Enhancing Emotion Recognition through Deep Learning and Brain-Computer Interface Technology

Tanvir Anjum Labir[1], Poly Rani Ghosh[2*], Halima Mowla Anna[3]

Abstract

Deep learning, a specialized branch of machine learning, uses complex neural networks for advanced data processing tasks in which feature extraction and progression require more than one layer of processing using a Neural Network. The Brain Computer Interface is a direct communication link between the brain's electrical activity and an external equipment. The actual brain data is gathered using the BCI technology with electrodes fitted in Brain cells and the research focuses on the recognition of multimodal emotions after feature extraction and multilayer processing with an Artificial Neural Network (ANN). Several organizations have lately released enormous datasets containing experimental data on people's physiological signals (EEGs, eye movements) while they experience different emotions. These datasets collections are being exclusively designed to encourage the development of successful deep-learning emotion identification algorithms where the volunteers had to do some set of tasks regarding the research purpose. In this study, we evaluate deep learning approaches more specifically by the Artificial Neural Network (ANN) using the SEED-IV Electroencephalogram (EEG) dataset. In this paper, we briefly represented the implementation of Emotion recognition using, we briefly represent the implementation of Emotion Recognition using Artificial Neural Networks (ANN), which is one of the topics of our research. Furthermore, we explore the operating principles of artificial neural networks, which are our primary model for identifying emotions. Finally, we offer a few proposals for implementing neural networks on EEG inputs. With the ANN and 3D convolutional layers, we finally achieved a 63.425% accuracy rate.

Keywords: Deep Learning, Brain-Computer Interface, Emotion Recognition, Artificial Neural Networks, EEG Data

Significance | Utilizing deep learning and BCI for emotion recognition enhances understanding and application of neural network technology in neuroscience research.

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1.Introduction

Emotion, a fundamental aspect of human experience, is a key differentiator between humans and machines. However, as technology advances rapidly, machines are now learning to detect and even express emotions through innovative applications of machine learning (Gavrilova, 2020). One of the most promising fields contributing to this capability is deep learning, a branch of artificial intelligence that allows machines to perform complex tasks by mimicking human cognitive functions (Deng & Yu, 2014; Schmidhuber, 2015). In this regard, emotion recognition particularly using neural networks has emerged as a significant area of research with potential applications ranging from healthcare to human-computer interaction (Bengio, Courville, & Vincent, 2013). The Brain-Computer Interface (BCI) is a critical technology that enables direct communication between the brain's electrical activity and external devices (Hardesty, 2017). By capturing and analyzing

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brain signals, primarily through electroencephalogram (EEG) recordings, researchers can extract valuable information about human emotions (Yang & Yang, 2014). EEG, a non-invasive technique that records brain waves using electrodes placed on the scalp, has traditionally been used in medical diagnostics, such as for epilepsy and sleep disorders (Abiodun et al., 2018). However, its utility extends beyond the medical domain. In recent years, EEG has become a tool for exploring cognitive and emotional states, as it provides a cost-effective and accessible way to capture brain activity in real-time (Zheng, Liu, Lu, Lu, & Cichocki, 2018).

Emotion recognition using EEG signals has gained momentum, particularly with the development of large datasets and the advancement of machine learning techniques (Hinton, Osindero, & Teh, 2006). The introduction of deep learning algorithms has significantly enhanced the accuracy of emotion classification, offering new ways to understand human emotions by analyzing complex neural patterns (Liu et al., 2020). One such dataset is the SEED-IV dataset, which contains EEG recordings of subjects experiencing various emotional states (Graves et al., 2008). This dataset is specifically designed to support the development of emotion recognition algorithms by providing multimodal physiological signals, such as eye movements and EEG, while participants perform tasks that elicit different emotions (Hochreiter & Schmidhuber, 1997).

In the realm of deep learning, artificial neural networks (ANN) have proven to be particularly effective in handling the high-dimensional and temporal nature of EEG data (Zhang, Itoh, Tanida, & Ichioka, 1990). ANNs, inspired by the human brain's structure, consist of multiple interconnected layers that process and learn from data through weight adjustments (Sugiyama, 2019). Their capability to automatically extract features from raw data without extensive manual intervention makes them ideal for EEG-based emotion recognition tasks. Convolutional Neural Networks (CNNs), a specific type of ANN, have achieved considerable success in image processing and classification tasks and are increasingly being adapted for EEG signal processing (Avilov, Rimbert, Popov, & Bougrain, 2020).

Previous research in this field dates back to Liu et al. (2020), who developed an algorithm for real-time emotion classification using EEG signals. Since then, significant advancements have been made, particularly in using modern deep learning techniques (Hyötyniemi, 1996). In 2015, Zheng et al. (2018) conducted experiments using deep learning for EEG-based emotion recognition, further refining the approach with the release of the SEED-IV dataset in 2016. These studies have employed various feature extraction techniques, such as differential entropy (DE) and power spectral density (PSD), combined with dimensionality reduction methods like principal component analysis (PCA) to enhance the performance of emotion recognition systems (Valueva, Nagornov, Lyakhov, Valuev, & Chervyakov, 2020).

The current study builds on this body of work by evaluating the performance of an artificial neural network (ANN) on the SEED-IV dataset for emotion recognition. The ANN model processes the EEG data using 3D convolutional layers, which are adept at handling spatiotemporal patterns inherent in EEG signals (Mouton, Myburgh, & Davel, 2020). By doing so, we aim to achieve a higher level of accuracy in recognizing emotions, thereby contributing to the growing field of emotion recognition through deep learning (Gajawada, 2019).

This is structured as follows: the next section provides a comprehensive review of the literature related to EEG-based emotion recognition and neural networks. In the methodology section, we outline the process of data collection and the implementation of the ANN model. Finally, the results section presents our findings, including a discussion of the accuracy achieved in emotion classification using the SEED-IV dataset, followed by suggestions for further improvements in neural network-based emotion recognition systems (Schmidhuber, 2015; Deng & Yu, 2014).

2. Literature review

As I have mentioned and will mention a noticeable number of times, EEG signal processing using neural network has gone through a fair number of phases of development. After the idea of Brain Computer Interface using neural network, it has gone through numerous development stages. Research data on brain computer interface is far more to include in a single project paper. In this chapter I have tried to include some essential studies on BCI from the beginning. I have further discussed the recent research data from various papers.

