A STUDY OF RECOGNISING HUMAN EMOTIONS BASED ON ELECTROENCEPHALOGRAPHY SIGNALS THROUGH BRAIN COMPUTER INTERFACE USING DEEP LEARNING

Dr.Devireddy Srinivasa Kumar
Professor, Department of CSE, Malineni Lakshmaiah Women's Engineering College, Guntur, AP, India

ABSTRACT
Emotions of human are an essential part of day to day human communication. The emotional states and dynamics of the human brain can be captured by electroencephalography (EEG) signals. These signals can be used as Brain–Computer Interface (BCI), to provide better human–machine interactions. Several studies have been conducted in the field of emotion recognition. However, one of the most important issues facing the emotion recognition process, using electroencephalography EEG signals, is the accuracy of recognition. This paper proposes a deep learning-based approach for emotion recognition through EEG signals, which includes data selection, feature extraction, feature selection and classification phases. To bridge the communication barrier and improve mobility for individuals who struggle to understand emotions, this paper presents a novel solution. A deep learning algorithm capable of recognizing and interpreting emotions from Electroencephalography EEG signals. This paper addresses a crucial challenge in improving the quality of life for affected individuals. By harnessing the power of EEG data analysis, the aim is to enhance their ability to engage with the world and others. In this study, a standard pre-processed Database of Emotion Analysis using Physiological signaling (DEAP) was used in this work.We trained and tested the algorithm, and found that the CNN model had the highest accuracy of 92%. These results demonstrate the feasibility of using EEG signals to accurately recognize human emotions.

KEYWORDS : Electroencephalography, Emotion, Brain Computer Interface, Galvanic Skin Response, Autonomic Nervous System, Heart Rate,

INTRODUCTION:
A brain computer interface (BCI) is a system that lets you control a computer with your thoughts. The basic idea is to use technology to read your brainwaves and interpret what you're thinking. Then, the computer can do what you want it to do.

Brain-Computer Interfaces (BCIs) are currently in their nascent phase of development, yet their potential to transform our interaction methods is immense technology. There are a few different ways to build a BCI. One is to use electrodes that are implanted in the brain. Another is to use sensors that sit on the surface of the skull. The most common way to measure brainwaves is with an electroencephalography (EEG). EEGs measure the electrical activity of the brain and are often used in research. BCI research is ongoing, and several different applications are being explored.

It has been possible to identify the kind of sensations that are hiding beneath the surface using a variety of methods and techniques, such as: Due to its reliable results, Electroencephalography (EEG) is widely used in the field of emotion recognition (ER) from facial expression, voice intonation, and signal from the Autonomic Nervous System (ANS) like heart rate and Galvanic Skin Response (GSR). It is also widely used because it is simple to record and reasonably priced. Emotion classification from EEG waves requires some techniques and procedures. One of these processes involves recording and then pre-processing raw signals. After cleaning up the dataset and organizing the data, the best feature is extracted and evaluated using machine Learning or deep learning techniques.

Step by step machine learning with end to end deep learning are the two primary machine learning approaches for EEG signal analysis. ML also known as conventional machine learning is characterized by its sequential nature, with the three primary stages consisting of pre-processing, feature extraction, and feature categorization using machine learning algorithms. However, it's hard to keep up with manual extraction, and the equations for (TD and FD) are full of complexity and noise (such as electromyography), so machine learning techniques are dubious. To get around this, researchers turned to deep learning, which favours an end-to-end approach.

Methods and Materials

Human Emotion Recognition: Review of Sensors and Methods by Andrius Dzedzickis, Artūras Kaklauskas, Vytautas Bucinskas [1] stated that Automated emotion recognition (AEE) is an important issue in various fields of activities which use human emotional reactions as a signal for marketing, technical equipment, or human–robot interaction. This paper analyzes scientific research and technical papers for sensor use analysis, among various methods implemented or researched. This paper covers a few classes of sensors, using contactless methods as well as contact and skin-penetrating electrodes for human emotion detection and the measurement of their intensity. The results of the analysis performed in this paper present applicable methods for each type of emotion and their intensity and propose their classification. The classification of emotion sensors is presented to reveal area of application and expected outcomes from each method, as well as their limitations. This paper should be relevant for researchers using human emotion evaluation and analysis, when there is a need to choose a proper method for their purposes or to find alternative decisions. Based on the analyzed human emotion recognition sensors and methods, we developed some practical applications for humanizing the Internet of Things (IoT) and affective computing systems.

