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Brain Signals to Emotions using Deep Learning Approaches

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Abstract—

People who have difficulty understanding emotions may find it difficult to communicate, but this paper offers a new approach that could help them move around more freely. Emotion recognition and interpretation using a deep learning algorithm. Improving affected individuals' quality of life is a critical challenge that this research tackles. Their capacity to interact with the environment and other people can be improved through the use of EEG data analysis. In this work, using the DEAP dataset, we trained and evaluated the algorithm, and discovered that the CNN model had the greatest accuracy of 92%. These findings prove that it is possible to accurately detect human emotions using EEG signals.

Keywords— Human Emotions, Electroencephalogram (EEG), Deep learning, Machine learning, Convolutional Neural Network, LSTM.

INTRODUCTION

A brain computer interface (BCI) is a system that lets you control a computer with your thoughts [1]. The main concept is to utilize technology to scan your brainwaves and understand what you're thinking. Then, the computer can do what you want it to do. Brain-Computer Interfaces (BCIs) are now in their fledgling phase of research, although its potential to revolutionize human interaction techniques is tremendous technology. There are a number different approaches to design a BCI. One is to employ electrodes that are implanted in the brain. Another is to utilize sensors that sit on the surface of the skull [2]. The most common approach to assess brainwaves is using an electroencephalograph (EEG). EEGs assess the electrical activity of the brain and are commonly utilized in research. BCI research is continuing, and various diverse applications are being researched. It has been able to determine the sort of feelings that are hidden under the surface utilizing a number of approaches and strategies, such as: Due to its trustworthy findings, Electroencephalography (EEG) is frequently employed in the area of emotion recognition (ER) [3] from facial expression, speech intonation [4], and signal from the Autonomic Nervous System (ANS) such heart rate and Galvanic Skin Response (GSR) [5]. It is also extensively utilized since it is easy to record and economically priced. Emotion categorization from EEG waves involves various methodologies and processes. One of these methods includes recording and then preprocessing raw signals. After cleaning up the dataset and arranging the data, the best feature is retrieved and assessed using machine Learning or deep learning algorithms. In order to analyze EEG signals, two main machine learning methods are used: step-by-step learning and end-to-end deep learning [6]. The three main steps of ML, or traditional machine learning, are preprocessing, feature extraction, and feature classification. These steps are carried out using various machine learning algorithms. Machine learning approaches are questionable because manual extraction is difficult to maintain and because TD and FD equations include a lot of complexity and noise (like electromyography). Because deep learning prefers an end-to-end approach, academics have begun using it as a workaround for this problem.

MOTIVATION

We want to discover new ways to evaluate human emotions from EEG data using state-of-the-art deep learning models; this will assist modernize neurological diagnosis. We want to explore and locate the most promising ways for recording and

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collecting the EEG waves that pique our attention and become beneficial, even though there are several approaches. Our study will center on extracting features, preprocessing them, and training DL classifiers to identify certain emotions. Nobody will be able to get their hands on our stuff since it will be universally available. In both physical and mental health contexts, our concept will be a beacon of hope for the handicapped people of the globe. They might also utilize it to their advantage while approaching their work. Upon completion of this study, individuals with total paralysis and mental health concerns will have the ability to express their emotions 93% of the time.

LITERATURE REVIEW

Mental state As our awareness of and ability to create emotions grows, scientists are investigating the possibility of building automated emotion identification systems. This is all due to the pervasiveness and relevance of emotions in our daily lives. As far as human interaction is concerned, it is essential [7]. Recognizing an individual's emotional condition is known as emotion recognition. Technological, psychological, and cognitive advancements have aided emotion recognition studies [8].

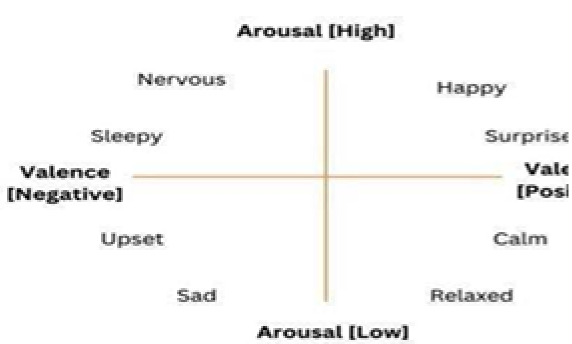


FIG. 1. VALENCE AND AROUSAL MODEL

Section C. BCI Interactions One way to command a computer is via the use of a brain-computer interface (BCI). The fundamental premise is to decipher your thoughts by reading your brainwaves using technology. After that, the computer will be able to respond to your commands. Brain-Computer Interfaces (BCIs) are still in the early stages of development, but they might revolutionize the way we use technology. A BCI may be constructed in several methods. Using electrodes implanted in the brain is one option. Utilizing sensors that rest above the skull is a further option. Electroencephalography is the gold standard for measuring brainwaves. Brain-computer interface (BCI) research is continuing, EEGs are often used to assess brain activity, and many applications are being investigated [9].