2.1 The idea of Brain Computer Interface

Brain computer interfaces (BCI) are tools that enable direct communication between the brain and a computer or other external device. They provide increased freedom by either strengthening or substituting human peripheral working capacity and have potential applications in fields such as rehabilitation, affective computing, robotics, gaming, and neuroscience. Significant global research efforts have resulted in common platforms for technology standardization, assisting in the resolution of highly complex and non-linear brain dynamics, as well as related feature extraction and classification challenges. Time-variant psycho-neurophysiologic fluctuations and their impact on brain signals pose a new challenge for BCI researchers as they work to transition the technology from laboratory experiments to plug-and-play everyday use. This review summarizes the most recent advances in the BCI field and highlights critical challenges.

2.1.1 The evolution of brain computer interface

Scientific interest in exploiting biological data has developed as a result of rapid technological advancement, particularly in the last 30 years. The initial BCI research started in the 1970s at UCLA in California with animal studies to create a new, direct communication link between the brain and external surroundings. A study titled "Toward Direct Brain-Computer Communications" was published by Jacques Vidal in 1973 (Clerc et al., 2017).

The earliest BCI development experiments were conducted on monkeys in 1969 and 1970, while the first human trials were carried out in the 1990s. Jonathan Wolpaw offered the BCI's first comprehensive definition in 2000 (Bamdad et al., 2015). Slow cortical potentials (SCP), which were once employed for patient communication in LIS (Locked-in Syndrome), are one of the most well-known indicators of brain activity. However, they have recently been supplanted by direct current (DC) EEG shifts, which were initially identified by Walter et al. in 1964.

In the 1970s, M. Sterman and his colleagues conducted various tests on cats in which they explored a rhythmic EEG activity of the frequency ranges 12-15 Hz, which was subsequently termed SMR (sensorimotor rhythm), as shown in Table 2. The SMR is also known as the rhythm.

The 1970s and 1980s saw a surge in interest in Event-Related Potentials (ERP) research as a brain response to external and internal stimulus. Already in 1988, L.A. Farwell and E. Donchin published a paper titled "Talking off the top of your head" on ERP deployment, and as the first, they offered a now-famous style of stimulus presentation that allowed letter choice (Kubler et al., 2020).

A report of a closed loop, bidirectional adaptive BCI regulating computer buzzer by an anticipatory brain potential, the Contingent Negative Variation (CNV) potential, was provided in 1990.[9] In the S1-S2-CNV paradigm, the experiment revealed how an anticipation state of the brain, expressed by CNV, affects the S2 buzzer in a feedback loop. Electro expect gram is the name given to the acquired cognitive wave that represents expectancy learning in the brain (EXG). Vidal's 1973 study included the CNV brain potential as part of the BCI challenge. In the 2010s, studies revealed that brain stimulation might be used to restore functional connectivity and related behaviors by modulating molecular processes of synaptic effectiveness (Miranda et al., 2015)

This gave rise to the idea that BCI technology may be used to restore function as well as enable it. DARPA has financed BCI technology since 2013 through the BRAIN program, which has supported research at the University of Pittsburgh Medical Center, Paradromics, Brown, and Synchron, among others.

Liu et al., who created an algorithm for real-time emotion classification in 2010, are credited with pioneering the field of emotion classification using EEG data (Liu et al., 2010). The study into EEG-based emotion identification using deep learning algorithms was started by Zheng et al in 2015. More recently, several studies have been conducted on diverse datasets in an effort to categorize emotions based on EEG signals using deep learning. The SEED-IV dataset and different multimodal classification methods for emotion identification were developed by Zheng et al in 2016. Additionally, attempts at more sophisticated models have been made utilizing autoencoders, spatial-temporal LSTMs, or graph-based methodologies. In 2018, Song and Zheng et al. created a technique for emotion identification that makes use of dynamic graph CNNs (Zheng et al., 2014). Similar techniques for categorizing emotions are used in all of these studies, however the network structures differ.

2.1.2 Categories of Brain-Computer Interface

As the power of sophisticated computers develops with our understanding of the human brain, we get closer to making some very stunning science fiction a reality. Consider sending impulses directly to someone's brain that would allow them to see, hear, or feel certain sensory inputs. Consider the possibility of manipulating computers or machines with nothing more than a thought. It's not just about convenience; for seriously handicapped people, the creation of a brain-computer interface (BCI) might represent the most significant technical advance in decades. A brain-computer interface, also known as a direct neural interface or a brain-machine interface, is a direct communication link between the brain and an external device. It is the pinnacle of BCI development. Since BCIs being a relatively new breakthrough in HCI, there are several routes to investigate. Following rigorous testing, three types of BCIs were developed: invasive BCIs, semi-invasive BCIs, and non-invasive BCIs.

2.1.3 Deep dive in invasive BCI

Invasive BCI research has concentrated on restoring damaged sight and delivering new usefulness to persons who are paralyzed. During neurosurgery, invasive BCIs are implanted directly into the grey matter of the brain (WG et al., 1965). Scientists can read the firings of hundreds of neurons in the brain by implanting chips against the brain with hundreds of pins smaller than the diameter of a human hair emerging from them and piercing the cerebral cortex. The language of the brain firings is then transferred to a computer translator, which decodes the neural language using specific algorithms. This is then forwarded to another computer, which gets the translated data and instructs the machine on what to perform (Bozinovsha et al., 1992).

Invasive BCI demands surgery to implant electrodes beneath the scalp to communicate brain impulses. The key advantage is that it provides more precise readings; nevertheless, the disadvantage involves surgery-related adverse effects. Scar tissue may grow after surgery, making brain messages weaker. Furthermore, according to the findings of Abdulkader et al,. 2015. Invasive BCI research has concentrated on restoring damaged vision and delivering new capabilities to persons who are paralyzed. During neurosurgery, invasive BCIs are inserted directly into the grey matter of the brain. Invasive devices give the best quality signals of BCI devices since they lay in the grey matter, but they are prone to scar-tissue build-up, letting the signal to become weaker, or possibly non-existent, as the body reacts to a foreign substance in the brain (Polikov et al.,2005). Invasive BCIs emphasizing on motor neuroprosthetics intend to either restore movement in patients with paralysis or offer assistive devices such as computer interfaces or robot arms.

