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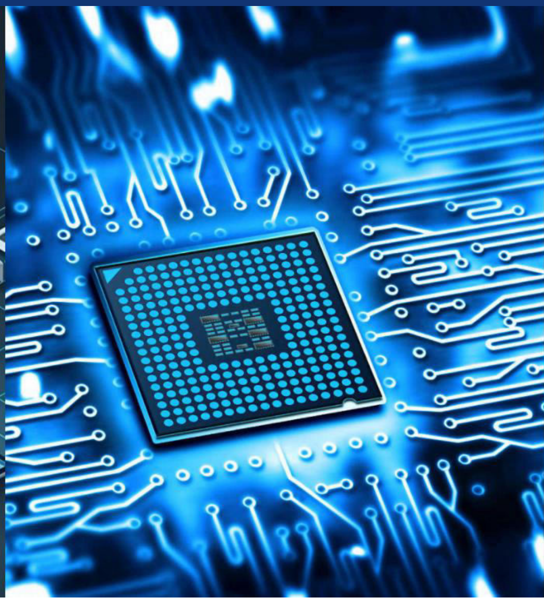

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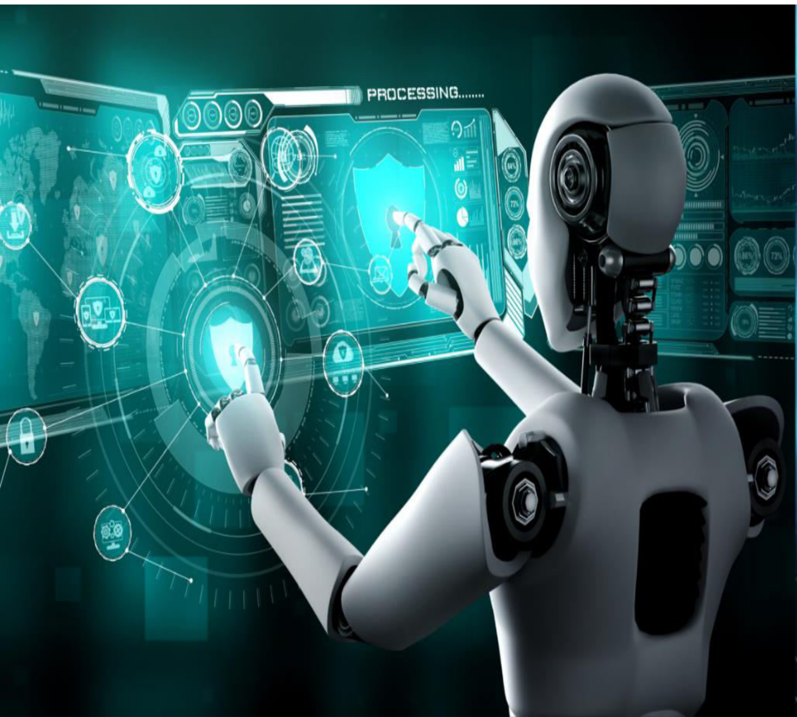