Emotion Perception from Face, Voice, and Touch: Comparisons and Convergence, Annett Schirmer, Ralph Adolphs [2] stated that Historically, research on emotion perception has focused on facial expressions, and findings from this modality have come to dominate our thinking about other modalities. Here we examine emotion perception through a wider lens by comparing facial with vocal and tactile processing. We review stimulus characteristics and ensuing behavioral and brain responses and show that audition and touch do not simply duplicate visual mechanisms. Each modality provides a distinct input channel and engages partly non overlapping neuroanatomical systems with different processing specializations (e.g., specific emotions versus affect). Moreover, processing of signals across the different modalities converges, first into multi- and later into a modal representation that enable holistic emotion judgments.

Arousal Effects on Pupil Size, Heart Rate, and Skin Conductance in an Emotional Face Task, Chin-An Wang at all (2018) [3] stated that Arousal level changes constantly and it has a profound influence on performance during everyday activities. Fluctuations in arousal are regulated by the autonomic nervous system, which is mainly controlled by the balanced activity of the parasympathetic and sympathetic systems, commonly indexed by heart rate (HR) and galvanic skin response (GSR), respectively. Although a growing number of studies have used pupil size to indicate the level of arousal, research that directly examines the relationship between pupil size and HR or GSR is limited. The goal of this study was to understand how pupil size is modulated by autonomic arousal. Human participants fixated various emotional face stimuli, of which low-level visual properties were carefully controlled, while their pupil size, HR, GSR, and eye position were recorded simultaneously. We hypothesized that a positive correlation between pupil size and HR or GSR would be observed both before and after face presentation. Trial-by-trial positive correlations between pupil diameter and HR and GSR were found before face presentation, with larger pupil diameter observed on trials with higher HR or GSR. However, task-evoked pupil responses after face presentation only correlated with HR. Overall, these results demonstrated a trial-by-trial relationship between pupil size and HR or GSR, suggesting that pupil size can be used as an index for arousal level involuntarily regulated by the autonomic nervous system.

Neural Decoding of EEG Signals with Machine Learning: A Systematic Review, Saeidi,M., Karwowski, W.,Farahani,F.V., Fiok,K.,Taiar, R.,Hancock. P. A., & Al-Juaid, A. (2021)[4] stated that Electroencephalography (EEG) is a non-invasive technique used to record the brain's evoked and induced electrical activity from the scalp. Artificial intelligence, particularly machine learning (ML) and deep learning (DL) algorithms, are increasingly being applied to EEG data for pattern analysis, group membership classification, and brain-computer interface purposes. This study aimed to systematically review recent advances in ML and DL supervised models for decoding and classifying EEG signals. Moreover, this article provides a comprehensive review of the state-of-the-art techniques used for EEG signal preprocessing and feature extraction. To this end, several academic databases were searched to explore relevant studies from the year 2000 to the present. Our results showed that the application of ML and DL in both mental workload and motor imagery tasks has received substantial attention in recent years. A total of 75% of DL studies applied convolution neural networks with various learning algorithms, and 36% of ML studies achieved competitive accuracy by using a support vector machine algorithm. Wavelet transform was found to be the most common feature extraction method used for all types of tasks. We further examined the specific feature extraction methods and end classifier recommendations discovered in this systematic review.

SYSTEM DESIGN: The system is designed with the following modules. Signal Acquisition module, Data Segmentation module, preprocessing module, Feature extraction module, Feature fusion module, classification module.