In May 2021, a Stanford University team announced a successful proof-of-concept test in which a quadriplegic participant was able to enter English phrases at a rate of roughly 86 characters per minute and 18 words per minute. The subject imagined moving his hand to make letters, and the system recognized handwriting based on electrical signals recorded in the motor cortex, decoding with hidden Markov models and recurrent neural networks (Will et al., 2021).

2.1.4 Deep dive in semi-invasive BCI

Semi-invasive BCI devices are implanted into the skull but do not reside within the grey matter. They create higher resolution signals than non-invasive BCIs in which the cranium's bone structure deflects and deforms signals and have a lesser risk of scar tissue formation in the brain than fully invasive BCIs. Intracortical BCIs from the stroke perilesional cortex have been demonstrated in preclinical studies (Gulati et al., 2015).

Endovascular

A thorough study released in 2020 documented several clinical and non-clinical investigations stretching back decades that investigated the viability of endovascular BCIs (Soldozy et al., 2020). The most significant advancement in partially invasive BCIs has occurred in the field of interventional neurology in recent years. In 2010, researchers at the University of Melbourne began working on a BCI that could be placed through the circulatory system (Martini et al., 2020). The idea for this BCI, named Stentrode, was invented by Australian neurologist Thomas Oxley (Mount Sinai Hospital) and funded by DARPA. The method was tested in preclinical experiments on sheep. The Stentrode, a monolithic stent electrode array, is intended to be given to the superior sagittal sinus through an intravenous catheter under imaging guidance, in the area close to the motor cortex (Opie et al., 2021). The Stentrode's capacity to assess brain activity is based on its closeness to the motor cortex. The operation is quite similar to the placement of venous sinus stents for the treatment of idiopathic intracranial hypertension (Teleb et al., 2014). The Stentrode transmits brain activity to a battery-free telemetry unit implanted in the chest, which connects wirelessly with a power and data transfer-capable external telemetry unit. While an endovascular BCI avoids craniotomy for implantation, complications like as coagulation and venous thrombosis are conceivable. Twenty mice implanted with Stentrode after 190 days revealed no signs of thrombus development, presumably due to endothelial integration of the Stentrode into the vessel wall. The Stentrode is undergoing first-in-human testing. Two participants with amyotrophic lateral sclerosis were able to wirelessly control an operating system to text, email, shop, and bank using direct thought through the Stentrode brain-computer interface in November 2020, marking the first time a brain-computer interface was implanted via the patient's blood vessels, eliminating the need for open brain surgery. Electrocorticography (ECoG) detects the electrical activity of the brain from beneath the skull in the same manner as non-invasive electroencephalography does, except that the electrodes are implanted in a thin plastic pad inserted above the cortex, beneath the dura mater (Serruya et al., 2004). Eric Leuthardt and Daniel Moran of Washington University in St Louis were the first to test ECoG technology on humans in 2004 (Fitzpatrick et al., 2006). In a later study, the researchers used an ECoG implant to allow a teenage male to play Space Invaders. According to this study, control is quick, takes little training, and may be an excellent balance between signal purity and invasiveness. Signals can be subdural or epidural, but they do not originate in the brain parenchyma. Due to the scarcity of participants, it was not thoroughly investigated until recently. Currently, the only way to obtain the signal for research purposes is to employ patients who require invasive monitoring for the location and excision of an epileptogenic focus. Because it has higher spatial resolution, a better signal-to-noise ratio, a wider frequency range, and fewer training requirements than scalp-recorded EEG, ECoG is a very promising intermediate BCI modality. It also has lower technical difficulty, lower clinical risk, and may have superior long-term stability than intracortical single-neuron recording (Fernando et al., 2020). This feature profile, as well as recent proof of high levels of control with little training needs, indicates the possibility for real-world use for persons with motor limitations (Pei et al., 2011; Yanagisawa et el., 2012). Light reactive imaging BCI systems are currently in the theoretical stage. Recent research by UCSF's Edward Chang and Joseph Makin found that ECoG signals might be utilized to decipher speech from epilepsy patients implanted with high-density ECoG arrays across the peri-Sylvian cortices (Makin et al., 2020). Using an encoder-decoder neural network, they obtained word error rates of 3% (a significant improvement over previous studies).

2.1.5 Deep dive in non-invasive BCI

The simplest and least intrusive approach is a series of electrodes placed to the scalp, known as an electroencephalograph (EEG). Brain impulses may be read by the electrodes. The essential mechanism is the same regardless of where the electrodes are placed: The electrodes detect minute voltage changes between neurons. After that, the signal is amplified and filtered. It is then processed by computer software in contemporary BCI systems, which displays the signals via pens that automatically write out the patterns on a continuous sheet of paper. Even though the skull blocks much of the electrical signal and distorts what does pass through, it is more acceptable than the other varieties due to its various shortcomings.

Non-invasive BCI approaches have lower signal clarity since the devices are put on the surface and are safe. The emphasis in this survey is mostly on non-intrusive approaches. The primary objective for this effort is to investigate the viability of simple human physiological illness diagnostics. Table 1 covers the many non-invasive devices.

There are different types of EEG devices available on the market, each with its own set of characteristics such as the number of electrodes, cost, and purpose, therefore EEG may be used to forecast psychiatric disorders. We can also forecast physiological illness with this gadget by recording brain signals. These signals can be forwarded to an expert doctor in a city for diagnosis (Veena et al., 2020).

2.2 Basic concept behind brain waves

Brain waves are rhythmic electrical voltages in the brain that are only a few millionths of a volt in magnitude. The primary frequencies of humans are represented by five commonly recognized brain waves. Different parts of the brain do not emit the same brain wave frequency at the same time. An EEG signal between electrodes implanted on the scalp is made up of several distinct waves. The huge amount of data obtained from even a single EEG recording complicates interpretation. All person's brain wave patterns are distinct (Abhang et al., 2016)

2.2.1 Idea of brain waves

Brain data are pre-processed by using temporal filters to pick the exact EEG sub frequency bands that contain the neuro signals of interest. A brain-computer interface collecting EEG motor rhythms, for example, is often intended to catch mu and beta oscillations in the 8-30 Hz frequency range. To choose the correct frequency band, a band-pass temporal filter must be created. Temporal filters are also used to reject power-line interference and scalp electrode polarization distortions.

The temporal filters are implemented using three techniques:

• finite impulse response (FIR) filters

• infinite impulse response filters (IIR), and so forth.

