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DEEP WAVE

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Abstract **Stress is a common problem that affects people of all ages, and reducing stress is critical. Studying electroencephalography signals is a growing field of research that aims to provide insights into brain function, behavior, and neurological illnesses. This data can help researchers better understand the mechanisms underlying neurological and psychiatric disorders, such as depression and anxiety. The objective of our project to develop an end-to-end web application that uses EEG data to classify individuals into three category states (normal, pain, and meditation). Our Deep Wave extract meaningful information from EEG data, such as brain activity patterns, and to draw predictions about brain function. Four to five people were used in the training, and data on their normal, painful, and meditative states were gathered. Each subject's EEGs ranged in length from five to twenty minutes. In this project, a prediction system is developed based on the power values of the brain signal using several deep learning models like Bidirectional Long Short Term Memory (Bi- LSTM), EEGNET, SVC, all of which performed well in predicting outcomes based on EEG data**

Keywords - ***Data Collection, Data Preprocessing, Resampling, Artifact/Deviations Removal, Feature Extraction, Training models***

I. INTRODUCTION

Today's civilization uses a variety of computer paradigms to measure the states and functioning of the brain. These paradigms help researchers in fields such as neuroscience, psychology, medicine, and engineering to quickly track the relevance of electrical activity in the brain to their specific goals. One useful tool in this context is the ability to create a summary of brain activity, which simplifies complex topics and enables researchers to focus their efforts more efficiently. By summarizing brain activity, researchers can gain insight into the functioning of the brain and identify patterns that may be relevant to their research.

II. EXISTING SYSTEM

EEG signals can be represented in many ways, and feature extraction involves selecting the most relevant features for a particular analysis. Common features extracted from EEG signals include power spectra, frequency bands. The Welch's method is a spectral density estimation method that is commonly used in signal processing to estimate the power spectral density (PSD) of a signal. The PSD describes how the power of a signal is distributed across different frequencies. The Welch's method estimates the PSD of a signal by dividing the signal into overlapping segments, applying a window function to each segment, and computing the periodogram (i.e., the squared magnitude of the Fourier transform) of each segment. The periodogram

III. ROPOSED SYSTEM

Researchers, psychiatrists could not easily access, read, or use a large amount of EEG signal data for his or her needs. Therefore, creating summaries of the EEG data is essential and beneficial in the current scenario. In this part, we will be discussing the story of what has been done in the field or in related fields in relation to analysis of EEG Signals. proposed a novel method for detecting Major Depressive Disorder (MDD) using EEG signals and a robust spectral- spatial EEG feature extractor called kernel eigen-filter-bank common spatial pattern (KEFB- CSP). The KEFB-CSP filters the multi-channel raw EEG signals into a set of frequency sub-bands covering the range from theta to gamma bands (i.e., CSPs) and finally applies the kernel principal component analysis (kernel PCA) to transform the vector containing the CSPs from all frequency sub-bands to a lower-dimensional feature vector called KEFB-CSP. The study involved 12 patients with MDD and 12 healthy controls, and from each participant, 54 resting-state EEGs of 6 s length were collected. The study also compared the proposed method with other EEG features including the powers of EEG frequency bands and fractal dimension, which had been widely applied in previous EEG-based depression detection studies.

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IV. METHODOLOGY

The EEG Stress Prediction Application follows a comprehensive methodology involving the acquisition, preprocessing, and analysis of EEG signals to predict stress levels. Initial data collection includes EEG signals from subjects during different mental states. The preprocessing phase ensures data quality, and feature extraction is conducted using a Deep Wave model. Various deep learning models, including Bi-LSTM, EEGNET, and SVC, are employed to develop predictive models based on brain signal power values. The training phase utilizes data from multiple subjects, with the Bi- LSTM model showing superior prediction accuracy. The application offers insights into brain responses during normal, painful, and meditative states, aiding in stress level classification. This innovative methodology combines advanced signal processing, machine learning, and neuroscience to enhance our understanding of stress- related neurological and psychiatric conditions.

