising the impulses before monitoring the electrical activity of the brain. Nowadays, people can use EEG technology easily thanks to portable, hassle-free headphones like the "EMOTIV", which are sold on the market. The following aspects are included in EEG signal recordings.

Electrode Positioning:

The 10/20 approach, which was initially put forth by the International Federation of EEG and Clinical Neurophysiology in 1958 [40], is frequently used to standardise the electrode placement scheme. It is based on where an electrode is placed and the area of the cerebral cortex that is immediately below it. The numbers 10 and 20 stand for the separation between electrodes from the tip of the nose, the frontal regions, and the inion, three landmarks on the skull. The inter-electrode distance is 10% to 20% of the total front-back or left-right distance using this method. The letters and numerals written on the electrodes to identify the lobe position are shown in Table 1. The electrodes are placed across the midline core brain areas, with the odd number representing the left hemisphere and the even number designating the right hemisphere.[40]

Number of electrodes:

The optimum number of electrodes for EEG recording is not predetermined. Instead, depending on the findings and interpretations of the study, the number of electrode channels employed during the experiment can range from 3 to more than 128.

International 10-20 EEG Placement System:

A standardised technique for placing electrodes on the scalp during an EEG investigation is the 10/20 system. With this technique, the scalp is divided into several sections, with electrodes positioned at locations in each section. With the help of this technology, electrode positioning can be done consistently for usage in a variety of investigations and research endeavours.

The "C" electrode serves as a reference point for the grid of electrodes used in the 10/20 system, which are spaced at 10% and 20% intervals along the scalp. The 10/20 scheme has also been modified by the American EEG Society to incorporate intermediate 10% spots, as shown in Figure 2. The EEG signals are recorded using a total of 21 electrodes in this updated version of the system. The 10/20 system is frequently used to examine brain activity and function in research and therapeutic settings. Unwanted signals, called artifacts or noise, distort the brain waves when the EEG signal is being monitored.

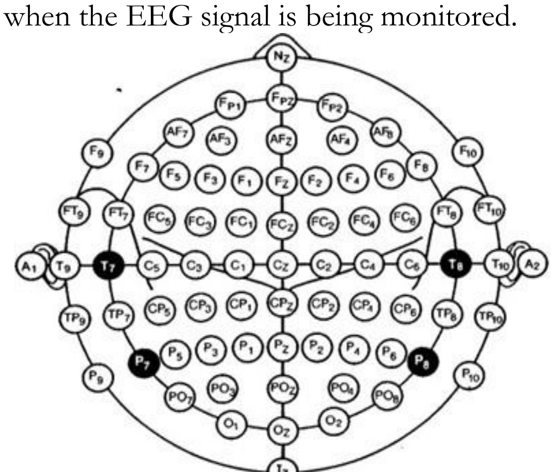

Figure 2. Modified 10/20 System source from [41]

The human body creates objects called physiological artifacts because of a variety of biological processes, such as breathing, head, jaw, and tongue movement, eye movement, and blinking. Blinking and other eye movements that happen below the range of 4Hz cause artifacts called electro-oculograms (EOGs). The electrocardiogram (ECG) is another artefact caused by heart rate, and electromyography (EMG), which is caused by head and muscle movement, is frequently seen above the frequency of 30 Hz. EMG and EOG artifacts are usually regarded as physiological artifacts for the HCI inquiry [42].

Methodology:

Experiment Design:

In this study, we used the experimental strategy to analyse the proposed techniques. The process includes the design of the experiment as well as the data collection, pre-processing, feature extraction techniques, implementation techniques, training and testing, and classification of the results. Each experimental module is explained in detail in the subsequent sections.

Subjects and Protocol:

The experiment recruited 25 volunteers who met specific participation criteria, including normal hearing, normal or corrected-to-normal vision, and no history of significant emotional or psychiatric disorders. Participants were requested to refrain from ingesting alcoholic beverages for 24 hours before the start of the experiment to ensure the dependability of the results.

This restriction was implemented to avoid any potential impact of alcohol on participants' cognitive and physiological states, which could influence the study's results. Before the formal experiment, all participants were thoroughly briefed on the study protocol. They were informed about the study's objectives, methodology, and experimental procedures. Each participant was provided with an informed consent form, which they were required to sign. The informed consent approach was designed to ensure that participants fully understood the study's objectives and willingly agreed to participate.

Participants were also informed that they might leave the experiment at any time if they disagreed with the findings or felt uncomfortable. The purpose of the instructions was to ensure that participants felt comfortable and well-informed. By providing a clear understanding of the study's objectives and procedures, the instructions aimed to minimize potential biases or misunderstandings. The informed consent method was critical to the experiment since it exhibited respect for the participants' autonomy and ensured their willingness to participate. Overall, the trial design attempted to uphold ethical standards and create trustworthy results by carefully selecting and informing subjects.

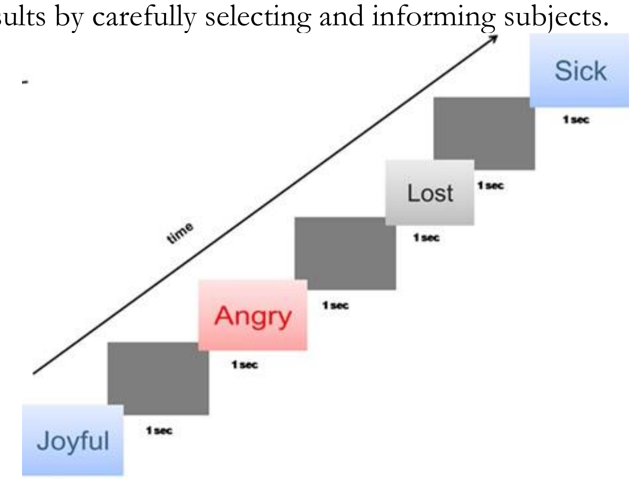

Figure 3. An EEG experiment designed to measure the response to different emotional words

Conduct of Experiment:

As illustrated in Figure 3, each image in this experiment appeared for one second (1 sec) before disappearing for one second (1 sec). Words for various emotions, including anger, joy, loss, and many more, were provided. The participants were not required to respond, as they were only shown the images. All stimuli were presented in three colour variations: red, blue, and grey. As illustrated in Figure 4, each image was uniform in size, with dimensions of 960 × 720 pixels.