By deleting any DFT coefficients that do not match frequencies of interest, the DFT may be successfully utilized to filter long-duration brain signals. The step-by-step approach is depicted in the flowchart as shown in . The DFT on the input EEG signal s(n) is conducted first as shown in figure 1. The DFT S (f) of an input EEG signal s (n) is computed as the sum of N samples at various frequencies f. Filtering is accomplished by eliminating undesired filter coefficients. To retrieve the filtered EEG signal, the signal is transformed back into the time domain using inverse DFT. To achieve the necessary filtering, a quick calculation technique known as FFT can be used (Birvinskas et al., 2013).

Temporal filtering may also be accomplished by employing FIR and IIR filters. The nonrecursive FIR filters use the last M input samples of a recorded EEG signal s(n) to generate a filtered EEG signal $s(n)_{FIR}$, as shown below:

$$S(n)_{FIR} = \sum_{k=0}^{M-1} (a_k s(\mathrm{n}-\mathrm{k}))$$

Where $\{a_k\}$ denotes the filter coefficients.

Similarly, recursive IIR filters may be created by using the latest N output samples as well as the last M input samples of a raw EEG signal, as shown below:

$$S(n)_{IIR} = \sum_{k=0}^{M-1} (a_k s(\mathrm{n}-\mathrm{k})) + \sum_{k=1}^{N-1} (b_k s(\mathrm{n}-\mathrm{k})) IIR$$

Where $\{a_k\}$ and $\{b_k\}$ are the filter coefficients IIR filters are capable of conducting filtering operations with a smaller number of filter coefficients than FIR filters (Smith, 1999) (Bansal et al., 2019).

2.2.2 Classification of brain waves

As we know there are widely known five basic brain waves. The characteristics of these basic brain waves are:

2.3 Deep Learning and Neural Network in BCI's

Deep learning (also known as deep structured learning) is a machine learning approach that is based on artificial neural networks and representation learning. Learning can take place under supervision, semi-supervised, or unsupervised (LeCun et al., 2015).

Deep-learning architectures such as deep neural networks, deep belief networks, deep reinforcement learning, recurrent neural networks, convolutional neural networks, and Transformers have been applied to fields such as computer vision as shown in figure 2, speech recognition, natural language processing, machine translation, bioinformatics, drug design, medical image analysis, climate science, material inspection, and board game programs, producing results comparable to and exceeding human expert skill in certain circumstances (Ciregan et al., 2012).

Artificial neural networks (ANNs) were motivated by biological information processing and distributed communication nodes. ANNs vary from biological brains in a variety of ways. Artificial neural networks, in particular, are static and symbolic, whereas the organic brain of most living species is dynamic (plastic) and analog (Marblestone et al., 2016).

2.3.1 Deep learning an overview

Deep learning is a type of machine learning method (Deng et al., 2013) that employs numerous layers to extract higher-level characteristics from raw input. In image processing, for example, lower layers may recognize boundaries, while higher layers may identify concepts meaningful to humans, such as digits, characters, or faces.

Each level of deep learning learns to turn the incoming data into a little more abstract and composite representation. The raw input in an image recognition application could be a matrix of pixels; the first representational layer could abstract the pixels and encode edges; the second layer could compose and encode arrangements of edges; the third layer could encode a nose and eyes; and the fourth layer could recognize that the image contains a face. Importantly, a deep learning process can figure out which traits belong at which level on its own. This does not exclude hand-tuning; for example, adjusting the number of layers and layer widths might yield variable degrees of abstraction (Bengio et al., 2013).

The term "deep" refers to the number of layers through which the data is changed. Deep learning systems, in particular, have a significant credit assignment path (CAP) depth. The CAP is the transformation chain from input to output. CAPs are used to represent possibly causative relationships between input and output. The depth of the CAPs in a feedforward neural network equals that of the network and is the number of hidden layers plus one (as the output layer is also parameterized). For recurrent neural networks, where a signal may pass through a layer several times, the CAP depth is theoretically infinite.There is no widely agreed-upon depth threshold that distinguishes shallow learning from deep learning, however most scholars believe that deep learning requires CAP depth greater than 2. It has been demonstrated that CAP of depth 2 is a universal approximator in the sense that it can simulate any function. More layers do not improve the network's function approximator capability. Deep models (CAP > 2) extract better features than shallow models, hence more layers aid in learning the features successfully.

2.3.2 Deep learning categories

As mentioned in the overview deep learning has some categories. Those are respectively deep neural networks, deep belief networks, deep reinforcement learning and Transformers.

An artificial neural network (ANN) having numerous layers between the input and output layers is known as a deep neural network (DNN). (Sugiyama et al., 2019) Different types of neural networks exist, but they all have the same components: neurons, synapses, weights, biases, and functions. These components work together to behave similarly to the human brain and may be trained in the same way as any other ML algorithm. A deep belief network (DBN) is a type of deep neural network built of numerous layers of latent variables ("hidden units"), with connections between the levels but not between units within each layer, in machine learning. A DBN may learn to probabilistically recreate its inputs when trained on a set of instances without supervision. The layers are then used to detect features. Following this learning stage, a DBN may be trained to do classification under supervision.

Deep reinforcement learning is a machine learning area that combines reinforcement learning with deep learning. The challenge of a computer agent learning to make judgments through trial and error is addressed by RL. Deep RL adds deep learning into the system, allowing agents to make decisions based on unstructured input data without the need for manual state space engineering. Deep RL algorithms can process very massive inputs (for example, every pixel presented to the screen in a video game) and select what actions to take to optimize an objective (e.g. maximizing the game score). Deep reinforcement learning has been applied in a variety of applications such as robots, video games, natural language processing, computer vision, education, transportation, finance, and healthcare.

A transformer is a deep learning model that uses the self-attention mechanism to weigh the relevance of each element of the input data differently. It is mostly utilized in natural language processing (NLP) and computer vision (CV) (Hilton et al., 2006).

2.3.3 Neural network in deep learning

An artificial neural network (ANN) having numerous layers between the input and output layers is known as a deep neural network (DNN). (Schmidhuber et al., 2015) Different types of neural networks exist, but they all have the same components: neurons, synapses, weights, biases, and functions. (Gavrilova et al., 2020)These components work together to behave similarly to the human brain and may be trained in the same way as any other ML algorithm. A DNN trained to detect dog breeds, for example, will run through a given image and compute the likelihood that the dog in the image is of a specific breed. The user may examine the findings and choose which probability the network should reveal before returning the recommended label. Each mathematical manipulation is considered a layer in and of itself, and sophisticated DNN have several layers, therefore the moniker "deep" networks (Hardesty et al., 2017).