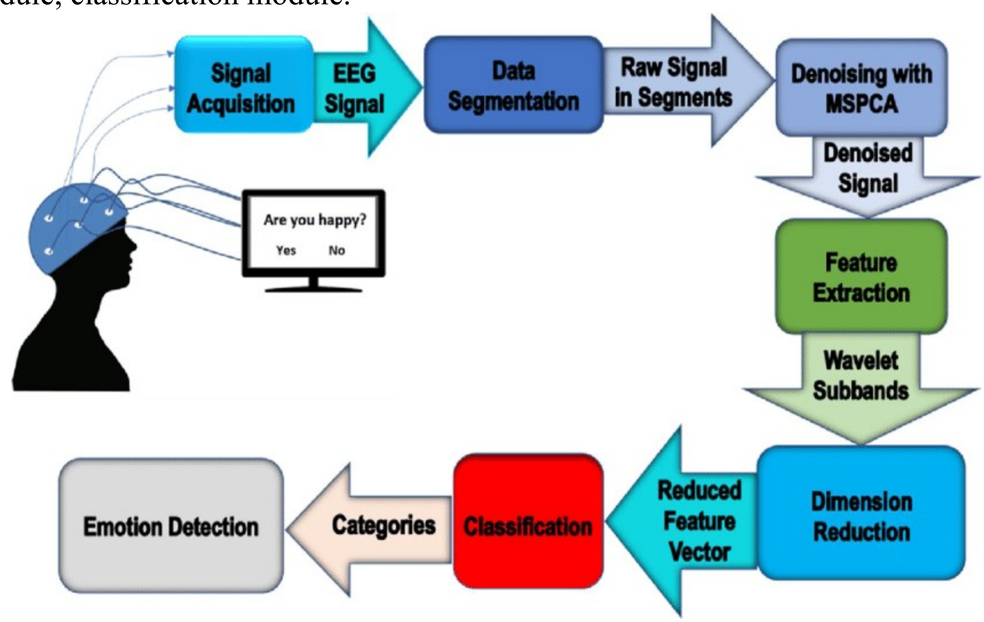

Fig 1) System Architecture

Signal Acquisition: EEG signals are normally acquired using a differential amplifier. This is a component that measures small electrical potential difference between two points and then amplifies several times that potential for recording. A dataset containing labeled facial expressions is collected. Each image in the dataset is labeled with the corresponding emotion (e.g., happy, sad, angry).

Data Segmentation: Data segmentation is the process of taking large amounts of data and breaking them down into smaller groups based on specific criteria. It is designed specifically to extract relevant data from a larger data set and make it accessible to users who can, in turn, analyze it for targeted purposes. Data segmentation can be carried out in a number of different ways.

Denoising MSPCA: Signal denoising is one of the most important issues in signal processing, and various techniques have been proposed to address this issue. A combined method involving wavelet decomposition and multi scale principal component analysis (MSPCA) has been proposed and exhibits a strong signal denoising performance.

Feature Extraction: Feature extraction is a machine learning technique that reduces the number of resources required for processing while retaining significant or relevant information. In other words, feature extraction entails constructing new features that retain the key information from the original data but in a more efficient manner transforming raw data into a set of numerical features that a computer program can easily understand and use. When working with huge datasets, particularly in fields such as image processing, natural language processing, and signal processing, it is usual to encounter data containing multiple characteristics, many of which may be useless or redundant. Feature extraction simplifies the data, these features capture the essential characteristics of the original data, allowing for more efficient processing and analysis.

Dimension Reduction: Dimension Reduction, is the transformation of data from a high-dimensional space into a low-dimensional space so that the low-dimensional representation retains some meaningful properties of the original data, ideally close to its intrinsic dimension. Working in high-dimensional spaces can be undesirable for many reasons; raw data are often sparse as a consequence of the curse of dimensionality, and analyzing the data is usually computationally intractable. Dimensionality reduction is common in fields that deal with large numbers of observations and/or large numbers of variables, such as signal processing, speech recognition, neuroinformatics, and bioinformatics.

Classification: Classification teaches a machine to sort things into categories. It learns by looking at examples with labels. When we talk about classification in machine learning, we're talking about the process of sorting data into categories based on specific features or characteristics. There are different types of classification problems depending on how many categories (or classes) we are working with and how they are organized.

Emotion Detection: Emotion detection has the potential to revolutionize how we interact with technology and understand human emotions. As the field continues to advance, we can expect to see more emotionally intelligent applications across various domains, enhancing user experiences and improving our ability to empathize and connect with one another.

The data flow diagram shows a visual representation of the flow of data within the system which includes raw data acquisition, Preprocessing, Feature extraction, Feature fusion, Feature selection, Classification and the final output will be classified emotion.