Data Collection:

EEG data for the experiment were collected from 25 volunteers using a 128-channel Electrical Geodesics Incorporated (EGI) system with a sampling rate of 250 Hz. At the time of data collection, 128 channel EGI system was the best for data collection. Most of the studies in that era had EEG systems with a smaller number of channels, which provided limited data on brain activities. The Net Station software was employed to record the EEG signals throughout the 5-minute experiment.

Methodology:

Experiment design and data collection have the vital role in brain study. A better experiment design and carefully collected data collection can extract more information from the brain. In brain study, since the difference between the activated state and baseline is minimal most of the time, processing of data also plays a significant role in the analysis. After the data collection, the main step is pre-processing, followed by feature extraction from the raw EEG data. Given the high proportion of sparse data, feature selection is crucial for improving classification performance. Figure 5 illustrates the process of the emotion classification phase.

Preprocessing:

Scalp signals can be contaminated by various types of noise or artifacts, complicating accurate data interpretation. To address this, different preprocessing procedures were performed using MATLAB’s EEGLAB toolbox. The preprocessing procedures involved applying average referencing, downsampling the data, and filtering the EEG signals.

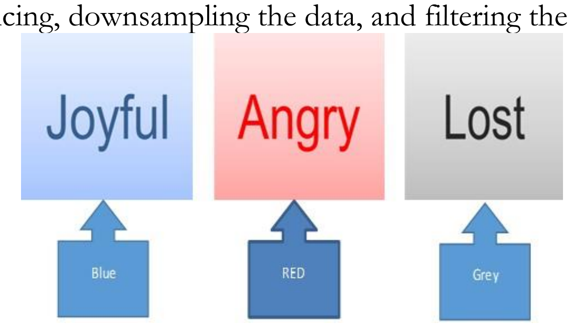

Figure 4. Stimuli were presented to measure the response to different emotional words

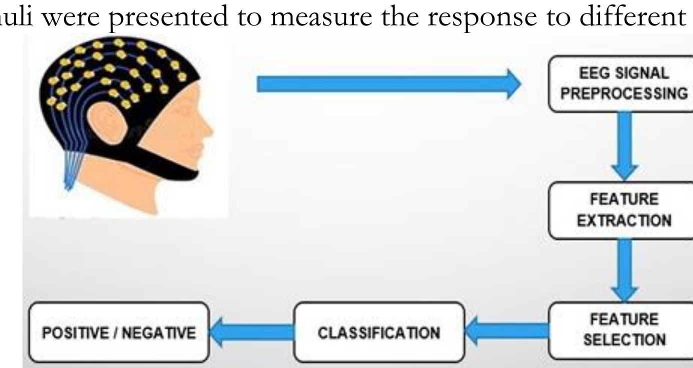

Figure 5. Steps for emotion classification

The filtering block uses a band-pass filter with a cut-off frequency of 0.5 Hz to remove the low-frequency noise, and a cut-off frequency of 50 Hz to remove high-frequency noise.

To improve data quality even further, we used Clean Line, a tool created exclusively for reducing line noise from EEG signals. The clean line noise function was used to remove any channel in the data that contained line noise.

Human selection and elimination of faulty channels was another critical stage in data preparation. Channels with irregularities or artifacts were found and eliminated after a rigorous examination of the data. This procedure is intended to increase the accuracy of our analysis by removing untrustworthy channels. We used Artefact Subspace Reconstruction (ASR) techniques and Clean Raw data to address noise in the EEG signal further. We were able to remove artifacts and bad channels from the data using these strategies, which improved the overall quality and reliability of the study. This procedure reduced the impact of noise and artifacts on the EEG data using these Preprocessing approaches, which ensure that the later analysis would be based on cleaner data.

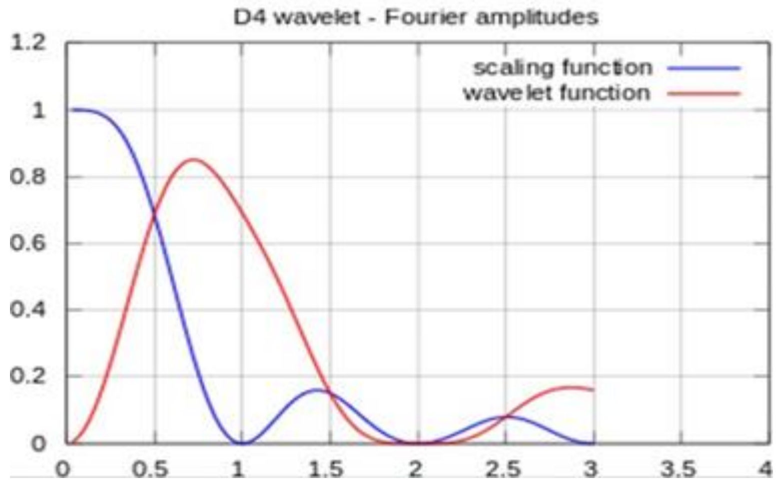

Figure 6. Daubechies Wavelet representing scaling and wavelet function

Feature Extraction:

The technique of locating and extracting pertinent patterns or features from EEG data that give significant information about emotions is known as feature extraction. Key information can be extracted from EEG signal properties such as frequency, amplitude, power, and phase. The aim is to select features that can accurately differentiate between distinct emotional states. For instance, research has indicated that emotional states are correlated with the power in the alpha and beta frequency regions [7]; therefore, these frequencies can be retrieved from the EEG signals. To classify emotions based on EEG, three feature extraction methods—WT, CNN, and PSD are used along with the raw data as features. MATLAB is used as a tool for the purpose of analysis.