2.3.4 Classification of Neural Network

In classification of neural networks, we can clearly see that there are three types: Artificial Neural networks (ANN), Recurrent Neural networks (RNN), and Convolutional Neural networks (CNN).

Artificial neural networks (ANNs), also known as neural networks (NNs) or neural nets, are computer systems that are inspired by the biological neural networks that comprise animal brains. (Yang et al., 2014) An ANN is built from a network of linked units or nodes known as artificial neurons, which are roughly modeled after the neurons in the human brain. Each link, like synapses in a human brain, can send a signal to other neurons. An artificial neuron receives impulses, analyses them, and can signal neurons to which it is linked. Each neuron's output is generated by some non-linear function of the sum of its inputs, and the "signal" at a connection is a real number. The connections are referred to as edges (Abidun et al., 2018). Neurons and edges usually have a weight that changes as learning progresses. The weight changes the intensity of the signal at a connection. Neurons may have a threshold that causes a signal to be transmitted only if the aggregate signal passes it. Neurons are often organized into layers. Different layers may apply various modifications to their inputs. Signals go from the first layer (the input layer) to the last layer (the output layer), sometimes many times.

A recurrent neural network (RNN) is a type of neural network in which node connections can form a cycle, allowing output from one node to influence future input to the same node. This enables it to display temporal dynamic behavior. RNNs, which are derived from feedforward neural networks, can handle variable length sequences of inputs using their internal state (memory), (Abiodun et al., 2018). As a result, they may be used for tasks like unsegmented, linked handwriting recognition or speech recognition (Graves et al., 2008). Recurrent neural networks are Turing complete in theory and may execute arbitrary algorithms to handle arbitrary sequences of inputs (Hyotyniemi et al., 1996).

A convolutional neural network (CNN) is a type of neural network (ANN) that is often used to evaluate visual information (Valueva et al., 2020). CNNs are also known as Shift Invariant or Space Invariant Artificial Neural Networks (SIANN), since they are based on the shared-weight architecture of convolution kernels or filters that slide along input features and give translation-equivariant outputs known as feature maps (Zhang et al., 1990). Because of the downsampling procedure used on the input, most convolutional neural networks are not translation invariant (Mouton et al., 2020). Image and video recognition, recommender systems, image classification, image segmentation, medical image analysis, natural language processing, brain-computer interfaces (Avilov et al., 2020), and financial time series are all used.

2.4 Emotion Recognition Using Neural Network

As we have seen that neural networks are of three types, we specify it down to our research topic for emotion recognition using EEG signals through neural networks.

In a neural network, EEG data signal is taken as input data and it is pre-processed, and then with some mathematical equations applied feature is extracted. Then the data goes for training by splitting the data into train test splitting. While training it makes some hidden layers inside the model and evaluates the data with the test data if those matches accuracy seems to be high else accuracy seems to be low.

2.4.1 Emotion recognition using CNN & LSTM's

First, the characteristics collected from the original EEG data are transferred to the CNN. There are numerous convolution-pooling layer pairings and one output layer in the CNN model. Features are concatenated into picture form before being sent to the CNN, where they are convolved with many one-dimensional filters in convolution layers. Following the pooling layer, the data is further subsampled to produce pictures of a lower size. The back-propagation technique is used to train network weights and filters in the convolution layers.

The input to these models is an array of size (1080, 64, 1440), where 1080 is the number of trials, 64 is the number of channels per trial, and 1440 is a combination of the other dimensions in the dataset. For each trial, we have a 64 × 1440 input matrix:

$$x = \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,1440} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,1440} \\ \cdots & \cdots & \cdots & \cdots \\ x_{64,1} & x_{64,2} & \cdots & x_{64,1440} \end{pmatrix}$$

Then Convolution filters W given by:

$$W_k = (W_1, W_2, W_3)$$

Where k = 128 (kernel size of 3 with 128 filters). After applying the filters to the input matrix, obtains an output:

$$\alpha = W_k * x + b_k$$

Where b_k represents the bias values. Because each filter operates on each channel, shifting to the right as it convolves across the channel, the convolution is one-dimensional, rather than on the full input matrix. It is then sent to a Max Pooling layer, which takes the maximum value across all windows. ReLU = max was the activation function employed (0, x). Adam was the optimizer that was utilized. The loss function used sparse categorical cross-entropy, given by:

$$\text{loss} = \sum_{n=1}^{N} \widehat{y_{i1}} \log(y_{i1}) + \widehat{y_{i2}} \log(y_{i2}) + \widehat{y_{i3}} \log(y_{i3}) + \widehat{y_{i4}} \log(y_{i4})$$

Finally, the 3d convolutional layer is being called, and the channels span across both the dimensionality reductions and the frequency bands.

Whereas LSTM is a type of recurrent neural network(RNN). The layers in this neural network contain a huge number of processing units called cells which take activation from the previous cell a^{t-1} and the output is calculated in the:

$$a^t = \sigma(w_{aa} a^{t-1} + w_{ax} x^t + b_a)$$

$$y^t = \tan h\,(w_{ya} a^t + b_y)$$

LSTMs are a version of RNNs that give a solution to the vanishing gradient issue [49], where each cell includes weights w_{aa}, w_{ax}, w_{ya}, and biases. Each LSTM cell has a state c. At timestamp t, a candidate for the cell state is represented by:

$$c'^t = \sigma(w_c[a^{t-1}, x^t] + b_c)$$

LSTMs contain three core gates that allow them to forget, update, and output information as needed, overcoming RNNs' vanishing gradient problem. The forget, update, and output gates are calculated as follows:

$$\Gamma_f = \sigma(w_f[a^{t-1}, x^t] + b_f)$$

$$\Gamma_u = \sigma(w_u[a^{t-1}, x^t] + b_u)$$

$$\Gamma_o = \sigma(w_o[a^{t-1}, x^t] + b_o)$$

The cell state and activation are then calculated:

$$c^t = \Gamma_u c'^t + \Gamma_f c^{t-1}$$

$$a^t = \Gamma_o \tanh(c^t)$$

The LSTM utilized has 100 cells, a thick layer of 128 neurons following the LSTM layer with ReLU activation, and Adam and Sparse Categorical Crossentropy.