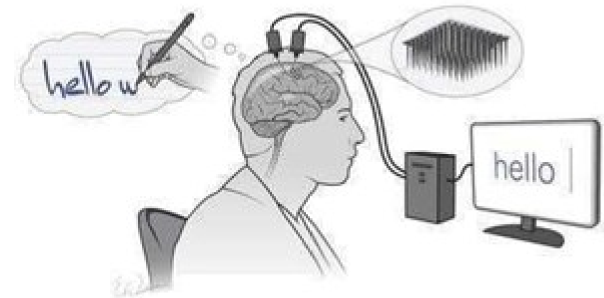
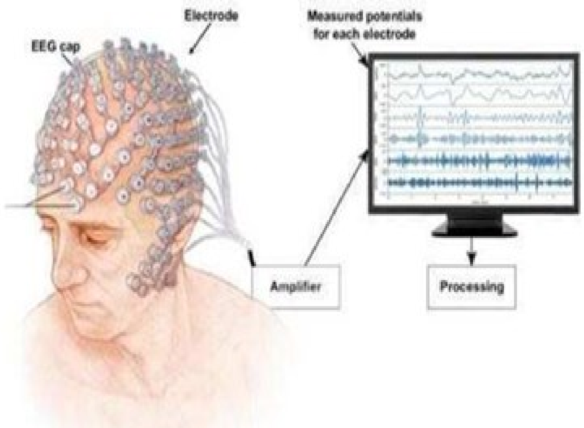


Fig. 2. Brain-Computer Interface Illustration

There has been a lot of research and development on methods for identifying emotions in real-time. The goal physiological indicator includes an electroencephalogram (EEG), which originates in the major nerve system due to its strong association with human emotional feelings. Electroencephalogram (EEG) signals have found uses outside of medicine, including in the entertainment, educational, monitoring, and gaming industries. Our brains can talk to computers and other tech via BCI using our EEG data [10]. Numerous industries are now showing promise with its use, such as neuro-advertising, medical, law enforcement, the entertainment industry, and market research. In order to put computers to good use, emotion detection software is a must. Given the pervasiveness of emotions in modern life, an increasing number of individuals are turning to online tools to gauge their emotional reputation. Here, we zero in on an issue in developing a model for human emotion recognition using electroencephalogram data [11].



Related Work

Due to their sophisticated features and immense appeal, emotion-aware mobile apps have been seeing a surge in popularity recently [12]. For such a scenario to work, a precise emotion recognition system in real time is required. Here, we provide a strategy for efficient emotion recognition on mobile devices. One possible workaround is to capture footage of the user's face using the camera app on their smartphone. Using a random selection of video frames, a face detection module is used to extract the regions of the images that include faces. The next step is to use a classifier based on the Gaussian mixture model to achieve emotion categorization using the dominant bins. The results show that the proposed system accomplishes high recognition accuracy in a reasonable period of time, according to the experiments. The model's strong points include its rapid response time, easy installation, and excellent identification capabilities. Some disadvantages of this paradigm include increased complexity, poorer performance, and incompatibility with large datasets.

Methane et al. [13] contended that sentiment analysis tools available on Twitter provide a way to gauge how the general population feels about certain topics or occurrences. In order to extract sentiment, most recent research have focused on lexical and syntactic characteristics. You may see these characteristics expressed explicitly in sentiment words, emoticons, exclamation points, and many more. This paper uses an award embedding method developed using unsupervised learning on massive Twitter datasets to make use of latent contextual semantic correlations and co-occurring statistical features among words in tweets. Analysis of real-time data was in the team's original intention. The notion has been put into practice in a way that is more practical and realistic. Furthermore, the research classifies emotions using emojis. Analyzing the results of the project will need more effort and time. Because it is dependent on the responses of a group, the model of response is indirect. Another study that used the SVM method and achieved a greater overall accuracy of 92% was the one by George et al. [14]. The DCT method, in conjunction with a box-and-whisker plot, was used to identify features. In the DEAP dataset, which had 32 individuals, the accuracy of emotion recognition was 92% higher when using Fast Fourier Transform (FFT) statistical features. This method is therefore more trustworthy than Sea et al.'s. Distinct varieties It is possible to relate performance variations in the domains of feature extraction and data preprocessing to discrepancies that have been observed [15].