Wavelet Transform:

The most popular and commonly used method of extracting time-frequency features from EEG is called WT. In this work, the wavelet transforms, which compute each component with its scale-dependent pattern resolution, were used to separate the signal into its frequency components. It provides information in varied resolutions as a result. Wavelet analysis converts the mother wavelets into wavelets of different sizes. By combining the wavelets and scaling function linearly, DWT uses those wavelets to define a function or image. Wavelet variation is also essential for detecting varied-scaled patterns. WT has windows with changeable scales, unlike Short Term Fourier Transforms (STFTs), which do not. Using scalar products with scaling signals and wavelets, Daubechies wavelet transforms compute running averages and differences as shown in Figure 6. Depending on the implementation and type of the transform being used, the scaling function coefficients for the Daubechies D4 transform may differ. There are four wavelets and four scaling function factors in the Daubechies D4 transform. Those are:

$$h_0 = \frac{1+\sqrt{3}}{4\sqrt{2}}; h_1 = \frac{3+\sqrt{3}}{4\sqrt{2}}; h_2 = \frac{3-\sqrt{3}}{4\sqrt{2}}; h_4 = \frac{1-\sqrt{3}}{4\sqrt{2}} \quad (1)$$

Each stage of the wavelet transform processes the incoming data using the scaling function. The scaling function is used to produce/smoothed values in the ordered wavelet transform if the original dataset has N values. The lower half of the N-element input vector is then used to store these smoothed values. During this process, the wavelet function coefficients are also determined.

$$g_0 = h_3; g_1 = -h_2; g_2 = h_1; g_3 = -h_0 \quad (2)$$

The wavelet function is used to transform the input data. The wavelet function is used to compute N/2 differences if the original dataset has N values. The inner product of the coefficients and the four data values yields the scaling and wavelet functions. The following are the formulae for the Daubechies D4 scaling function:

$$a_i = h_0 s_2 i + h_2 i + 2 + h_3 s_2 i + 3 \quad (3)$$

$$a[i] = h_0 s[2i] + h_1 s[2i + 1] + h_2 s[2i + 2] + h_3 s[2i + 3] \quad (4)$$

Daubechies D4 Wavelet function:

$$c_i = g_0 s_2 i + g_1 s_2 i + 1 + g_2 s_2 i + 2 + g_3 s_2 i + 3 \quad (5)$$

$$c[i] = g_0 s[2i] + g_1 s[2i + 1] + g_2 s[2i + 2] + g_3 s[2i + 3] \quad (6)$$

The wavelet transform calculates both scaling and wavelet function values at each step. To implement the feature extraction using the Wavelet Transform, a multi-level discrete wavelet decomposition of a signal representation was carried out using MATLAB. The 'db4' wavelet was used for the decomposition, and level 5 decomposition was used. The appcoef function was then used to retrieve the level 5 approximation coefficients from the decomposition structure. The detail coefficients for levels 5, 4, 3, 2, and 1 were extracted using the detcoef function accordingly.

Finally, a single vector was created by concatenating all the retrieved coefficients (cA5, cD5, cD4, cD3, cD2, cD1) together. The resulting vector contained, in that order, the detailed coefficients for each level of the decomposition and the approximation coefficients at level 5 of the decomposition. This was employed to learn the signal's frequency information across many sub-bands.

Convolutional Neural Network:

To analyse EEG signals, including audio and time series data, 1-D CNNs, a modified form of 2-D CNNs, have been developed. In some cases, these networks have been found to perform better than 2-D CNNs due to characteristics including reduced computational complexity and improved temporal data handling [43]. According to research [44], 1-D CNNs outperform 2-D CNNs when processing 1-D data for applications. Given these benefits, 1-D CNNs are frequently the best choice in certain situations. These benefits include things like decreased computing cost and better handling of temporal data. 1-D and 2-D convolutions have very different computing complexity; for instance, when convolution is applied on a 2-D picture with a KxK kernel, the computational cost is proportional to the size of the image (NxN) and the size of the kernel (KxK). More specifically, the computational cost is $O(N^2K^2)$, which indicates that as the size of the image and kernel grow, so does the amount of time and resources needed to complete the convolution operation.

However, the computational cost is linearly related to the size of the signal and the size of the kernel when a 1-D convolution is applied to a signal with the same dimensions (N and K). Particularly, the computational cost is ~O(NK), which denotes that the convolution operation's time and resource requirements scale linearly with the size of the signal and kernel. Training 2-D CNNs usually requires specialized hardware, such as GPU clusters or cloud computing resources. In contrast, 1-D CNNs can be implemented on a standard computer and executed much faster, especially when using a small number of neurons and hidden layers. Because they require less processing power, 1-D CNNs are well-suited for real-time and low-cost applications, especially on mobile and handheld devices [45] [46]. Like 2-D CNNs, 1-D CNNs have an output layer that is an MLP with several neurons that is equal to the number of classes. The unprocessed 1-D signal is sent to the passive input layer. Which is also an adaptable approach because the CNN topology in the output layer allows the sub-sampling factor to be adjusted to consider changes in the input layer's dimension.

To implement 1-D CNN in MATLAB, a set of 1dimensional signals represented by changeable images served as the network's input, while its output was a collection of features gleaned from those signals. Different vector filters were used to assess the proposed model's efficacy; only findings for filters with a size of 1x130 were reported. The input images had a dimension of one (1-D). The filters employed in the convolutional layer had a 130-dimensional size. In the convolutional layer, 100 filters (or feature maps) were applied. The pooling region employed in the pooling layer had a dimension of 11. Figure 7 displays the maps and specifics of each tier. The randn and rand functions were used to randomly initialise the weights W and biases b of the filters in the network. For testing, the first 8 photographs were chosen, and they are now kept in a variable. Then, to convolve the filters with the input images, the cnnConvolve 1D function was used. The convolved characteristics were the function's output. After convolution, the features were pooled using the cnnPool1D function. This function returned the pooled features after receiving the pooling dimension and the convolved features as input.

The combined features were then reconfigured, joined to an already-existing feature vector, and saved in a variable. This can be used to represent the input image's features. Each neuron in our CNN network is identifiable by a distinct triple of integers, which are (layer, map, position). If a layer only contains one map, the value of a neuron is provided by the formula $x'_m(a) = x'(a)$. The general formula for a neuron's value is:

$$x'_m(a) = s(\sigma^l_m(a)) \quad (7)$$

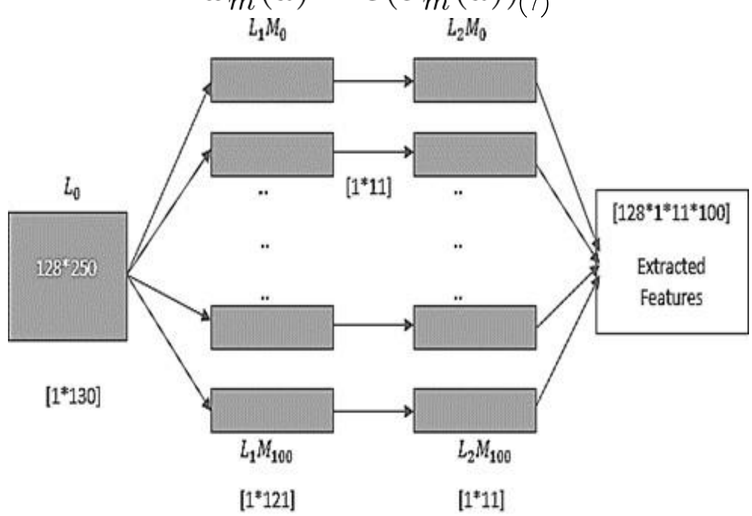

Figure 7. The proposed CNN model has L layers and M convolutional maps

A sigmoid function, which is a roughly linear function that produces values between 0 and 1, determines the value of s for each layer. Convolutional layers frequently utilise the sigmoid function to symbolise the convolution of the input signal. The traditional sigmoid function, which was used in this investigation, has the following definition:

$$s(\sigma) = \frac{1}{1 + exp^{-\sigma}} \quad (8)$$

Although other vector filters were used, as was already noted, the study's conclusions were based on the outcomes obtained with a filter size of (1x130). It was found that this filter size was most suited for the 128 channels and 250 samples. Every filter in the model was a neuron with input and output weights. A feature map was produced by copying the filters across the whole visual field and giving them all the same weight vector and bias. A scalar product with the symbol σ_m^{-a} denotes the connections between input neurons (vectors) and the neurons in the map in each layer. This scalar product creates the weight connections between these neurons. Weight sharing was employed in this study to improve learning effectiveness and decrease the number of free parameters that needed to be memorised. Specifically, 100 weights were established in accordance with the following procedure while creating a feature map.

$$g_{ij}^k = tang(Y^k * x)_{ij} + d_{k(9)}$$

The weights of the filters are represented by y^k, the bias is represented by d_k, and the input vector is represented by x, where the feature map is defined by g^k at the k-th layer. The size of the feature map dictated the number of output features, which was then pooled by downsampling the feature map with a filter size of 1*11. A total of 1100 features were output for each row vector, which were then further reduced using feature selection methods.

Power Spectral Density. Frequency-dependent signal fluctuations are shown using PSD. It's employed to disperse typical power in relation to frequency. The spectra of the noise signal may be considered when calculating spectra with FFT; this can be done away with by averaging. Welch's PSD algorithm is used to average the signal's spectra across windows. An average power spectrum of these segments is then determined after first cutting the input signal into tiny pieces. FFT makes it simple to determine the periodogram, a term used to represent the DFT evaluation of PSD. DFT can be used to calculate PSD as:

$$P(x(t)) = \frac{1}{L}\left|X(e^{jw})\right|^2 \quad (10)$$

When L is increased, the periodogram's mean value will get closer to the real PSD, but the variation won't go away entirely [90]. The variation of the projected periodogram is reduced via ensemble averaging. The steps for calculating a Welch-based PSD are as follows. 1) Divide the input data into Z samples and L slots. 2) Use the FFT to calculate the periodogram for each slot.

$$P_j(w) = \frac{1}{KZ}\left|\sum_{z-1}^{n=0} X_j(n)w(n)e^{-jwn}\right|^2 \quad (11)$$

Where $\sum_{z-1} w^2(n)$ is the average power of the given window. The values of the Normalised PSD (NPSD) are computed for the Theta band, Alpha band, and Beta band. The NPSD was calculated using Equation 12 and is shown below. Where the total PSD of the other two bands is multiplied by the calculated PSD of one band.

$$\text{NPSD Band} = \frac{\text{PSD Band}}{\text{Total PSD Band}} \quad (12)$$

The PSD of a signal was calculated using MATLAB's pwelch function. The Welch's method is used by the function, which necessitates averaging numerous periodograms of overlapping input data segments. The function additionally accepts optional inputs for the window function, the degree of segment overlap, and the number of points used in the FFT calculation, in addition to the input signal. The single-sided power spectral density was calculated using this function. The Welch method is used to divide a time series into overlapping subcategories of signal components.

Feature Selection:

Feature selection is a technique used to identify the most important characteristics in a dataset, aiming to improve machine learning model accuracy and reduce training time. Region of interest (ROI), principal component analysis (PCA), independent component analysis (ICA), t-test, and other techniques are only a few of the numerous feature selection techniques available. The performance and effectiveness of the model can be increased by using these methods, which are created to locate and extract the most pertinent features from a dataset. Finding the dataset's most informative features is done using a t-test. The power of various frequency bands or the amplitude of various electrodes are two examples of EEG parameters that can be compared between two groups of participants (such as healthy vs. diseased, or with various cognitive states), using a t-test.

The t-test, a valuable tool for feature selection in EEG research that enables researchers to pinpoint the most instructive elements from a dataset and use them for classification or prediction tasks, was used in the current work. A t-test was conducted to identify columns with p-values below 0.05. This two-sample test compares the means of two groups and provides a p-value to assess the significance of the difference. The analysis was performed using the built-in ttest2 function, with Vartype set to "unequal" to account for differing variances between the samples. The training dataset's columns with p-values under 0.05 are regarded as statistically significant in terms of their ability to predict the target variable. Based on their p-values, these important columns were arranged in descending order and saved in a variable. Which helped decide which attributes would provide the best predictions.

Training and Testing:

Monte Carlo random sampling is frequently used in EEG research to model the impact of various experimental settings on EEG data. To replicate various forms of brain activity, such as various neuronal firing patterns or levels of synchronisation, researchers can employ Monte Carlo random sampling. Researchers may replicate various levels of noise in the EEG data using this technique, such as measurement error or interference from outside sources [47]. In this work, the Monte Carlo technique is used to produce random sampling from the filtered EEG data. The fundamental principle of Monte Carlo random sampling is to create a group of samples that closely resemble the characteristics of the underlying distribution using random numbers. To perform Monte Carlo, a loop from 50 to the length of the features with p-values less than 0.05 (or a maximum of 5000) was developed. The process was repeated for 100 iterations. For the training and test sets of data, the chosen features were kept in the different variables.

Classification:

A technique called classification uses a set of labelled data as a reference to predict the category or label of a given data point based on its attributes. In EEG analysis, we can train a model to identify particular brain activity patterns connected to various cognitive or emotional states. A classification model is a model that can distinguish between the brain signals for a happy emotional state vs a sad emotional state. For classification, there are many different types of machine learning algorithms, such as Support Vector Machine (SVM), Naive Bayes (NB), and Random Forest (RF). In this study, the result is found using different classifiers, but the best result with SVM is mentioned. The other reason is that SVM is the most successful for classifying EEG in most of the studies mentioned in the literature. SVM is trained using an EEG dataset of various participants for different brain conditions, such as various forms of brain activity or various cognitive states.