V.MODULE

Any technology that enables direct connection between the brain and an outside object, such a computer, is referred to as a BCI (brain-computer interface). BCI comes in a variety of forms, including as invasive, non- invasive, and semi- invasive. Invasive BCIs involve implanting electrodes directly into the brain, while non- invasive BCIs use external sensors to measure brain EEG (Electroencephalography) is a type of non-invasive BCI that measures electrical activity in the brain through electrodes placed on the scalp. EEG is a way of recording brain activity and can be used to detect changes in brain states such as sleep, wakefulness, and alertness. Additionally, the use of machine learning and artificial intelligence is enabling BCI systems to better understand and interpret brain signals, leading to more accurate and effective control of external devices

The placement of electrodes in an 8-channel EEG follows the international 10-20 system, which is a widely accepted standard for electrode placement in EEG recordings. To establish proper contact between the electrodes and the scalp, the subject's hair is frequently cleaned or wetted. A conductive gel or paste is then used to connect the electrodes to the scalp. The 10-20 system divides the scalp into regions, and each region is assigned a letter and a number. The letters represent the different regions of the brain, and the numbers represent the specific location within that region. For an 8-channel EEG, the following electrode placements are typically used: 1. F1: On the left side of the forehead, just above the eyebrow 2. F2: On the right side of the forehead, just above the eyebrow 3. C1/P1: On the left side of the head, halfway between the ear and the top of the head 4. C2/P2: On the right side of the head, halfway between the ear and the top of the head 5. T1: On the left side of the head, halfway between the ear and the back of the head 6. T2: On the right side of the head, halfway between the ear and the back of the head

Collecting the required data is the beginning of the whole process. The data required to train and evaluate the model is collected by inserting tiny electrodes on the scalps of people in different states. The data frame has 13 columns. A sample is in each row. The data was sampled at 250 Hz (i.e) 250 samples are taken per second. The EEG gadget has eight channels. The accelerometer is represented by channels acc1-3. These channels can detect Internal 9 movement of the patient. The final two columns display the passing of time. The plot for the entire time course for all channels is shown below.

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Deep learning algorithms and machine learning algorithms can be applied to EEG signals to classify brain activity patterns or to predict outcomes based on EEG data. Here, we have used 3 different models to classify EEG signals into 3 categories, such as normal or pain or mediation. The models incorporated are EEG-NET, Bi-LSTM and SVC. The mean AUC (Area under the curve) for SVC is larger when compared with Bi-LSTM and EEGNET. The larger the area, the better the model. A model with high sensitivity is able to correctly identify most of the positive cases, while a model with high specificity is able to correctly identify most of the negative cases. In this scenario, the Bi-LSTM model performed well. The accuracy of the models is depicted in the image below.

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The paper discusses the benefits of Agna meditation, a simplified nine-center meditation technique developed by

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Vethathiri Maharishi. The results of the paper showed that the experimental group that practiced Agna meditation had significant improvements in their mental and physical health compared to the controlled group. The improvements were observed in various parameters such as body mass index (BMI), pulse rate, blood pressure (BP), and mental frequency measured by electro encephalograph (EEG). Chandana et al.,[5] The paper analyzes the changes in EEG signals before and after Sudarshana Kriya Yoga practice. The methods used in this paper include placing 21 electrodes on the scalp of the subject to pick up the EEG signal, analyzing data from four electrode positions (FP1, FP2, O1, and O2), and filtering the EEG data with elliptic filters to get its associated frequency components. EEG data for 20 seconds was considered for analysis. The quantitative analysis of EEG signals before and after the practice shows significant changes in brain activity. From energy calculation, it is found that initially, most of the subjects were not in a relaxed state. The study Internal 7 concludes that the practice induces extreme relaxation and increases activity in the right part of the brain. Marta Kopanska et al., [6] used QEEG to distinguish the quantitative distribution of brain waves before, during, and after the Sudarshan Kriya Yoga (SKY) course in people who had previously had SARS-CoV-2 infections. The paper found that individuals who had previously been infected with SARS-CoV-2 had changes in their brainwave patterns, which were indicative of nervous system disturbances. However, after participating in the SKY breathing technique course, the participants showed improvements in their brainwave patterns, suggesting that the SKY technique may be a potential prophylactic and therapeutic tool for improving cognitive functions and emotional control. The study has limitations due to a small number of study participants and age range.

VI. SYSTEM ARCHITECTURE

The models operating on the production server would work with the real-life data and provide summary of signals to the users. Fig.3.1 represents our System Architecture. The users can upload files to get their queries done.