2.4.2 Emotion Recognition using ANN

A perceptron is a basic artificial neuron with an input and output layer. This neuron contains two functions: Summation function and Activation function.

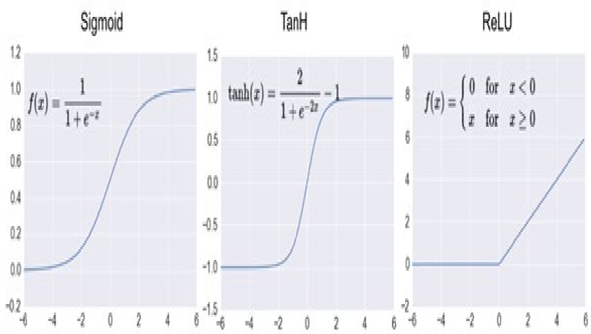
The inputs given to a perceptron are processed by the summation function and followed by the activation function to get the desired output as shown in figure 3.

This is a primitive perceptron, however with multiple inputs and large amounts of data, a single perceptron is insufficient. We must continue to grow the number of neurons. Here's a basic neural network with an input layer, a hidden layer, and an output layer. It's important to understand that while a neural network has a single input and output layer, it may also have several hidden layers. The example neural network shown above has one input layer, two hidden layers, and one output layer as shown in figure 4.

Activation Function

Because we employ a backpropagation approach to decrease error and update the weights, any activation function should be differentiable.

Types of activation function



Sigmoid

1. Ranges from 0 to 1.
2. A small change in x would result in a large change in y.
3. Usually used in the output layer of binary classification.

Tanh

1. Ranges between -1 and 1.
2. Output values are centered around zero.
3. Usually used in hidden layers.

RELU (Rectified Linear Unit)

1. Ranges between 0 and max(x).
2. Computationally inexpensive compared to sigmoid and tanh functions.
3. Default function for hidden layers.
4. It can lead to neuron death, which can be compensated by applying the Leaky RELU function.

Working of Neural Network

Artificial neural network works based on two principles.

1. Forward Propagation as shown in figure 5.
2. Backward Propagation

Forward Propagation

1. Assume we have data and want to use binary classification to acquire the desired result.
2. Consider a sample with attributes X1, X2, and these features will be run through a series of procedures to predict the outcome.
3. Each characteristic is paired with a weight, with X1, X2 representing features and W1, W2 representing weights. These serve as input to neurons.
4. Both functions are carried out by a neuron. a) Summation b) Activation
5. All characteristics are multiplied by their weights and the bias is added up in the summation. (Y=W1X1+W2X2+b).
6. This summing function is used in conjunction with an Activation function. This neuron's output is multiplied by the weight W3 and sent as input to the output layer.
7. The identical mechanism occurs in each neuron, although the activation functions in hidden layer neurons differ from those in the output layer.

Backward Propagation

Let us return to our calculus foundations and update the weights using the chain rule we learnt in school.

Chain Rule

The chain rule gives a method for computing the derivative of composite functions, with the number of functions in the composition dictating the number of differentiation steps required as shown in figure 6. For instance, if a composite function f(x) is defined as

$$f(x) = (g \circ h)(x) = g[h(x)]$$
$$then\ f'(x) = g'[h(x)]\,.\,h'(x)$$

Applying the chain rule to a single neuron,

Our major aim in neural networks will be to reduce error, and to accomplish so, we must update all of the weights via backpropagation. We need to identify a weighting modification that will result in the least amount of inaccuracy as shown in figure 7. To do this, we compute $\frac{dE}{dW1}$ and $\frac{dE}{dW2}$.

Considering

$$S\ (Summation) = x1W1 + x2W2$$
$$A\ (Activation) = sigmoid = \frac{e^x}{(1+e^x)}$$

Using Chain Rule

$$\frac{dE}{dW1} = \frac{dE}{dA} * \frac{dA}{dS} * \frac{dS}{dW1}$$
$$\frac{dE}{dW2} = \frac{dE}{dA} * \frac{dA}{dS} * \frac{dS}{dW2}$$

Table 1. Overview of Non-Invasive Methods for Brain Activity Monitoring

Sl no.	Non-Invasive Method	Description
1	EEG	Electrical signals are recorded using flat metal discs
2	MEG	Magnetic fields are recorded using the neuroimaging method
3	fMRI	Measures the variation of blood oxygen level during brain activities
4	PET	Imaging technique used to observe the metabolic process in the body
5	fNIRS	Near-infrared spectroscopy uses the electromagnetic spectrum to diagnose physiological diseases
6	fMEG	Study of brain activity of fetus in the uterus
7	SPECT	Neuro tomographic imaging which is based on gamma rays

Table 2. Relationship between different frequency bands of brain activity, their corresponding frequency ranges, and associated brain states.

Frequency band	Frequency	Brain states
Gamma(γ)	>35 Hz	Concentration
Beta(β)	12-35 Hz	Anxiety-dominant, active, external attention, relaxed
Alpha(α)	8-12 Hz	Very relaxed, passive attention
Theta(θ)	4-8 Hz	Deeply relaxed, inward-focused
Delta(δ)	0.5-4 Hz	Sleep

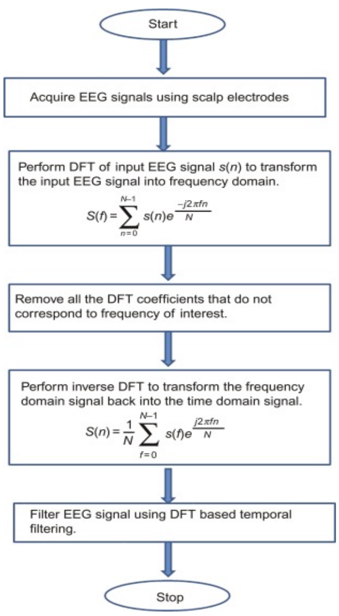


Figure 1. Flowchart of EEG waves step by-step approach.