For instance, a researcher uses SVM [23] to categorise various forms of brain activity, such as various neuronal firing patterns or various degrees of synchronisation, depending on the strength of various frequency bands in the EEG data. The researcher can employ a variety of features, including connection measurements, coherence, the power of various frequency bands, the amplitude of various electrodes, and other derived features.

Performance Parameters:

In this study, the main performance parameters are accuracy, sensitivity, and specificity, which are described as

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}}\text{x100} \qquad (13)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \qquad (14)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \qquad (15)$$

A True Positive (TP) occurs when the model accurately predicts the real feeling. A True Negative (TN) occurs when the model properly predicts that the actual emotion does not belong to the provided class. A False Positive (FP) occurs when the model mistakenly predicts that the actual emotion belongs to the provided class. A False Negative (FN) occurs when the model mistakenly predicts that the actual emotion does not belong to the provided class.

Results:

In this section, the results are discussed comprehensively. The findings include noteworthy observations, which include any differences or similarities in the results acquired from various feature extraction approaches. This section also includes a comparison based on the accuracy of various approaches.

Feature Results:

The comparison summary of all four techniques is mentioned in Table 2. Accuracy, Specificity, and Sensitivity of Raw features, PSD, WT, and CNN are shown. The CNN model for feature extraction performed best, with an average accuracy of 0.8, sensitivity of 0.74, and specificity of 0.86. The model was trained on a labelled dataset of EEG, using CNN layers for the purpose of feature extraction and SVM to do classification of the dataset. The model's high accuracy score implies that it can classify emotions successfully. The combination of the WT and SVM approach for EEG emotion analysis produced an average accuracy of 0.75, with specificity and sensitivity scores of 0.79 and 0.71, respectively. These data indicate that the approach has moderate accuracy but can appropriately distinguish between different moods. The high specificity score of 0.79 implies a good capacity to identify negative emotions, which could be useful in recognising illnesses such as anxiety or depression. However, the method's lower sensitivity score of 0.71 suggests that it may be less efficient at detecting pleasant emotions.

Table 2. Performance measures of different techniques

Technique	Specificity	Sensitivity	Accuracy (%)
CNN	0.86	0.74	80
WT	0.79	0.71	75
PSD	0.76	0.68	72
Raw Features	0.73	0.57	65

The obtained specificity score of 0.76 suggests that the model is capable of reliably recognising negative cases. The sensitivity score of 0.68, on the other hand, indicates that the model's ability to identify affirmative cases is only moderately successful. This suggests that additional changes may be required to increase the model's accuracy in detecting positive cases. The results show that the combination of PSD and SVM model for EEG-based analysis of positive and negative emotions is promising, with an overall accuracy of 0.72. The model demonstrated strong performance in detecting true negative cases, with a specificity score of 0.76, indicating its ability to correctly identify instances where the analysed emotion is absent. However, its ability to detect true positive cases was more limited, as reflected by a sensitivity score of 0.68, suggesting that the model occasionally misidentified the presence of the emotion. Despite this drawback, the model's total accuracy score suggests that it may be beneficial for predicting both positive and negative emotions from EEG data. The RAW features were also classified using an SVM model, which achieves modest accuracy, with an overall accuracy rate of 0.65, meaning that the model correctly predicts emotional state in around 65% of cases. The model's specificity value of 0.73 indicates that it effectively recognizes true negative occurrences when the analysed emotion is missing from the EEG data. Conversely, the sensitivity score of 0.57 suggests that the model is less effective at detecting true positive instances, where the EEG data confirms the presence of the analyzed emotion.

This suggests that the model may have missed certain cases where the emotion is present, leading to erroneous negative results. Table 3 shows the outcomes of each subject individually against every method. As previously discussed, each feature extraction method was fed to SVM for classification, and the results were gathered for further analysis. Table 3 presents the results of all 25 subjects, and the average accuracy of each method is compared and mentioned.

Figure 8 depicts a graphical depiction of the outcomes for each subject. The blue line represents the raw features, the red line represents the PSD, the green line represents the WT, and the yellow line represents the CNN method. The result shows that the CNN feature extraction method outperforms the others for each subject. In Figure 9, we presented the average accuracy of all four methods. We can see from the bar graph that the CNN approach, along with SVM and t-test feature selection method, performs better than WT, PSD, and raw data for emotion classification based on text stimuli.

Table 3. Performance measures of different techniques

Subject No.	Percentage Accuracy			
	Raw Data	PSD	WT	CNN
Subject 1	64	70	72	87
Subject 2	66	72	76	90
Subject 3	65	72	76	75
Subject 4	63	70	75	77
Subject 5	81	75	74	76
Subject 6	65	75	70	85
Subject 7	60	74	77	77
Subject 8	67	70	80	80
Subject 9	65	73	75	78
Subject 10	60	77	79	80
Subject 11	66	71	76	78
Subject 12	64	72	75	84
Subject 13	68	73	74	81
Subject 14	62	74	78	82
Subject 15	66	75	73	79
Subject 16	65	76	77	75
Subject 17	64	77	79	85
Subject 18	66	78	76	80
Subject 19	67	79	75	76
Subject 20	64	80	73	83
Subject 21	63	69	75	80
Subject 22	65	71	73	82

Subject 23	62	73	77	80
Subject 24	66	75	72	81
Subject 25	64	77	78	80
Average Accuracy	65	72	75	80

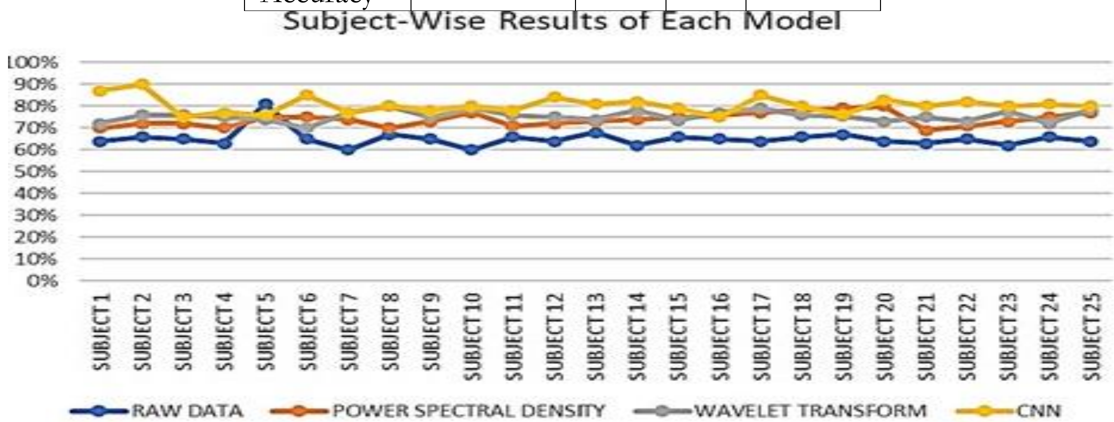

Figure 8. Analysis of Subject Outcomes and Average Accuracy for Feature Extraction Methods

Discussion:

In this study, the data is collected based on a novel experiment design that is used only in this study. That's why the comparison is done based on the existing methods with the collected data set. The existing techniques are implemented on the collected data, which are compared with the proposed hybrid model. The result is discussed in Figure 9.