In order to determine the player's emotional state, the authors of this article [16] present a novel automated emotion recognition system that analyzes EEG data from video games using deep learning methods. Twenty-eight participants had their electroencephalograms recorded using 14 channels of portable and wearable EEG equipment made by Emotive Epos+. The generated schema is simple enough to classify players' views on games into four groups. These results demonstrate that the model-based framework for emotion identification may successfully infer emotional states from EEG recordings. While keeping accuracy at 99.99%, the network decreases computation time. According to Sea et al. [17], I used the DEAP dataset and used two different feature extraction techniques, namely VMD and EMD, to investigate and evaluate EEG-derived emotional reactions to stimuli. Emotions were also classified by scientists using DNN. With a valence accuracy of 62% and an arousal accuracy of 63%, the results showed that this method was effective. According to the research, the deep neural network classifier outperformed support vector machine classifiers in the emotional recognition model. According to the study's authors, VMD-based features outperformed EMD-based strategies and significantly accelerated signal processing. A number of amplitude rate masking schemes between their no-components may be used to enhance EMD accuracy and allow for higher frequency resolution.

Researchers Amira et al. [18] in I used the arousal/valence dimensions model with the DEAP dataset to evaluate the practicality of real-time emotion categorization. It was proposed that characteristics be extracted from the EEG data using the DWT method. Specifically, SVM and KNN classifiers were used to achieve remarkable accuracy

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in this research. The results showed that the gamma band of the EEG signal is more accurate than the low frequencies. Both the valence and arousal accuracy rates were 84% and 86%, respectively. Numao et al. used the PSD approach to extract features using the MLP classifier. [19]. Although their primary goal was in developing emotion identification systems that make use of electroencephalogram (EEG) data, the researchers also used the DEAP database to examine people's subjective responses to musical compositions. According to research, people's brain waves change as they listen to music. When the listener is unaware of the music, emotion recognition algorithms that use EEG data perform better. The overall accuracy rate for valence was 64% and for arousal it was 73%. Because of its efficiency and short implementation time, MLP (a kind of ANN) is used in this study for classification prediction tasks. Researchers investigated the problem of overall emo-recognition systems' underused brain pathways in [20]. Thirty participants had their brainwaves monitored while watching eighteen different films. The researchers discovered that when studying the high-frequency features of EEG data, electrodes positioned in the temporal, frontal, and occipital lobes produced better findings. Among the many emotions studied, scientists settled on six: fear, pleasure, sorrow, disgust, neutrality, and anger. We used the SVM method to extract features, then the STFT algorithm for classification. Arousal levels were differentiated with a success rate of 54.52% and emotional valences with an accuracy of 87.36%, according to the study. In search of possible medicinal uses, Girardi et al. [21] examined emotional biometrics. To build a cost-effective emotion recognition algorithm, researchers collected data from GSR, EEG, and EMG sensors. Measuring the intensity and valence of participants' emotions was the main goal of this investigation.

The feature extraction and SVM classifier were implemented using the PSD and CSP approaches, respectively, on a DEAP database. By using low-cost equipment that produced equivalent levels of valence (56% and 60%, respectively) as the gold standard, this study circumvented the issue of costly sensors. In order for the technology to provide trustworthy results, particularly in the medical field, more effort is needed to improve it by pre-processing data. Another study [22] that used 32 participants' EEG data to infer their emotional state likewise validated the accuracy of the Convolutional Neural Network (CNN) findings. The research indicated that valence results were 95.09% accurate and arousal results were 96.09% correct. In their study, Jian Goo et al. [23] emphasized the significance of emotion recognition in emotional computing. Complex facial expressions, which go beyond the seven standard emotions, combine two or more expressions—for example, glad, disgusted, and soon—into one. For these reasons, we have released the iCV-MEFED dataset, which includes 50 categories of compound emotions with labels assessed by psychologists. Particularly challenging is the fact that complex facial[1] emotions may exhibit traits common to various types of facial expressions. While there is still a need for more research on compound facial emotion recognition, the proposed dataset may help lay the groundwork. In terms of extracting features, the model produces trustworthy results. Thanks to the lightning-fast processing and calculations, a tonne of work could be done in record time. There was no real-time data analysis throughout the project. Given that the model is subject to evolution, a more robust approach is required.