After acquisition, signals are sent to pre-processing stage, where noise reduction, artefacts correction/removal tasks are performed to enhance the raw signal. The translation phase detects discriminative information in the signal, after which different features are retrieved and mapped onto a vector. Because of overlapping and distortion concerns with the signal, extracting this important information is a difficult operation. The size of the feature data is decreased to allow it to be given to the translation algorithm, which reduces complexity without sacrificing significant information.

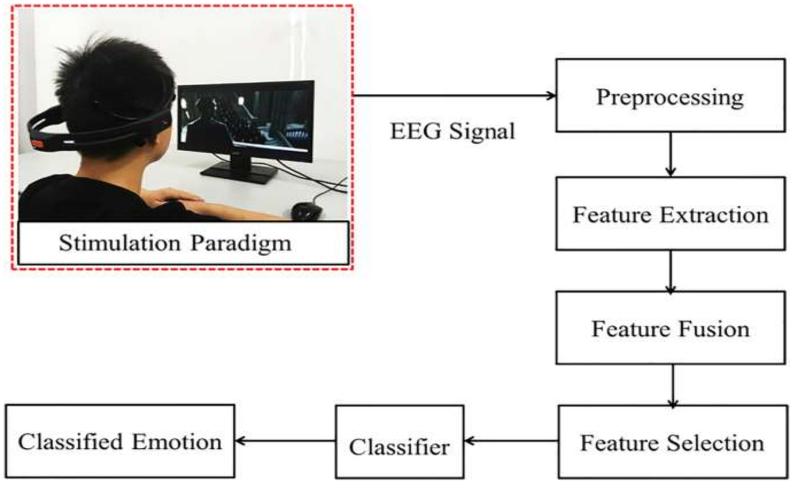

Fig 2) Data flow diagram

Feature fusion refers to the integration of multiple visual cues or features representing different aspects of visual characteristics to create a more comprehensive feature representation for tasks like object detection.

Feature selection is the process of selecting the most relevant features of a dataset to use when building and training a machine learning (ML) model.

Emotion classification, the means by which one may distinguish or contrast one emotion from another, is a contested issue in emotion research and in affective science. Researchers have approached the classification of emotions from one of two fundamental viewpoints

1. that emotions are discrete and fundamentally different constructs
2. that emotions can be characterized on a dimensional basis in groupings

In discrete emotion theory, all humans are thought to have an innate set of basic emotions that are cross-culturally recognizable. These basic emotions are described as "discrete" because they are believed to be distinguishable by an individual's facial expression and biological processes.[12 Theorists have conducted studies to determine which emotions are basic. A popular example is Paul Ekman and his colleagues' cross-cultural study of 1992, in which they concluded that the six basic emotions are anger, disgust, fear, happiness, sadness, and surprise.[13] Ekman explains that there are particular characteristics attached to each of these emotions, allowing them to be expressed in varying degrees in a non-verbal manner. Each emotion acts as a discrete category rather than an individual emotional state.

Fig 3) pictures of different emotions. Credit: Ollyy/Shutterstock.com

Scientists have found that humans experience 27 distinct categories of emotion, thereby challenging the long-held assumption in psychology that humans have just six main categories, namely happiness, sadness, anger, fear, disgust and surprise.

- Happiness: A positive emotion characterized by feelings of joy, contentment, and satisfaction.
- Sadness: A negative emotion that involves feelings of loss, disappointment, or sorrow.
- Fear: An emotional response to perceived threats, characterized by feelings of anxiety and apprehension.
- Disgust: A reaction to something considered unpleasant or offensive, often evoking feelings of revulsion.
- Anger: An emotional response to perceived injustice or frustration, marked by feelings of hostility and aggression.
- Surprise: A brief emotional state resulting from an unexpected event, which can be either positive or negative.

Fig 4) Basic Human Emotions

OTHER EMOTIONS

The primary emotions are really special and exciting, but they aren't the only emotions we are capable of feeling. There are thousands of different types of emotions!

Emotions are sort of like colors. There are primary colors (red, blue, and yellow) that create new colors when mixed together (i.e. red and blue make purple). And even those six colours can have different types of colours (i.e. dark blue and light blue).

Emotions are the same! The primary emotions may mix together to form other types of emotions. For example, when we mix together happiness and surprise, we would feel something like delight. Also, the primary emotions can feel more or less intense. For example, happy may be really intense (ecstatic) or quite dull (content).