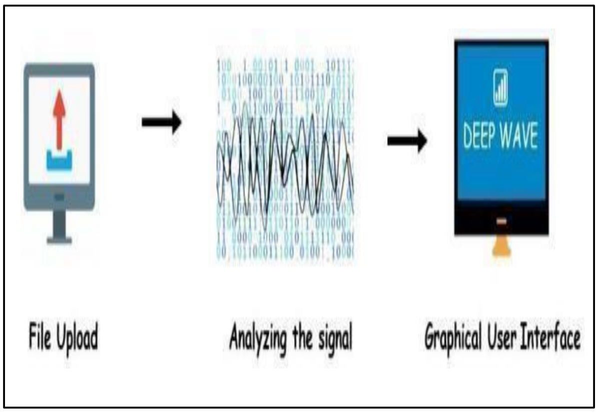

Fig 1: Flow diagram

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	channel1	channel2	channel3	channel4	channel5	channel6	channel7	channel8	acc1	acc2	acc3	time_std	timestamp
0	0	0	0	0	0	0	0	0	0	0	0	06:34:10.157	3,850,157
1	-35,350.18	-7,390.31	12,181.99	-9,093.72	-7,515.35	-10,726.76	-12,477.06	-27,147.45	0	0	0	06:34:10.172	3,850,172
2	-35,368.04	-7,402.03	12,179.02	-9,106.61	-7,515.91	-10,731.5	-12,481.24	-27,149.17	0	0	0	06:34:10.176	3,850,176
3	-35,360.32	-7,410.03	12,170.82	-9,124.81	-7,520.22	-10,738.9	-12,491.81	-27,154.78	0	0	0	06:34:10.180	3,850,180
4	-35,346.73	-7,403.21	12,171.58	-9,120.27	-7,521.79	-10,738.31	-12,494.38	-27,157.5	0	0	0	06:34:10.184	3,850,184
5	-35,342.58	-7,390.47	12,180.78	-9,100.02	-7,518.88	-10,732.1	-12,490.11	-27,154.64	0	0	0	06:34:10.188	3,850,188
6	-35,359.48	-7,387.52	12,184.52	-9,093.38	-7,518.59	-10,729.37	-12,490.62	-27,150.91	0	0	0	06:34:10.192	3,850,192
7	-35,376.89	-7,390.31	12,178.26	-9,109.48	-7,521.97	-10,732.66	-12,497.13	-27,149.37	1.202	0	0	06:34:10.196	3,850,196
8	-35,362.47	-7,408.84	12,173.45	-9,126.13	-7,522.93	-10,737.46	-12,501.06	-27,149.84	8.16	0	0	06:34:10.200	3,850,200
9	-35,345.97	-7,410.01	12,173.34	-9,125.5	-7,523.98	-10,741.11	-12,500.97	-27,152.27	0.99	0	0	06:34:10.204	3,850,204
10	-35,360.41	-7,404.44	12,180.14	-9,112.94	-7,523.42	-10,742.63	-12,498.74	-27,156.09	0	0	0	06:34:10.207	3,850,207

Fig 2 : Data collection

VII. DATAFLOW DIAGRAM

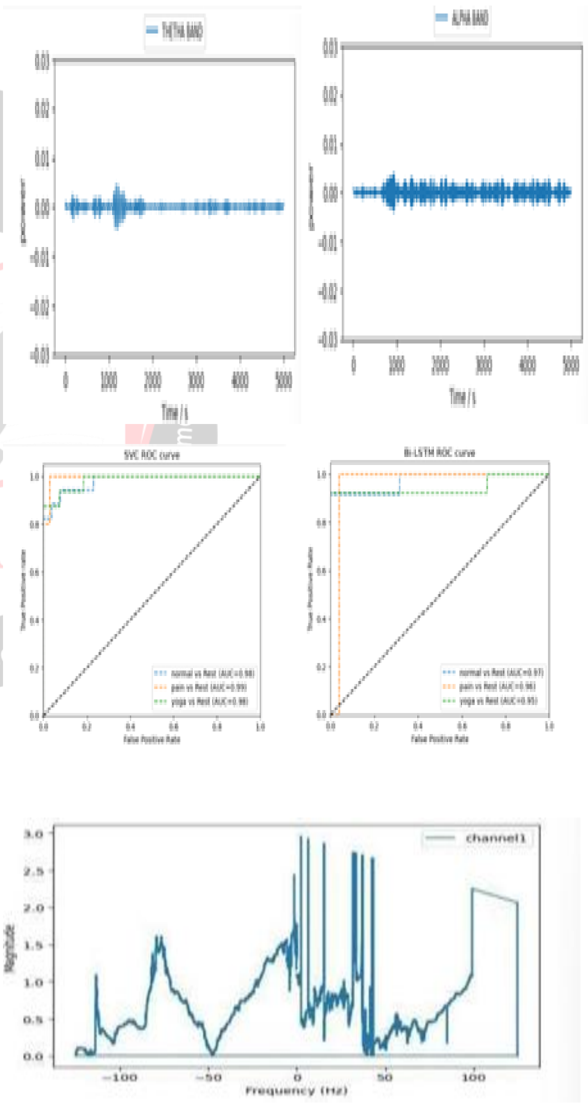

Fig 3 : Output graph

Analyzing EEG (Electroencephalogram) signals involves various steps and techniques to extract meaningful information from the brain's electrical activity. Here is an overview of the steps involved in EEG signal analysis:

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Preprocessing:

Filtering: Remove noise and artifacts using band-pass, high- pass, and low-pass filters to extract frequency components relevant to the analysis.