Intelligent systems built on the Internet of Things (IoT) have a hard time reading people's emotions from their natural language, according to a suggestion by Xin Kang et al. [24]. The fundamental cause of the problem is an inadequate comprehension of the universal rules that govern the expression of emotions. In this research, we propose using a Bayesian inference method to investigate hidden semantic features in natural language context data, which would aid in the expression learning process. Thanks to the findings of Bayesian inference, we can comprehend the multi-level semantic connections between words and emotions. Because we included a The underlying premise is that the distribution of emotions across different papers may be influenced by establishing a hierarchy at the corpus level. The concept allows for real-time data processing and requires minimal effort to deploy. Only text synthesis is the model's competence.

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METHODOLOGY

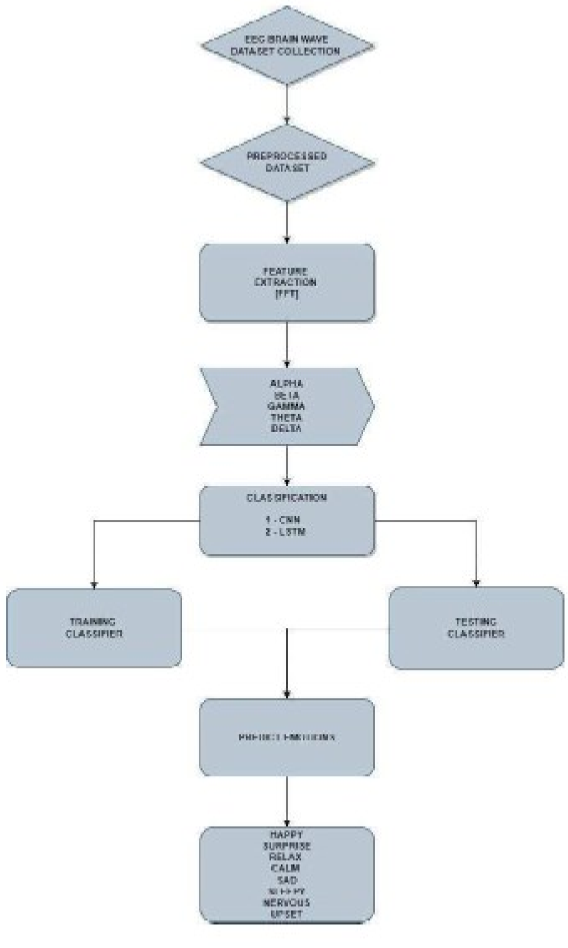

Fig.4. Methodology of our system

For this study, our system used the DEAP dataset. Separate from one another, the DEAP dataset consists of: • The findings of an individual study that examined the effects of arousal, valence, and dominance on the appraisal of 120 one-minute music videos. The participants ranged in age from fourteen to sixteen years old. Results from an experiment with 32 participants who watched 40 of the aforementioned music videos, including ratings, physiological data, and film captured by face-camera. Every participant was monitored by recording their electroencephalogram (EEG) and other physiological indicators in addition to providing the ratings described above. Twenty-two individuals were also videotaped front-on. The DEAP dataset consists of two parts: first, video of the participants' faces while they watched forty music videos; second, ratings and physiological recordings from thirty-two persons. We documented the EEG and physiological data. One subject's data is partitioned into an EEG data array and a label array.

DATA FILE THAT HAS BEEN PREPROCESSED

The DEAP dataset, on the other hand, has been preprocessed and is available to us as a zip folder containing 32 files. It was created by running programs on the raw data in MATLAB and PYTHON. Preprocessed experimental physiological data is accessible in a variety of formats, including Matlab and Python (NumPy), and includes tasks such as down sampling, EOG removal, filtering, segmentation, and more. You may get the data in two formats: one for Pickled Python / (NumPy) and another for Matlab. It has been segmented, preprocessed, and down sampled (to 128Hz). This data version is perfect for those who want to test a regression or classification method fast without first analyzing the whole dataset. Every single participant's zip file contains either a 32.dat (Python) or a mat (Mat Lab) file.