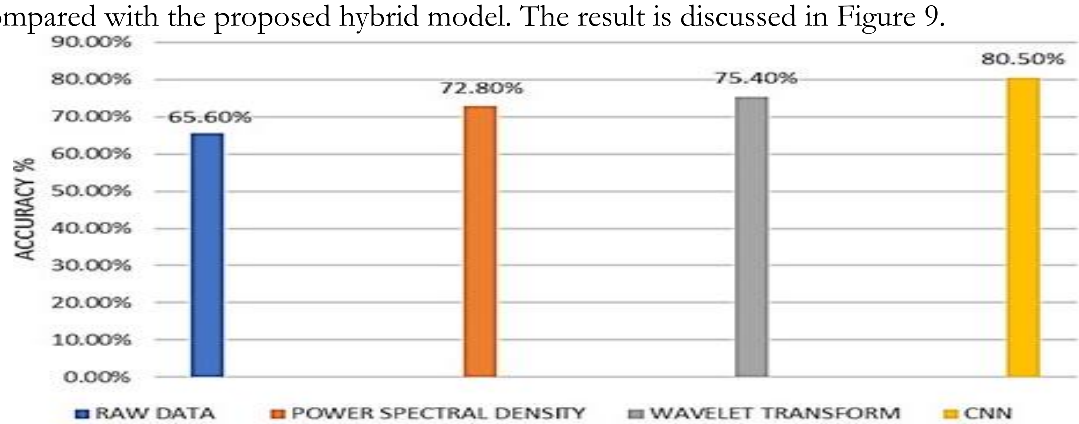

Figure 9. Average Accuracy of Feature Extraction Methods

Conclusions:

In recent years, EEG-based emotion analysis has received increased attention as a promising method for analysing emotional reactions in a variety of disciplines, including marketing research, mental health diagnosis, and affective computing. However, most earlier studies used visual or natural stimuli to induce emotional reactions, with only a few studies investigating the use of text stimuli. This vacuum in the literature is filled by this study, which investigates the efficiency of using text stimuli to induce emotional reactions in participants. This is a significant addition since text-based stimuli are routinely employed in real-world communication and are more naturally valid in some settings. This study is, to the best of our knowledge, one of the few to investigate the use of text stimuli in EEG-based emotion analysis.

The findings of the study show that using text stimuli efficiently stimulates distinct emotional reactions, as seen by significant changes in EEG data patterns between positive and negative emotions. This shows that text stimuli could be used as stimuli in EEG-based emotion analysis. Furthermore, our findings emphasise the importance of advanced feature extraction approaches, including convolutional neural networks (CNN), wavelet transform (WT), and power spectral density (PSD) analysis, in boosting the accuracy of EEG-based emotion categorization. The CNN approach attained an accuracy of 80%, whereas the WT and PSD methods achieved promising results of 75.40% and 72.80%, respectively. The use of text-based stimuli in EEG-based emotion analysis has been relatively unexplored, and the current study adds to the body of knowledge on the subject. The findings have substantial implications for the use of EEG-based emotion analysis in the real world, as well as prospective avenues for future research in this area.

Ethical Approval Statement:

Data were taken from 30 participants; however, data from only 26 participants were used for the final analysis after the application of exclusion criteria. Data from two participants were excluded due to the presence of many artifacts, while two other participants showed low accuracy during the initial analysis of the baseline and the task. All participants submitted the written consent form before the start of the experiment. The age of all participants was between 24 and 34 years, and the mean age was 30 years. The study protocol was approved by the Universiti Teknologi PETRONAS (UTP) ethics committee under UTP Reg. No 13–10, and the EEG data were recorded at UTP.

Authorship contribution statement:

Ihsan Ullah: Conceptualization of this study, Methodology, Data curation, Software, Investigation, Writing – original draft.

Raheel Zafar: Conceptualization of this study, Supervision, Validation, Writing - Original draft preparation.

Hammad Dilpazir: Validation, Analysis, Writing – review & editing.

Muhammad Javvad Ur Rehman: Conceptualization of this study, Supervision, Validation, Writing

Abdullah Waqas: Validation, Writing – review & editing, Administration.

Rana Fayyaz Ahmad: Validation, Data curation, Software, Administration.

References:

[1] "Emotion recognition: from speech and facial expressions," pp. 307–326, Jan. 2022, doi: 10.1016/B978-0-12-820125-1.00028-2.

[2] A. Bakhshi, A. Harimi, and S. Chalup, "CyTex: Transforming speech to textured images for speech emotion recognition," *Speech Commun.*, vol. 139, pp. 62–75, Apr. 2022, doi: 10.1016/J.SPECOM.2022.02.007.

[3] R. Febrian, B. M. Halim, M. Christina, D. Ramdhan, and A. Chowanda, "Facial expression recognition using bidirectional LSTM - CNN," *Procedia Comput. Sci.*, vol. 216, pp. 39–47, Jan. 2023, doi: 10.1016/J.PROCS.2022.12.109.

[4] G. Muhammad Sajjad, Fath U Min Ullah, Christodoulou and J. J. P. C. R. Ullah, Mohib, Faouzi Alaya Cheikh, Mohammad Hijji, Khan Muhammad, "A comprehensive survey on deep facial expression recognition: challenges, applications, and future guidelines," *Alexandria Eng. J.*, vol. 68, pp. 817–840, 2023, doi: https://doi.org/10.1016/j.aej.2023.01.017.