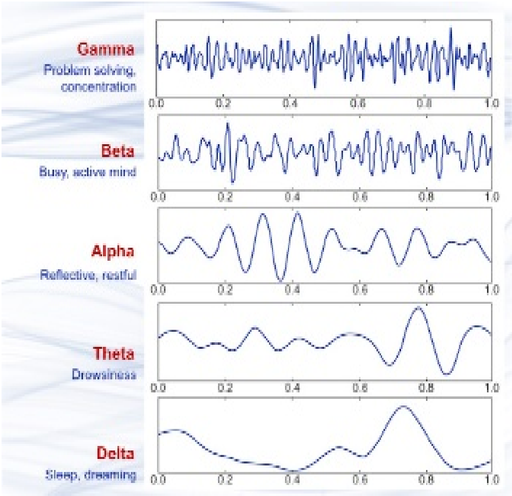


Figure 2. Brain wave samples with dominant frequencies belonging to beta, alpha, theta, and delta bands and gamma waves

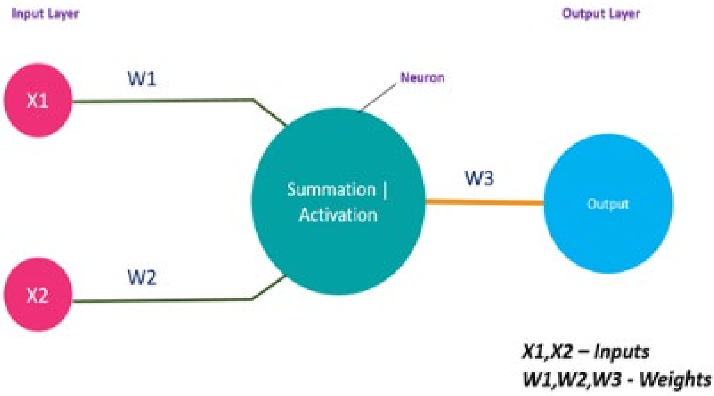


Figure 3. Perceptron

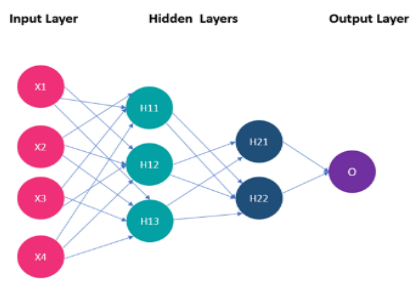


Figure 4. Neural Network

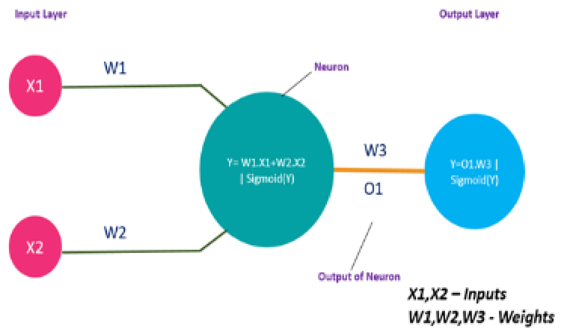


Figure 5. Forward Propagation

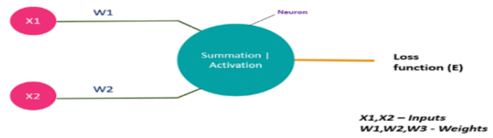


Figure 6. Chain Rule

Figure 7. Forward and Backward propagations.

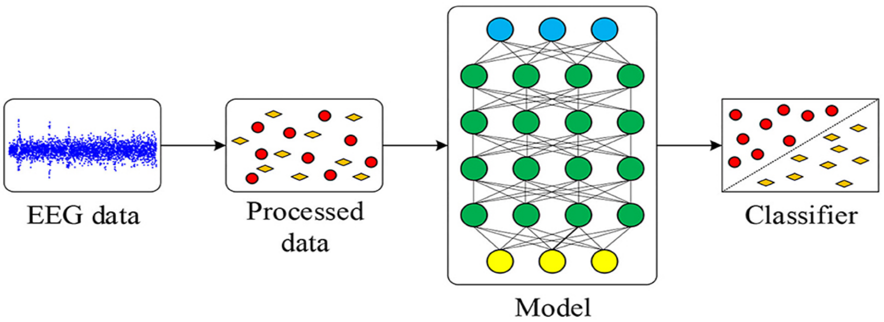


Figure 8. Emotion recognition procedure.

After calculating changes in weights for error, we will update the weights using the gradient descent process.

$$W1new = W1old - \eta \frac{dE}{dW1}$$
$$W2new = W2old - \eta \frac{dE}{dW2}$$

For all samples, forward and backward propagation will be continuous until the error achieves a minimal value.[50]

3. Methodology

The processes or strategies used to find, select, process, and analyze information on a topic are referred to as research methodology. The methodology portion of a research paper helps the reader to examine the overall validity and reliability of the study objectively. The methods section provides solutions to two major questions: How was the information gathered or generated? How was it examined? And in this section, I detailed my study's research technique. First, I explained how I restricted my study topic. The time frame for my investigation was then given. Following that, I detailed how I gathered the relevant data for my investigation. Finally, I discussed some of the limits I encountered throughout my research, followed by data analysis.

3.1 Narrowing down the study topic

Brain-Computer Interface is a significant component of Medical Science and Technology. Because this problem is so vast, many businesses are tackling it piecemeal. So, it goes without saying, I had to narrow down the topic for my thesis. In my thesis, Brain Computer Interface in the Context, I essentially expressed an interest in identifying emotions via brain signals utilizing electronic components. After briefly exploring advanced planning and implementation methods of identifying EEG via computer, I decided to focus my future research on Neural Networks.Brain-computer interface (BCI) is a futuristic concept that we require in all disciplines. Recently, researchers have shown an interest in using BCI to control objects directly using brain signals rather than electrical equipment. Many successful studies are making people's lives easier than in the past. I picked emotion identification using EEG signals via neural networks as a component of advanced BCI. This research will assist gadgets in more precisely recognizing EEG signals and processing data.

3.2 Time Schedule

This study lasted three months. I had split the three months into three sections. The initial stage was evaluating literature, briefly studying BCI, and narrowing down the topic. The second phase involved gathering all of the essential data. The third step is for data analysis and report writing.

3.3 Data Sources

We studied Brain-Computer Interface in a variety of formats. Our data sources included books, journals, research papers, news items, and numerous websites. Before narrowing down my topic, my major resources were books and periodicals. I dug deep into advanced materials after I had narrowed down my topic. My advanced study materials included specific research papers, scholarly publications, corporate websites, and news stories.

3.4 Data Analysing

The primary focus of my thesis was data analysis. So, after picking a few papers and articles, I began comparing and merging those dates and findings till I arrived at a good outcome that I could recommend for implementation.