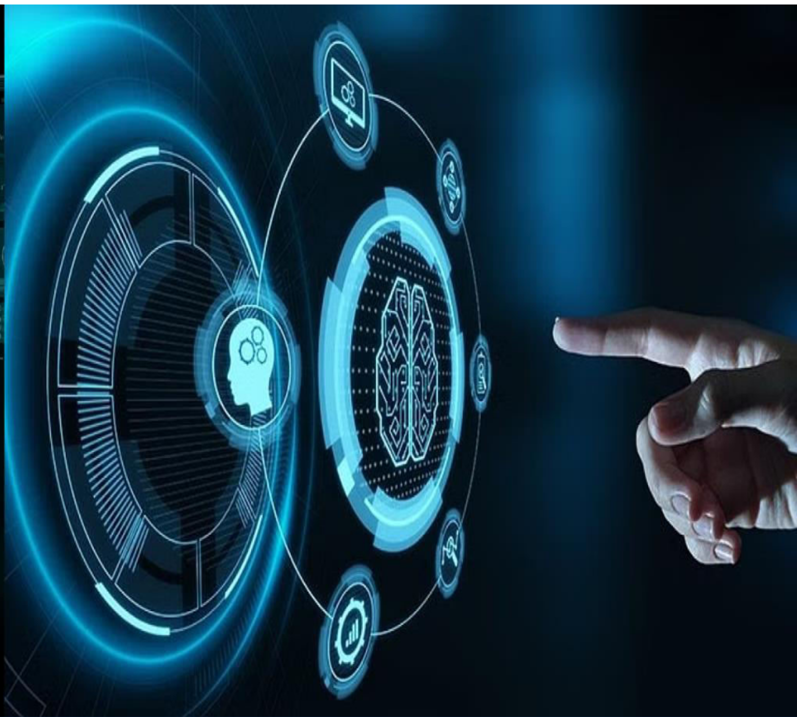

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Electro Encephalogram (EEG) Data Visualization Using Streamlit Framework

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ABSTRACT: Electroencephalograms (EEG) are frequently used in clinical and neuroscience settings to analyze brain activity. Electrodes are applied to a patient's scalp during an EEG in order to record electrical activity through voltage differentials. European Data Format (EDF) is the standard format used to record these multichannel voltage signals. One minute's worth of EEG data recorded at a rate of 250 Hz is represented by a 1 MB EDF file, which is notable for its size. Dealing with big datasets like the TUH EEG Corpus makes this problem much more difficult. Our mission is to provide effective, easily available, and user-friendly EEG data analysis tools to doctors and researchers. These improvements boost our knowledge of brain activity and its therapeutic uses, which may pave the way for breakthroughs in neurology and neuroscience.

KEYWORDS: Artificial Intelligence, machine learning, Deep Learning

I. INTRODUCTION

Multimedia stimulus from the outside, which conveys human feeling, offers a deep emotional experience. Mood swing, which is based on physiological arousal, is a multimodal psychophysiological reaction that is an implicit and abstract symbolic psychological activity. Many researchers have dedicated their time to studying the relationships between the EEG signal, multimedia features, and human emotion, as well as ways to achieve computer affective intelligence, due to the effectiveness and instantaneous influence of videos on human and various psychophysiological cues affected by emotion fluctuations. [1]

On the other hand, [2] scientists are at odds about how videos affect human mood and how to recognize emotions in videos. Additionally, the kinds of films and physiological aspects of humans that are essential for emotion The associate editor is in charge of organizing this manuscript's evaluation and granting publication approval. There is still more research to be done on analysis and machine-learning techniques for achieving artificial affective intelligence.

1.1 Artificial Intelligence

The capacity for thought and learning in a computer programmer or machine is known as artificial intelligence (AI). [3] It is also an area of research that aims to create "smart" computers. Mental functions that were previously regarded to require intelligence are no longer considered necessary as machines get more and more powerful. The field of artificial intelligence (AI) in computer science focuses on building intelligent machines that behave and think like people. Among the tasks for which artificially intelligent computers are intended are: Recognition of faces, Learning, Planning, Making Decisions, etc., Artificial intelligence refers to the application of computer science programming to mimic human cognition and behaviour through the analysis of information and environment, problem solving or prediction, and self-teaching to adapt to a range of activities.

1.2 Machine Learning

A burgeoning field of study [4] called "machine learning" allows computers to automatically learn from historical data. For the purpose of creating mathematical models and forecasts based on knowledge or historical data, machine learning employs a variety of techniques. It is currently being utilized for a number of different activities, including Facebook auto-tagging, email filtering, speech recognition, image identification, recommender systems, and many more. According to some, machine learning is a branch of artificial intelligence that focuses primarily on creating algorithms that let a computer learn on its own from data and past experiences. Arthur Samuel coined the phrase "machine learning" in 1959.

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In a nutshell, machine learning allows a machine to learn from data automatically, get better at things via experience, and make predictions without explicit programming.