[5] Y. Izountar, S. Benbelkacem, S. Otmane, A. Khababa, M. Masmoudi, and N. Zenati, "VR-PEER: A Personalized Exer-Game Platform Based on Emotion Recognition," *Electron. 2022, Vol. 11, Page 455*, vol. 11, no. 3, p. 455, Feb. 2022, doi: 10.3390/ELECTRONICS11030455.

[6] W. Lin and C. Li, "Review of Studies on Emotion Recognition and Judgment Based on Physiological Signals," *Appl. Sci. 2023, Vol. 13, Page 2573*, vol. 13, no. 4, p. 2573, Feb. 2023, doi: 10.3390/APP13042573.

[7] D. M. Zolezzi, L. M. Alonso-Valerdi, and D. I. Ibarra-Zarate, "EEG frequency band analysis in chronic neuropathic pain: A linear and nonlinear approach to classify pain

severity," *Comput. Methods Programs Biomed.*, vol. 230, p. 107349, Mar. 2023, doi: 10.1016/J.CMPB.2023.107349.
[8] Z. Zhou, M. A. Asghar, D. Nazir, K. Siddique, M. Shorfuzzaman, and R. M. Mehmood, "An AI-empowered affect recognition model for healthcare and emotional well-being using physiological signals," *Clust. Comput. 2022 262*, vol. 26, no. 2, pp. 1253–1266, Nov. 2022, doi: 10.1007/S10586-022-03705-0.
[9] D. Li, L. Xie, Z. Wang, and H. Yang, "Brain Emotion Perception Inspired EEG Emotion Recognition With Deep Reinforcement Learning," *IEEE Trans. Neural Networks Learn. Syst.*, vol. 35, no. 9, pp. 12979–12992, 2024, doi: 10.1109/TNNLS.2023.3265730.
[10] F. Z. Canal *et al.*, "A survey on facial emotion recognition techniques: A state-of-the-art literature review," *Inf. Sci. (Ny).*, vol. 582, pp. 593–617, Jan. 2022, doi: 10.1016/J.INS.2021.10.005.
[11] M. K. Abadi, M. Kia, R. Subramanian, P. Avesani, and N. Sebe, "Decoding affect in videos employing the MEG brain signal," *2013 10th IEEE Int. Conf. Work. Autom. Face Gesture Recognition, FG 2013*, 2013, doi: 10.1109/FG.2013.6553809.
[12] J. Atkinson and D. Campos, "Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers," *Expert Syst. Appl.*, vol. 47, pp. 35–41, Apr. 2016, doi: 10.1016/J.ESWA.2015.10.049.
[13] A. A. Anthony and C. M. Patil, "Speech Emotion Recognition Systems: A Comprehensive Review on Different Methodologies," *Wirel. Pers. Commun. 2023 1301*, vol. 130, no. 1, pp. 515–525, Mar. 2023, doi: 10.1007/S11277-023-10296-5.
[14] N. Alswaidan and M. E. B. Menai, "A survey of state-of-the-art approaches for emotion recognition in text," *Knowl. Inf. Syst.*, vol. 62, no. 8, pp. 2937–2987, Aug. 2020, doi: 10.1007/S10115-020-01449-0/TABLES/5.
[15] D. Mehta, M. F. H. Siddiqui, and A. Y. Javaid, "Facial Emotion Recognition: A Survey and Real-World User Experiences in Mixed Reality," *Sensors 2018, Vol. 18, Page 416*, vol. 18, no. 2, p. 416, Feb. 2018, doi: 10.3390/S18020416.
[16] C. Marechal *et al.*, "Survey on AI-Based Multimodal Methods for Emotion Detection," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 11400, pp. 307–324, 2019, doi: 10.1007/978-3-030-16272-6_11.
[17] M. K. Ahirwal and M. R. Kose, "Audio-visual stimulation based emotion classification by correlated EEG channels," *Heal. Technol. 2019 101*, vol. 10, no. 1, pp. 7–23, Dec. 2019, doi: 10.1007/S12553-019-00394-5.
[18] K. Zaman, S. Zhaoyun, S. M. Shah, M. Shoaib, P. Lili, and A. Hussain, "Driver Emotions Recognition Based on Improved Faster R-CNN and Neural Architectural Search Network," *Symmetry 2022, Vol. 14, Page 687*, vol. 14, no. 4, p. 687, Mar. 2022, doi: 10.3390/SYM14040687.
[19] I. Sneddon, M. McRorie, G. McKeown, and J. Hanratty, "The Belfast induced natural emotion database," *IEEE Trans. Affect. Comput.*, vol. 3, no. 1, pp. 32–41, Jan. 2012, doi: 10.1109/T-AFFC.2011.26.
[20] M. Asif, S. Mishra, M. T. Vinodbhai, and U. S. Tiwary, "Emotion Recognition Using Temporally Localized Emotional Events in EEG With Naturalistic Context: DENS# Dataset," *IEEE Access*, vol. 11, pp. 39913–39925, 2023, doi: 10.1109/ACCESS.2023.3266804.
[21] L. Jin and E. Y. Kim, "E-EmotiConNet: EEG-based Emotion Recognition with Context Information," *Proc. Int. Jt. Conf. Neural Networks*, 2022, doi: 10.1109/IJCNN55064.2022.9892017.
[22] X. Wu, W. L. Zheng, Z. Li, and B. L. Lu, "Investigating EEG-based functional connectivity patterns for multimodal emotion recognition," *J. Neural Eng.*, vol. 19, no.