3.5 Limitations

This section discusses the difficulties I encountered while working on my thesis. The constraints of a study are those elements of design or technique that affect or influence the interpretation of the research findings. They are the limitations on generalizability, application to practice, and utility of findings that are the result of how the researcher initially chose to design the study, the method used to establish internal and external validity or the result of unanticipated challenges that emerged during the study. During my study, I encountered a lot of constraints. The primary difficulty I had was in gathering data for this thesis. This section briefly discusses the drawbacks.

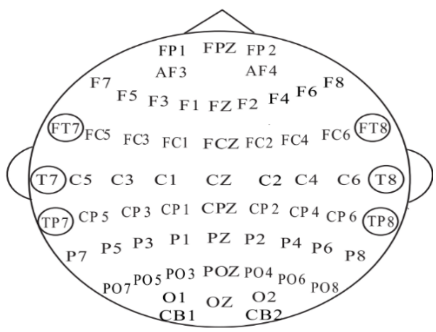
1. It was difficult to learn about my thesis initially since I had not taken any particular course on the subject. 2. There was less scope to discuss on emotion recognition using EEG signals in Bangladesh that I might have utilized to improve my evaluation.

4. General Findings

In this chapter, we will discuss the dataset the experiment, and the results. How the dataset was pre-processed and features were extracted. Then what do we get the result from the experiment and compare and criticize the previous experiment?

4.1 About the SEED-IV dataset

SEED-IV, a publicly available dataset, was used in this study. Film snippets were employed by the researchers to induce certain emotions in individuals. The individuals were then asked to categorize their emotions while watching the clips into one of four distinct groups (happy, sad, neutral, or fear). Each individual took part in three sessions of emotion classification, with each session consisting of 24 trials (6 per emotion). There was a total of 15 people in attendance. Furthermore, as indicated below, the researchers employed 62 EEG channels dispersed across the brain as shown in figure 8.



4.2 Preprocessing & feature extraction

Each session is divided into nonoverlapping 4-second chunks. During model training, each segment is treated as a single data sample done by the main researchers of the seed-iv dataset (Liu et al., 2020).

The raw EEG data is initially downsampled to a sampling rate of 200 Hz before being processed. The EEG data is then processed using a bandpass filter between 1 Hz and 75 Hz to eliminate noise and artifacts. Following that, we extract power spectral density (PSD) and differential entropy (DE) characteristics from each segment at five distinct frequency bands: 1) delta is 14 Hz, 2) theta is 48 Hz, 3) alpha is 814 Hz, 4) beta is 1431 Hz, and 5) gamma is 3150 Hz (Hochreiter et al., 1997). The computation of a random variable x's PSD and DE Image that is responsive

$PSD = E[x^2]$

$$DE = -\int_{-\infty}^{\infty} P(x)\ln\big(P(x)\big)dx$$

The EEG signals are assumed to have a Gaussian distribution: $x \sim N(\mu, \sigma^2)$ Then, the calculation

$$DE = -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma}} exp\frac{(x-\mu)^2}{2\sigma^2} \ln\left(\frac{1}{\sqrt{2\pi\sigma}} exp\frac{(x-\mu)^2}{2\sigma^2}\right)dx$$
$$= \frac{1}{2}\ln 2\pi e\sigma^2$$

I employed a mix of feature-extracted and dimensionality-reduced data to arrange the data into a manner appropriate for training deep neural networks. The original researchers used two feature extraction techniques and two dimensionality reductions each trial, yielding four features: **de-MovingAve**, **de-LDS**, **psd-MovingAve**, and **psd-LDS**. Each combination produced an array with the dimensions (8, 9, 5, 64), which represented the 8 9 channel positions on the skull, 5 frequency bands per channel, and 64 timestamps per frequency band. Concatenating the four feature sets resulted in an array with the dimensions (4, 8, 9, 5, 64) in each trial. Our total dataset size was 1080 trials (15 people, 72 trials for each participant) (1080, 4, 8, 9, 5, 64)

Furthermore, each trial was labeled depending on the emotion produced, with 0 representing neutral, 1 representing sad, 2 representing fear, and 3 representing happiness, yielding a matching array of labels with size 1080.

4.3 Experimental Result

We divided the processed SEED-IV dataset into two parts: training and validation. Furthermore, models were trained inside the training set using cross-validation (Gajawada et al., 2019). The spatial dimensions of all models were flattened onto the channel axis. Outside of the cross-validation dataset, we present the models' final validation accuracy. Because this is a classification task, we use the straightforward metric of classification accuracy, noting that a rudimentary model may obtain a 25% accuracy with four categories. On the dataset, our models achieved the following validation set accuracy (n = 216). We get a training accuracy of 78.125% and a test accuracy of 63.425 %.

We note that a recent article reported the highest performing accuracy of 70.33% on this dataset, we get the third-best accuracy of 63.425%. These models employ generative architectures that do not employ spatial convolution across electrode placement. As a result, we can observe that a straight ANN with the 3dconv method performs well on the dataset. We observe that the training accuracy of our highest-performing model was only around 7% higher, however as previously noted, the model employs aggressive strategies to counteract overfitting (Zheng et al., 2018).

We should mention that the dataset takes feature labels into account (neutral, happy, sad, fear). More context may probably be accessible in potential brain-computer interface application areas, and so accuracy at this level for a very simple model signals promise.

5. Conclusion

In this study, we explored emotion recognition using EEG signals through deep learning models, focusing on neural networks such as CNN, LSTM, and ANN. Utilizing the SEED-IV dataset, we pre-processed EEG signals and extracted features like power spectral density and differential entropy across multiple frequency bands. The CNN-LSTM hybrid model showed promising results in classifying emotions into categories such as happy, sad, fear, and neutral, leveraging convolutional layers for spatial pattern detection and LSTMs for temporal dependencies. The findings emphasize the potential of neural networks in advancing brain-computer interface (BCI) technologies for emotion recognition. However, challenges like data variability and model generalization remain. Future research should aim to improve model accuracy and robustness by integrating more diverse datasets and exploring alternative neural network architectures. This could further enhance emotion-based applications in healthcare, education, and human-computer interaction.

Author contributions

T.A.L. conceptualized the project and developed the methodology. P.R.G. conducted a formal analysis, and drafted the original writing and contributed to the methodology, conducted investigations, provided resources, visualized the data. H.M.A contributed to the reviewing and editing of the writing

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Competing financial interests

The authors have no conflict of interest.

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