1.3 Deep Learning

Generally speaking, [5] we are always engaged in two types of tasks, either consciously or subconsciously: classification (classifying sensations from our senses-such as hot or cold cups, etc.) and prediction (predicting the temperature in the future based on past temperature data, for example). In our daily lives, we perform classification and prediction tasks for a variety of tasks or occurrences, including the ones listed below Grasping a hot or cold cup of tea, water, coffee, etc. Email classification, like spam/non- spam.

Classifying daylight hours as either day or night. Prediction is the long-term planning of the future based on our existing situation and possessions. All living things on the planet will do these duties at some point in their existence. For instance, crows classify potential nesting sites, while bees choose certain areas to develop their colonies. Depending on the day and night classification, the bat will arrive throughout the night and sleep in the morning. This determines when and where honey can be obtained.

II. LITERATURE REVIEW

The millions of neurons that make up the human brain are crucial in regulating how the body responds to both internal and external motor and sensory cues. These neurons will serve as messengers between the brain and the body, carrying information. Analysing either brain pictures or signals can help us understand the cognitive behaviour of the brain. It is possible to picture human behaviour in terms of motor and sensory states, such as clenching of the hands, memory, attention, and eye and lip movements. These phases are associated with particular signal frequencies that aid in the comprehension of the functional behaviour of the intricate brain structure. The effective technique known as electroencephalography (EEG) assists in obtaining brain signals from the surface area of the scalp that correlate to different states.

The signals fall into one of five main categories delta, theta, alpha, beta, and gamma. Their frequency range from 0.1 Hz to over 100 Hz. The main subject of this study is the characterization of EEG signals in relation to different physiological states of the human body. It also covers the experimental configuration for EEG analysis.

This work provides a probabilistic-graphical model that concurrently analyses [7] spatial and temporal dependencies seen in electroencephalograms (EEGs) to infer properties of immediate brain activity. Our description involves a factor-graph-based model that utilizes customized factor-functions defined by domain knowledge to infer pathologic brain activity. The objective of this model is to identify brain regions that cause seizures in individuals with epilepsy. We solve graph inference exactly in polynomial time by using an inference technique based on the graph-cut algorithm. We validate the model by demonstrating that it accurately identifies seizure-generating brain areas using clinically gathered intracranial EEG data from 29 epilepsy patients. According to our findings, our model performs better than two traditional methods for seizure-onset localization (5–7% better AUC: 0.72, 0.67, 0.65), and the suggested inference method yields a 3–10% increase in AUC (0.72, 0.62, 0.69) over sampling.

Electroencephalograms (EEGs) [8] can be used to diagnose brain illnesses such as epilepsy. However, manual EEG data processing is known to have relatively low inter-rater agreement (IRA) and necessitates highly skilled doctors. In addition, the amount of data and the speed at which it is added to the collection make manual interpretation an expensive, time-consuming, and resource-intensive procedure. On the other hand, by lowering manual error and speeding up diagnosis, automated analysis of EEG data presents a chance to enhance patient care. In this study, we concentrate on determining if the brain activity is abnormal or normal, which is one of the initial steps in interpreting an EEG session. We suggest a unique recurrent neural network (RNN) architecture called Chrono Net to handle this particular task.

It is made to function well with EEG data and is motivated by recent advancements in the field of image categorization. The formation of a chrono net involves stacking several 1D convolution layers, which are then followed by deep gated recurrent unit (GRU) layers. Each 1D convolution layer has several filters with exponentially increasing lengths, and the stacked GRU levels are feed-forwardly densely coupled. We assessed Chrono Net's performance using the recently

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published TUH Abnormal EEG Corpus dataset. In contrast to earlier research employing this dataset, Chrono Net develops meaningful representations of patterns of brain activity by directly utilizing time-series EEG as input. On this dataset, Chrono Net performs better than previously published results, creating a new benchmark.