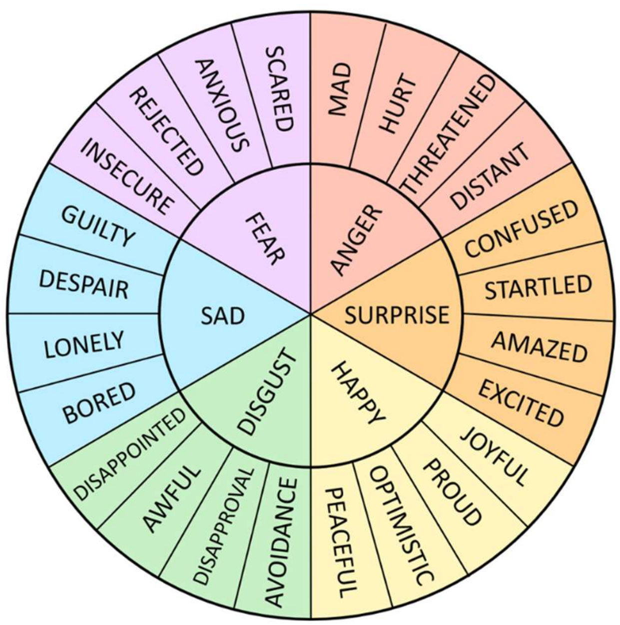

Fig 5) Other Emotions

Since there are **so** many emotions, it can sometimes be hard to tell which emotion we are feeling. That is why it can sometimes be useful to think about which primary emotion we are feeling and break it down from there. For example, if we know we are feeling sort of sad, we can try to figure out if it's mixed with anything else (like fear or anger) or if it is a really intense versus a very dull feeling. This is a really helpful way to learn how to understand and cope with our emotions. The more we practice understanding our own emotions, the better we become at expressing and coping with our emotions!

USE CASE DIAGRAM:

A Use Case Diagram in Unified Modeling Language (UML) is a visual representation that illustrates the interactions between users and system. It captures the functional requirements of a system, showing how different users engage with various use cases, or specific functionalities, within the system. Use case diagrams provide a high-level overview of a system's behavior, making them useful for stakeholders, developers, and analysts to understand how a system is intended to operate from the user's perspective, and how different processes relate to one another. They are crucial for defining system scope and requirements.

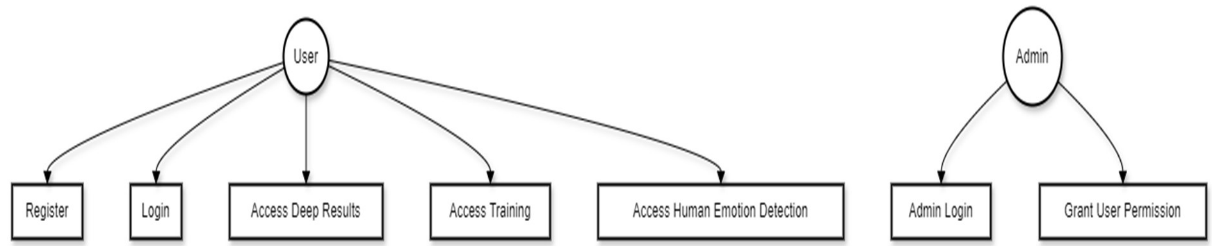

Fig 6) Use Case Diagram

<u>CLASS DIAGRAM:</u> In software engineering, a class diagram in the Unified Modeling Languages is a type of static structure diagram that describes the structure of a system by showing the system classifier their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.