METHODOLOGY

Part A. Deep Knowledge A state-of-the-art ML method, DL models data at a higher degree of abstraction by using many processing layers with complex structures [25]. Deep Learning and Neural Networks have shown exemplary performance in several domains, including image identification, speech recognition, and natural language processing [26]. In this dissertation, we use a Deep Learning model trained on the DEAP dataset to categorize human emotions from brain signals. These models relied on raw data, which might have included noise. Hence, FFT approaches are used to clean the dataset in every model by removing noise from 4 to 45 hertz. B. LSTM, or Long Short-Term Memory A complex RNN with long-term data retention capabilities [27]. As it pertains to RNNs,

Deals with the problem of gradients that vanish. How well the network remembers information depends on the data. The long-term dependencies of the system are kept stable by the gated mechanisms of the network. Memory may be made accessible or kept on demand according to the network's gating

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mechanism. According to [28], an LSTM cell has three gates. The Long Short-Term Memory (LSTM) unit receives four variables simultaneously via one input gate and three extra gates, in contrast to other models' neuron-level unilabiate input. Model training teaches us how to train the neural network, which includes how to set the input data values and the weights of the neurons, which govern the firing of each neuron. [29] In this study, we choose names for the 14 electrodes that go with the channels in an effort to simplify training and improve the accuracy of emotion recognition. We sampled our DEAP dataset at 128 Hz after preprocessing, thus The electroencephalogram (EEG) data was down-sampled to 128 Hz for the sake of this experiment. The original EEG data covers a frequency range of 4.0 to 45.0 Hz. We utilized 256-window size, 2-second average band power, 16-step size, 128-sample rate, and 5 frequency bands. Four scales—valence, arousal, liking, and dominance—were chosen. After extracting features from the dataset using the FFT preprocessing tool, we moved on to training and testing. Part C: CNN Fukushima first proposed this network structure in 1988. Unfortunately, its limited functionality meant that it was not widely used. In the 1990s, LeCun et al. [30] used a gradient-based learning strategy to conquer the problem of handwriting digit classification. Convolutional neural networks (CNNs) are an emerging subfield of machine learning. Convolutional neural networks (CNNs) are designed to automatically extract and classify complicated features from visual input. The input, hidden, and output layers are the three components that make up a convolutional neural network. Using the input image as a starting point, the hidden layer performs deep feature extraction and classification, while the top layer stands in for the desired outcome. The CNN's hidden layers consist of convolutional, pooling, dropout, and SoftMax layers. A convolutional layer extracts the deep characteristics of an image by applying filters and strides during a convolutional operation. in reference to [31][32][33][34][35]. In a network architecture, the four fundamental layers are the convolutional (Conv), activation (a), pooling (p), and fully connected (FC) layers. References [36], [37], [38], [39], [40], and [41]... components that constitute a CNN To meet the requirements of emotional epoch+, which call for a window size of 256 by 256, our method employs a convolutional, activation, and pooling layer, along with four channels and five bands. An approach for cleaning and processing the dataset, the FFT processing function uses Fast Fourier Transform (FFT) techniques to convert the time domain of the DEAP dataset to the frequency domain. Preprocessing is the time between data collection and analysis when data is recognized and modified. In a subsequent step, we train and assess the data using convolutional algorithms. We shaped and determined the characteristics of our dataset using Rectified Linear Units (ReLUs), which are non-linear parameters that operate on multi-layer neural networks. At this point, we remove any negative values from the segmented image. A predefined threshold triggers the activation of this function at the node level. Because of tanh (which is used for activation and produces better results for multi-layer neural networks), the output is zero when the input is negative. after which We use a flatten approach (to collect big data for better performance), a sequence of pooling layers (i.e., pool (max pool), pool size = 2), and a succession of pooling layers to guarantee that our neural network works at its best. In the end, we put the model through its paces by means of a fully connected (FC) layer that is then fed into a Soft max function.

A. CNN Model Outcomes The accuracy rate in this model is 92%. In addition, the Adam optimizer was used, along with cross-entropy for both the error function and activation: The three activators are SoftMax, Tanh, and Lu. A max-pooling session with a pool size of 2 lasts for one day.