Electroencephalograms (EEGs), which are obtained by placing electrodes on the patient's scalp and measuring electrical activity via voltage changes, are a standard procedure for examining brain function. The European Data Format (EDF) is widely used to store these multichannel voltage signals. An unpruned EEG's EDF file can get fairly large; one megabyte (MB) of an EDF file corresponds to about one minute of 250 Hz sampling-rate EEG recording. Furthermore, complete datasets from the TUH EEG Corpus can have volumes exceeding 800GB. Large- scale EEG recordings necessitate the use of effective visualization and analysis tools. In this effort, we streamline the process of retrieving EDF data from our server with the goal of improving the user experience.[9]

This work introduces a new method of nonlinear spectral analysis that has been applied to the processing of human encephalograms. The basis of this method is the idea of the Rényi entropy, or generalized entropy of a particular probability distribution, which enables the definition of the set of generalized fractal dimensions of an electroencephalogram (EEG) and the determination of the fractal spectra of encephalographic signals. The fractal dimension spectra, in contrast to the Fourier spectra, provide information about the frequency and amplitude features of the EEG and can be utilized in conjunction with established EEG analysis techniques to improve the latter. Driven by brain activity volume visualization, the technique offers fresh insights into human thinking processes.

III. RELATED WORK

Mood swings, physiological arousal, and external stimulation are all influenced by and intimately tied to one another. It's fascinating and important to investigate the relationships that exist internally between these three factors. Video is currently the most often used multimedia stimulus due to its ability to convey rich emotional meanings through both visual and audio cues. Human electroencephalography (EEG) features, in addition to video features, can offer valuable information for video emotion detection since they are a direct and immediate authentic input on human perception with originality.

A. Material and Methods

Using the stream lighted frame in the suggested system, we build a web application that allows us to view the output in a data visualization format. EEG data visualization based on EEG signals has been used in the ways. With the use of this visualization technique, the data were trained to anticipate the signals for each model. We may display the visualizations using EDF file data by utilizing this model.

B. Data Pre-Processing

Prior to gathering data, we must decide what information is required and how it will be gathered. A hypothesis can also be assessed using the data that has been gathered. The most crucial and initial stage of research is typically data collection. Depending on theinformation needed, different disciplines of research require different approaches to data gathering. Data cleansing is the process of finding and eliminating information that is incorrect, missing, or unnecessary. This may entail managing outliers, completing in missing values, and eliminating duplicate records. Data integration is the process of merging information from several sources, including text files, spreadsheets, and databases. To generate a single, unified picture of the data is the aim of integration.

C. Session Selection

This module analyses and identifies a number of symptoms that are frequently connected to illnesses, including fever, headaches, and physical pain. Healthcare practitioners can adjust disease prediction models by adding, removing, or changing symptoms. This module makes it easier to identify possible illnesses based on symptom presentations by mapping symptoms to recognized disorders.

D. Channel Selection

Users can choose and view particular EEG channels or electrodes with the EEG Channel Selection module. Users can concentrate on specific interest channels for in-depth analysis and visualization

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E. Frequency Selection

The EEG Frequency Selection module is designed to enable users to explore and analyze EEG data by selecting specific frequency bands, including alpha, beta, and gamma. This module allows users to visualize EEG activity within these frequency ranges, providing insights into different aspects of brain activity.When pip installs a package, it automatically installs any dependent Python packages without checking if these conflict with previously installed packages. It will install a package and any of its dependencies regardless of the state of the existing installation. Because of this, a user with a working installation of, for example, Google Tens or flow, can find that it stops working having used pip to install a different package that requires a different version of the dependent numpy library than the one used by Tensorflow. In some cases, the package may appear to work but produce different results in detail.