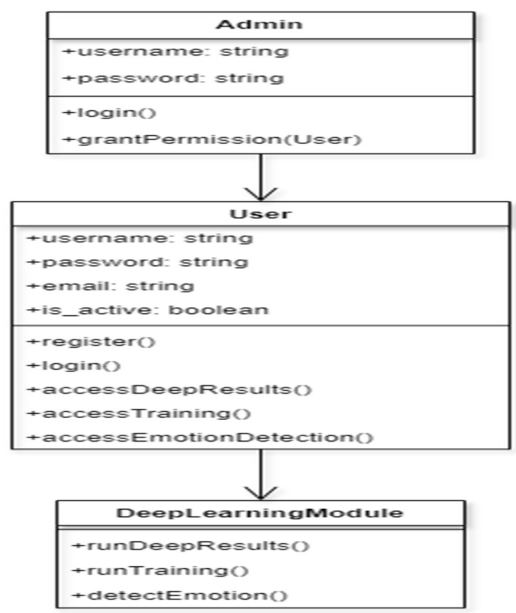

Fig 7) Class diagram

<u>SEQUENCE DIAGRAM:</u> A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

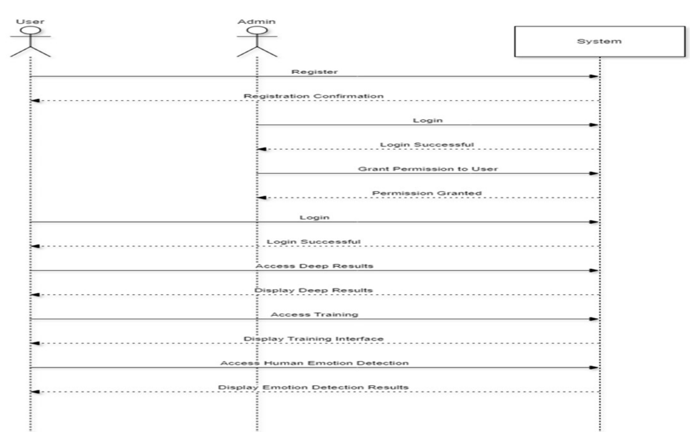

Fig 8) Sequence Diagram

ACTIVITY DIAGRAM: Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

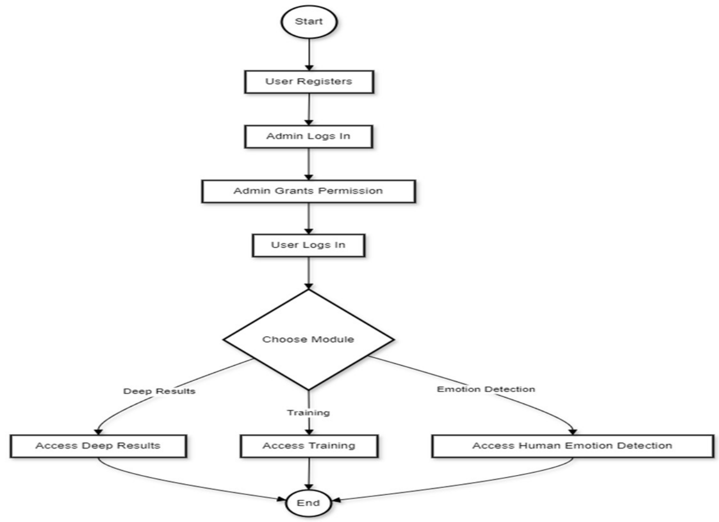

Fig 9) Activity Diagram

SYSTEM TEST

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub-assemblies, assemblies and/or a finished product.

Integration Testing

Software integration testing is the incremental integration testing of two or more integrated software components on a single platform to produce failures caused by interfaced effects.

The task of the integration test is to check that components or software applications, e.g. components in a software system or – one step up – software applications at the company level – interact without error.

Test Results: All the test cases mentioned above passed successfully. No defects encountered.

Acceptance Testing

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

Test Results: All the test cases mentioned above passed successfully. No defects encountered.

S.no	Test Case Description	Expected Result	Actual Result	Remarks (If Fails)
1	User Registration	User should be able to register successfully with valid details.	Pass/Fail	If the email already exists, registration should fail.
2	User Login	Registered users should be able to log in with correct username and password.	Pass/Fail	Unregistered users should not be able to log in.
3	Admin Login	Admin should be able to log in with valid credentials and access the admin home page.	Pass/Fail	Invalid login details should not grant access.
4	Data Pre-processing	EEG signals should be pre-processed successfully (e.g., filtering, normalization).	Pass/Fail	Check for data anomalies or pre-processing errors.
5	Feature Extraction	Features such as time-frequency domain features should be successfully extracted from pre-processed signals.	Pass/Fail	Validate feature consistency with expected outputs.
6	Model Training (CNN)	The CNN model should train on the extracted features with no errors.	Pass/Fail	Check for convergence or training errors.
7	Model Accuracy Evaluation	The trained CNN model should achieve an accuracy above a predefined threshold (e.g.,	Pass/Fail	Investigate model performance issues if it fails.