1, p. 016012, Jan. 2022, doi: 10.1088/1741-2552/AC49A7.
[23] Y. Y. Lee and S. Hsieh, "Classifying Different Emotional States by Means of EEG-Based Functional Connectivity Patterns," *PLoS One*, vol. 9, no. 4, p. e95415, Apr. 2014, doi: 10.1371/JOURNAL.PONE.0095415.
[24] K. A. Lindquist, T. D. Wager, H. Kober, E. Bliss-Moreau, and L. F. Barrett, "The brain basis of emotion: a meta-analytic review," *Behav. Brain Sci.*, vol. 35, no. 3, pp. 121–143, Jun. 2012, doi: 10.1017/S0140525X11000446.
[25] J. Marín-Morales *et al.*, "Affective computing in virtual reality: emotion recognition from brain and heartbeat dynamics using wearable sensors," *Sci. Reports 2018 81*, vol. 8, no. 1, pp. 13657-, Sep. 2018, doi: 10.1038/s41598-018-32063-4.
[26] B. L. Fredrickson, "Positive Emotions Broaden and Build," *Adv. Exp. Soc. Psychol.*, vol. 47, pp. 1–53, Jan. 2013, doi: 10.1016/B978-0-12-407236-7.00001-2.
[27] X. Hu *et al.*, "EEG correlates of ten positive emotions," *Front. Hum. Neurosci.*, vol. 11, p. 242491, Jan. 2017, doi: 10.3389/FNHUM.2017.00026/BIBTEX.
[28] A. Q.-X. Ang, Y. Q. Yeong, W. Wee, A. Q.-X. Ang, Y. Q. Yeong, and W. Wee, "Emotion Classification from EEG Signals Using Time-Frequency-DWT Features and ANN," *J. Comput. Commun.*, vol. 5, no. 3, pp. 75–79, Mar. 2017, doi: 10.4236/JCC.2017.53009.
[29] Y. Li *et al.*, "The influence of positive emotion and negative emotion on false memory based on EEG signal analysis," *Neurosci. Lett.*, vol. 764, p. 136203, Nov. 2021, doi: 10.1016/J.NEULET.2021.136203.
[30] S. G. Koolagudi, · K Sreenivasa Rao, S. G. Koolagudi, · K S Rao, and K. S. Rao, "Emotion recognition from speech: a review," *Int. J. Speech Technol. 2011 152*, vol. 15, no. 2, pp. 99–117, Jan. 2012, doi: 10.1007/S10772-011-9125-1.
[31] C. Lima, J. A. Lopes, V. Souza, S. Barros, I. Winkler, and V. Senna, "Analysis of brain activation and wave frequencies during a sentence completion task: a paradigm used with EEG in aphasic participants," *PeerJ*, vol. 11, p. e15518, Jun. 2023, doi: 10.7717/PEERJ.15518/SUPP-2.
[32] P. J. Lang, M. M. Bradley, and B. N. Cuthbert, "International Affective Picture System," *PsycTESTS Dataset*, Nov. 2020, doi: 10.1037/T66667-000.
[33] Z. Z. and S. W. J. Pan, W. Fang, Z. Zhang, B. Chen, "Multimodal Emotion Recognition Based on Facial Expressions, Speech, and EEG," *IEEE Open J. Eng. Med. Biol.*, vol. 5, pp. 396–403, 2024, doi: 10.1109/OJEMB.2023.3240280.
[34] "Discovering Psychology Hockenbury Hockenbury." Accessed: Dec. 02, 2025. [Online]. Available: https://bookstation.org/book/Discovering Psychology Hockenbury Hockenbury-4962221
[35] "Hettler, W. (1976). The Six Dimensions of Wellness. National Wellness Center. - References - Scientific Research Publishing." Accessed: Dec. 02, 2025. [Online]. Available: https://www.scirp.org/reference/referencespapers?referenceid=2754783
[36] "What Is Well-Being? Definition, Types, and Well-Being Skills | Psychology Today." Accessed: Dec. 02, 2025. [Online]. Available: https://www.psychologytoday.com/us/blog/click-here-for-happiness/201901/what-is-well-being-definition-types-and-well-being-skills
[37] L. Lovén, M. Pakanen, E. Gilman, and S. Pirttikangas, "Wellbeing in smart environments: Definition, measurement, prediction and control," *UbiComp/ISWC 2018 - Adjun. Proc. 2018 ACM Int. Jt. Conf. Pervasive Ubiquitous Comput. Proc. 2018 ACM Int. Symp. Wearable Comput.*, pp. 693–697, Oct. 2018, doi: 10.1145/3267305.3267692;JOURNAL:JOURNAL:ACMCONFERENCES;PAGEGROUP:STRING:PUBLICATION.
[38] F. H. Lopes Da Silva, "Electrophysiological Basis of MEG Signals," *MEG An Introd. to*

Methods, pp. 1–24, Sep. 2010, doi: 10.1093/ACPROF:OSO/9780195307238.003.0001.
[39] "(PDF) A New Methodology of Usability Testing on the Base of the Analysis of User's Electroencephalogram." Accessed: Dec. 02, 2025. [Online]. Available: https://www.researchgate.net/publication/286220374_A_New_Methodology_of_Usability_Testing_on_the_Base_of_the_Analysis_of_User's_Electroencephalogram
[40] M. Seeck *et al.*, "The standardized EEG electrode array of the IFCN," *Clin. Neurophysiol.*, vol. 128, no. 10, pp. 2070–2077, Oct. 2017, doi: 10.1016/J.CLINPH.2017.06.254.
[41] C. Stamoulis, R. E. Vanderwert, C. H. Zeanah, N. A. Fox, and C. A. Nelson, "Neuronal networks in the developing brain are adversely modulated by early psychosocial neglect," *J. Neurophysiol.*, vol. 118, no. 4, pp. 2275–2288, Oct. 2017, doi: 10.1152/JN.00014.2017.
[42] Z. He *et al.*, "Advances in Multimodal Emotion Recognition Based on Brain-Computer Interfaces," *Brain Sci.*, vol. 10, no. 10, pp. 1–29, Oct. 2020, doi: 10.3390/BRAINSCI10100687.
[43] J. Zhu, H. Chen, and W. Ye, "A Hybrid CNN-LSTM Network for the Classification of Human Activities Based on Micro-Doppler Radar," *IEEE Access*, vol. 8, pp. 24713–24720, 2020, doi: 10.1109/ACCESS.2020.2971064.
[44] S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 3, pp. 664–675, Mar. 2016, doi: 10.1109/TBME.2015.2468589.
[45] S. Kiranyaz, T. Ince, O. Abdeljaber, O. Avci, and M. Gabbouj, "1-D Convolutional Neural Networks for Signal Processing Applications," *ICASSP, IEEE Int. Conf. Acoust. Speech Signal Process. - Proc.*, vol. 2019-May, pp. 8360–8364, May 2019, doi: 10.1109/ICASSP.2019.8682194.
[46] S. Kiranyaz, O. Avci, O. Abdeljaber, T. Ince, M. Gabbouj, and D. J. Inman, "1D convolutional neural networks and applications: A survey," *Mech. Syst. Signal Process.*, vol. 151, p. 107398, Apr. 2021, doi: 10.1016/J.YMSSP.2020.107398.
[47] A. K. Liu, A. M. Dale, and J. W. Belliveau, "Monte Carlo simulation studies of EEG and MEG localization accuracy," *Hum. Brain Mapp.*, vol. 16, no. 1, pp. 47–62, 2002, doi: 10.1002/HBM.10024.