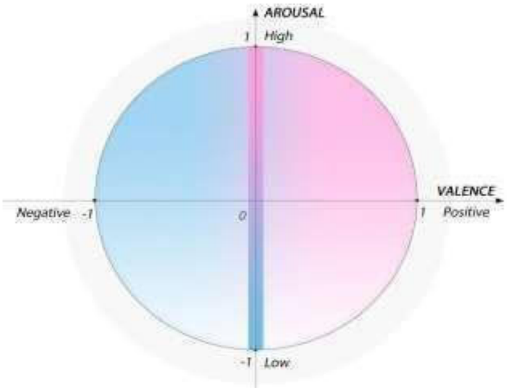

Fig 1 Valence Arousal Emotion Model

Fig 1 represents the valence arousal modal Final prediction using Stream lit method by streamlit frame work to implement the sentiment analysis for data of EEG Signal the Web Application module serves as the main interface for users to interact with the EEG data. It combines the Session Selection, Channel Selection, and Frequency Selection modules into a cohesive and user- friendly web application.

F. Web Application

Given the effectiveness and instantaneous of video influence on human and various psycho physiological cues affected by emotion fluctuations, many researchers have devoted themselves in studying the relations among EEG signal, multimedia features and human emotion, and explored methods to achieve computer affective intelligence. However, researchers cannot reach an agreement on how videos influence human emotion and the mechanism of video emotion recognition.

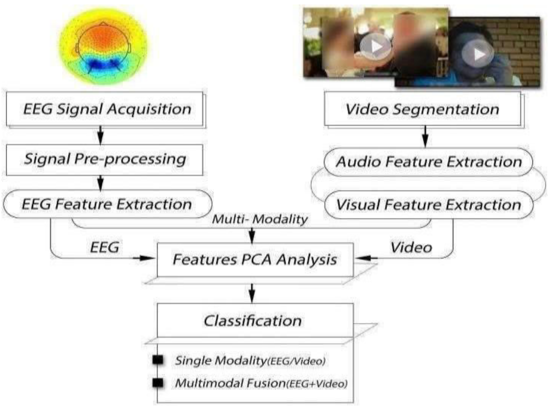

Fig 2 Video Emotion Classification Procedure

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Fig 2 shows These neurons will act as information carriers between human body and brain. Understanding cognitive behaviour of brain can be done by analysing either signals or images from the brain. Human behaviour can be visualized in terms of motor and sensory states such as, eye movement, lip movement, remembrance, attention, hand clenching etc. These states are related with specific signal frequency which helps to understand functional behaviour of complex brain structure. Electroencephalography (EEG) is an efficient modality which helps to acquire brain signals corresponds to various states from the scalp surface area.