Artifact Removal: Identify and remove artifacts caused by eye regression methods.

Segmentation: Divide the EEG signal into epochs or segments to focus on specific events or time intervals of interest.

Feature Extraction:

Time-domain features: Extract statistical measures (mean, variance, skewness, kurtosis, etc.) from EEG segments.

Frequency-domain features: Use techniques like Fast Fourier Transform (FFT) or wavelet analysis to decompose the signal into frequency components and extract features such as power spectral density, dominant frequencies, or spectral entropy.

Time-frequency analysis: Employ techniques like Short-Time Fourier Transform (STFT), wavelet transform, or Hilbert- Huang transform to capture both time and frequency information simultaneously.

Feature Selection:

Choose the most relevant features based on statistical methods, domain knowledge, or machine learning algorithms to reduce dimensionality and improve classification or analysis accuracy. Classification or Analysis:

Machine Learning: Apply classification algorithms (e.g., SVM, Random Forest, Neural Networks) to classify EEG signals into different states (e.g., different brain activities, mental states, or pathologies).

Event-related analysis: Analyze event-related potentials (ERPs) by averaging EEG segments related to specific events to extract and characterize brain responses.

Connectivity analysis: Investigate functional connectivity patterns between different brain regions using coherence, phase synchronization, or Granger causality analysis.

Visualization and Interpretation:

Visualize EEG data using scalp maps, spectrograms, topographical plots, or connectivity matrices to understand spatial and temporal patterns in brain activity.

Interpret results in the context of the experimental design, clinical application, or research objectives.

Validation and Evaluation:

Validate the analysis results using appropriate statistical methods or cross-validation techniques to ensure reliability and generalizability.

Further Advanced Techniques (Optional):

Deep learning approaches: Use convolutional neural networks (CNNs), recurrent neural networks (RNNs), or other deep learning architectures for end-to-end learning from raw EEG signals.

Dynamic causal modeling (DCM): Model effective connectivity and causal relationships between brain regions in response to stimuli or tasks.

These steps form a generalized framework for EEG signal analysis, but the specific techniques and approaches may vary based on the research objectives, data characteristics, and desired outcomes. EEG analysis often requires a combination of signal processing, machine learning, and domain-specific knowledge for accurate interpretation and meaningful insights.

VIII. CONCLUSION

A conclusion for an EEG signal project would summarize the key findings, implications, and potential future directions based on the analysis and research conducted. Here's an example of how you might structure a conclusion for an EEG signal project.electrical signals captured from the human brain. Through a systematic approach encompassing preprocessing, feature extraction, classification. In conclusion, this EEG signal project has delved into the intricate realm of brain activity analysis, aiming to decode and interpret, and interpretation, several notable observations and outcomes have been established.The preprocessing phase proved pivotal in enhancing the quality of the EEG data, effectively mitigating noise and artifacts that could otherwise confound the analysis. Employing filtering techniques and artifact removal methods ensured a cleaner dataset for subsequent analysis. Feature extraction techniques, both in the time and frequency domains, provided valuable insights into the characteristics of brain activity. Extracted features such as power spectral density, event-related potentials, and connectivity measures facilitated the identification of distinct brain states, responses to stimuli, and functional connectivity patterns among brain regions. The classification or analysis phase, utilizing machine learning algorithms or event-related analyses, yielded promising results. The ability to accurately classify brain states or distinguish between cognitive tasks based on EEG patterns signifies the potential of this methodology in various applications, ranging from clinical diagnostics to cognitive neuroscience research. Furthermore, the visualization and interpretation of EEG data offered a compelling narrative, showcasing spatial and temporal dynamics of brain activity. Scalp maps, spectrograms, and connectivity matrices vividly depicted brain states and interactions, aiding in a deeper understanding of cognitive processes or pathological conditions under scrutiny. However, it's important to

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acknowledge the limitations encountered during this project. Challenges related to the inherent variability of EEG signals, the need for more sophisticated artifact removal techniques, and the complexity of interpreting dynamic brain activities require further exploration and refinement. Moving forward, future endeavors in EEG signal analysis could benefit from advancements in deep learning methodologies, leveraging neural network architectures to directly process raw EEG data for improved classification and feature extraction. Additionally, exploring real-time analysis and the integration of multimodal data sources could enrich the depth and scope of EEG-based investigations.

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