		>70%).		
8	Emotion Prediction	The model should accurately predict emotions (e.g., happy, sad, neutral) based on input EEG signals.	Pass/Fail	Review prediction results for incorrect classifications.
9	Real-Time Emotion Detection	The system should perform real-time emotion detection with low latency.	Pass/Fail	Measure response time and prediction accuracy.
10	Model Robustness to Noisy Data	The model should maintain accuracy within acceptable limits when exposed to noisy EEG data.	Pass/Fail	Analyse model performance with varying noise levels.
11	Cross-Validation Performance	The model should show consistent performance across different cross-validation folds.	Pass/Fail	Ensure that performance is stable across all folds.
12	Comparison with Baseline Models	The proposed model should outperform baseline models (e.g., SVM, Random Forest) in terms of accuracy.	Pass/Fail	Check if the proposed model's performance is superior.
13	System Integration and Deployment Testing	The entire system should work as expected when integrated and deployed on the target platform.	Pass/Fail	Validate end-to-end system functionality.

FUTURE ENHANCEMENT:

Here are the potential future enhancements for the EEG-based emotion recognition project:

1. Integration of Natural Language Processing (NLP): The project could be updated to incorporate voice data input rather than text-based input. This would allow for more natural and seamless interaction with the system.
2. Therapy Recommendations and Medication Prediction: The system could be enhanced to offer relevant therapy suggestions and predict pharmaceutical needs based on the user's or patient's emotional state. This could help in providing more personalized and timely mental health care.
3. Virtual Psychiatrist Connection: By predicting pharmaceutical needs and emotional states, the system could be developed to quickly and easily connect users to virtual psychiatrists when necessary.
4. Location-Based Doctor Referral System: Implementing a feature that can locate the nearest doctor, enabling patients to easily contact medical professionals if their health deteriorates or for any other reason.
5. Anxiety Reduction and Cost Efficiency: These enhancements could potentially lower the incidence of anxiety and reduce physician costs by providing timely interventions and efficient healthcare connections.
6. Multi-Modal Emotion Recognition: While not explicitly mentioned in the conclusion, combining EEG data with other physiological signals or behavioural cues could potentially improve the accuracy and robustness of emotion recognition.
7. Real-Time Application Development: Creating real-time applications that utilize this emotion recognition technology in various fields such as healthcare, security, or human-computer interaction.
8. Personalization and Adaptation: Developing algorithms that can adapt to individual differences in EEG patterns and emotional expressions over time, improving accuracy for each user.

9. Ethical and Privacy Considerations: As the technology advances, there will be a need to address ethical concerns and ensure robust privacy protections for users' emotional and brain data.
10. These enhancements could significantly expand the capabilities and applications of the EEG-based emotion recognition system, potentially revolutionizing how we understand and respond to human emotions in various contexts.

CONCLUSION

The use of EEG to identify human emotions has been the topic of several investigations. In this research, a different dataset was used that makes use of a deep learning system to identify human emotions. The outcomes show that CNN has a high accuracy rating of 92%. It has been shown that employing clean data for the training set - data devoid of other emotions and behaviours along with a stronger and more suitable classification algorithm can boost performance to a good level.

The paper notes that as the world becomes more technologically advanced, so does the software available to us. EEG-based human emotion recognition using deep learning is one such example. This type of system is designed to read and interpret EEG signals to identify human emotions.

Several potential applications for this type of software are mentioned:
1. Helping people with conditions such as autism or social anxiety disorders
2. Use in security contexts
3. Applications in advertising

The conclusion also suggests potential future enhancements to the project:
1. Integrating Natural Language Processing (NLP) in the form of voice data input rather than text-based data input
2. Enhancing the system to offer relevant therapy and predict pharmaceutical needs based on the user's or patient's state
3. Including a location-based doctor referral system

These enhancements could potentially lower the incidence of anxiety and physician costs, allow for quick connection to virtual psychiatrists, and enable patients to easily locate and contact doctors when needed.

Overall, the conclusion emphasizes the potential of this technology to improve communication and quality of life for individuals who struggle with emotion recognition or expression, while also highlighting areas for future development and application.

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