G. Outcome

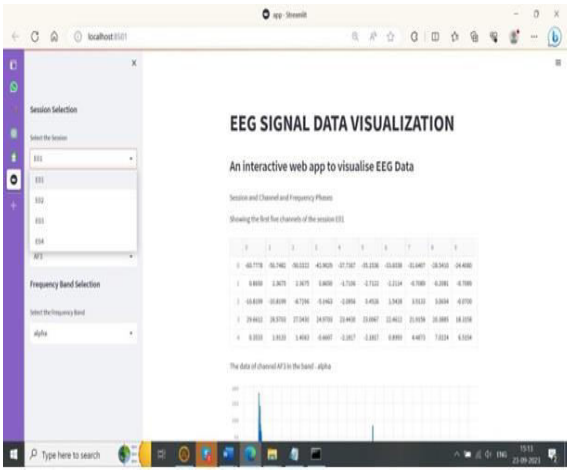

Fig 3 Design of Streamlit Framework

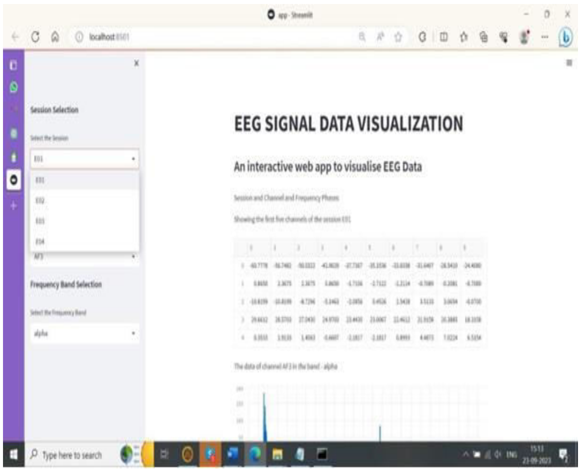

Fig 4 Frequency analyser

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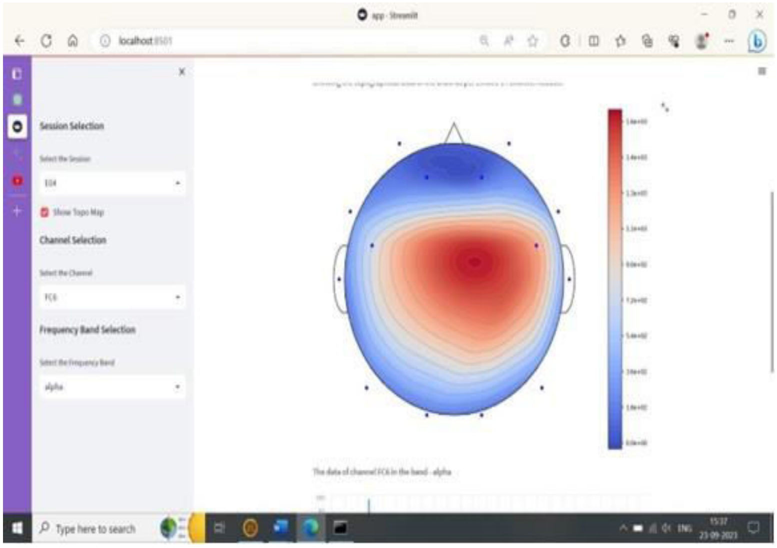

Fig 5 Design of streamlit

Fig 3, Fig 4 and Fig 5 Shows the streamlit is a free and open-source framework to rapidly build and share beautiful machine learning and data science web apps. It is a Python-based library specifically designed for machine learning engineers. Data scientists or machine learning engineers are not web developers and they're not interested in spending weeks learning to use these frameworks to build web apps. Instead, they want a tool that is easier to learn and to use, as long as it can display data and collect needed parameters for modelling. Streamlit allows you to create a stunning-looking application with only a few lines of code.

IV. RESULT ANALYSIS

The proposed algorithm demonstrates a notable improvement in accuracy compared to existing methods, achieving an accuracy of 88% as opposed to the 75% accuracy of current approaches. This advancement suggests a significant enhancement in the ability to analyze and interpret electroencephalogram (EEG) data, potentially leading to more precise diagnoses and treatments in neuroscience and clinical settings.

Table 1 Accuracy Representation

Algorithm	Accuracy
Existing	75
Proposed	88

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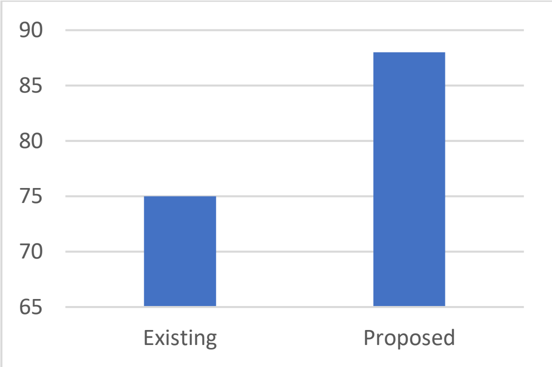

Fig 6 Representation of Algorithm Accuracy

V. CONCLUSION

In conclusion, creating a thorough web application for visualizing EEG data and utilizing the Stream lit architecture provides a strong means of investigating and examining the brain activity recorded by electroencephalograms. Session selection, channel selection, frequency selection, and the web application module are the four essential modules that are incorporated, and they give users an interactive and flexible platform for deriving insights from EEG data. Because of its modular design, it is flexible enough to adjust to different EEG datasets and user requirements. This application is a major step towards improving the accessibility and insightfulness of EEG data processing, which will ultimately lead to advances in our knowledge of brain function and health.

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