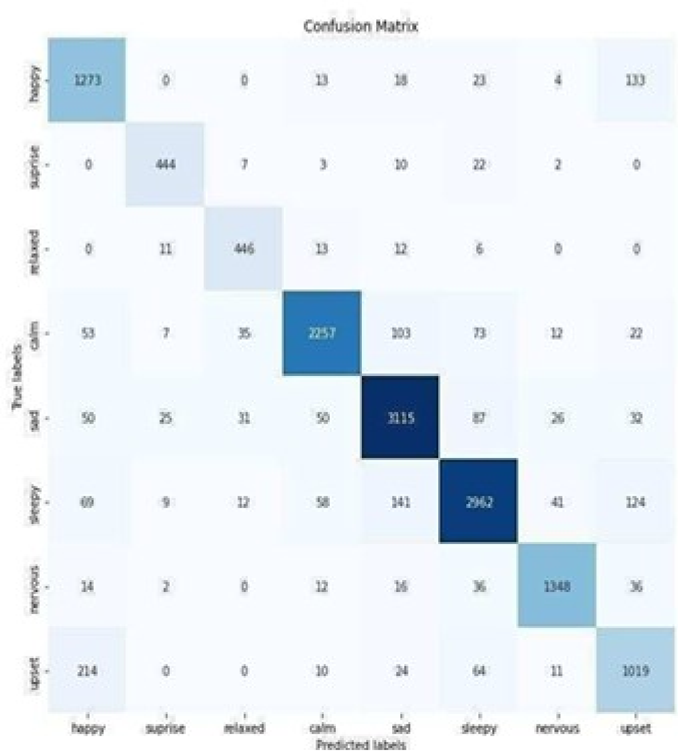

Fig. 5. Confusion Matrix of CNN

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The B. LSTM Model [long short-term memory] We have successfully attained an accuracy rate of 87% using this model. In addition, we have used the following tools: adam optimizer, activation, and cross-entropy for the error function: RELU and SoftMax are the activators.

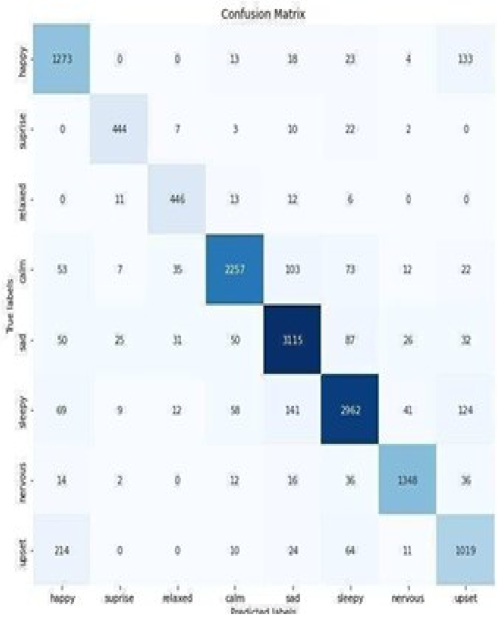

Fig. 6. Confusion Matrix of LSTM

CONCLUSION

There have been a number of studies looking at the feasibility of using EEG to detect emotional states in humans. We used a deep learning system to detect human emotions in our study, which is based on a completely different dataset. The results demonstrate that CNN's accuracy rating is rather high at 92%. Results may be improved by using a more robust and appropriate classification algorithm in conjunction with clean data for the training set, which is data free of other emotions and behaviors. The software we have access to evolves in tandem with the world's increasing technical sophistication. Human emotion identification based on EEG and deep learning is one such example. An EEG signal may be used to determine a person's emotional state by use of this kind of technology. This kind of software might have a lot of uses. People with autism or social anxiety problems, for instance, might benefit from its use. It could also find usage in advertising or security settings. Consider the potential impact of installing this software on security cameras. This might aid in crime prevention by allowing them to recognize when individuals are angry or scared. This project might be taken to the next level by including Natural Language Processing (NLP) using voice data input instead of text-based data input. The ability to provide appropriate treatment and anticipate pharmaceutical requirements according to the user's or patient's condition is another area that might be improved. With the ability to foresee medication requirements, we can further reduce anxiety rates and healthcare expenditures; the chatbot can then link you up with a virtual psychiatrist in no time at all. A location-based doctor referral system would also be a part of this project. It would find the nearest doctor and allow patients to contact them if their health worsens or for any other reason.

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