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INTRODUCING CONTINUOUS-TIME NETWORKS TO THE ELECTROENCEPHALOGRAPHY (EEG) ANALYSIS

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Abstract : Electroencephalography (EEG) data analysis plays a crucial role in understanding brain function and diagnosing neurological disorders. However, traditional methods often struggle with the non-linear and dynamic nature of EEG signals. Our work introduces Liquid Time Constant (LTC) networks, a novel deep learning architecture specifically designed for time-series analysis, to the field of EEG data analysis. LTC networks offer several advantages over conventional methods. The uniqueness of the liquid time constant mechanism enables them to adaptively capture temporal dependencies in the data, leading to superior performance in tasks like signal classification and prediction. Additionally, their inherent stability and bounded behaviour make them well-suited for real-time applications.

***IndexTerms* - Liquid Time-Constant networks, Deep Learning. Deep recurrent neural networks (DRNNs), Ordinary differential equations (ODEs), Computational neuroscience, Brain-computer interfaces (BCI), EEG data analysis, Time-series analysis.**

I. INTRODUCTION

Electroencephalography, or EEG, is a non-invasive method for recording electrical activity in the brain. This is commonly accomplished by putting electrodes on the scalp to detect the electrical impulses produced by neurons firing in the brain. EEG is frequently used in clinical settings to diagnose illnesses like epilepsy, sleep problems, and brain traumas. [9].

It is also utilized in studies to investigate brain activity patterns related to various cognitive and neurological functions. EEG recordings can provide vital insights into brain activity, helping researchers and healthcare workers understand how the brain works under different settings [15].

A deep learning model is a type of computer architecture that uses numerous layers of interconnected neurons to mimic complex, nonlinear functions. These neurons employ activation functions, introducing nonlinear transformations to the input data at each layer [16]. During training with labeled data, the model modifies its parameters (such as weights and biases) using optimization algorithms such as stochastic gradient descent to reduce the discrepancy between expected outputs and ground truth labels. By iteratively updating these parameters, the deep learning model learns to recognize complicated patterns and correlations in the data, thus serving as a sophisticated function approximator capable of reflecting extremely nonlinear mappings between input and output regions.

Deep learning in EEG is applying deep learning models to analyze and interpret electroencephalography (EEG) data, which measures the electrical activity of the brain. These models use many layers of interconnected neurons to automatically learn and extract complicated patterns from EEG signals, allowing for tasks like brain-computer interfacing, seizure detection, cognitive state classification, and other applications in neuroscience and clinical research. [3].

By employing deep neural networks, EEG signals can be classified with good accuracy, enabling the detection of neurological conditions. Furthermore, deep learning allows for the extraction of significant features directly from raw EEG data, avoiding the need for labor-intensive human feature engineering. This not only streamlines the analysis process but also enhances the robustness and reliability of results. Additionally, deep learning techniques play an important role in the development of brain-computer interfaces, allowing people to communicate with technology using their brain activity. Overall, the incorporation of deep learning into EEG analysis marks a significant achievement, paving the way for additional insights into brain function and its applications in healthcare, neurology, etc.

For DL-based EEG applications, several challenges need addressing. These include the necessity for large annotated datasets specific to EEG signals, ensuring model interpretability for understanding brain activity patterns, and addressing concerns regarding bias and generalizability across diverse populations [17]. Despite these hurdles, ongoing research efforts are actively tackling these challenges to enhance the accuracy and clinical relevance of Deep Learning models for EEG analysis. While DL holds significant promise in advancing our understanding of brain function through EEG, several unresolved issues persist.

A. ***Limited Data Availability***: Deep learning algorithms often require huge volumes of labeled data for effective training. In fields like EEG analysis, acquiring such datasets can be challenging due to factors like limited access to EEG recordings, especially those containing rare or specific neurological conditions. Limited data can cause overfitting, in which the model performs well on the training data but fails to generalize to unseen examples.

B. ***Interpretability:*** DL models are often criticized for their black-box nature, meaning it can be challenging to understand and interpret the decision-making process. In fields like healthcare, where transparency and interpretability are crucial, the lack of explainability poses ethical and practical concerns. Interpretable DL models and techniques for post-hoc interpretability, such as saliency maps or attention mechanisms, are active areas of research but have not yet reached widespread adoption.

C. ***Generalizability:*** DL models trained on one population or dataset may not generalize well to diverse patient populations or different EEG recording conditions. This limitation can affect the model's performance when applied in real-world clinical settings with varying demographics and data characteristics.

D. ***Integration with Clinical Workflow:*** Integrating DL-based EEG analysis tools into existing clinical workflows poses challenges related to usability, compatibility with electronic health records (EHRs), and workflow efficiency. Clinicians may require additional training and support to effectively incorporate these tools into their practice.

DL-based medical devices, including those for EEG analysis, require rigorous validation and regulatory approval before clinical use. Clinical trials and regulatory processes can take a long time and a lot of resources to ensure the safety, efficacy, and reliability of these systems.

II. LITERATURE SURVEY:

Emotion plays an important part in human communication and connection, influencing many elements of daily life. [1]. In the realm of Human-Computer Interaction (HCI) systems, understanding and responding to user emotions have become increasingly significant. Electroencephalogram (EEG) signals offer a valuable source of information regarding human emotion, making them a focal point for emotion recognition research [1]. In recent years, different approaches for emotion recognition based on EEG signals have been investigated, comprising the extraction of distinct aspects followed by categorization using various algorithms. However, in this context, a novel approach leveraging deep learning techniques is proposed. This research proposes employing Long Short-Term Memory (LSTM) networks to learn features directly from raw EEG data, followed by classification with thick layers to distinguish low/high arousal, valence, and liking dimensions of emotion. The suggested method is evaluated using the DEAP dataset, showing good results with average accuracies of 85.65%, 85.45%, and 87.99% for arousal, valence, and liking classifications, respectively. Notably, these results surpass those achieved by traditional techniques, underscoring the effectiveness of deep learning in an emotion recognition from the EEG signals [1]. This approach holds considerable potential for enhancing human-computer interaction systems by enabling more nuanced and responsive interactions based on users' emotional states.

Liquid Time-constant Networks [7] presents a novel approach that integrates several key features to enhance computational performance. The Adaptive Learning mechanisms allows the network to dynamically adjust its parameters in response to changing input patterns, enabling efficient adaptation to various tasks and environments. Moreover, the utilization of Reservoir Computing architecture within the LTC framework offers a powerful tool for processing temporal data, exploiting the network's inherent memory capabilities for improved sequential processing tasks. The architecture also emphasizes the development of Better Attention Maps, facilitating more precise focus on relevant features in the input data, which enhances the network's ability to extract meaningful information and improve overall performance. Furthermore, the computational efficiency of LTC networks is highlighted, demonstrating their potential to attain high levels of performance with limited computational resources, making them suited for real-time applications and resource-constrained contexts [7].

There is also an improved version available of LTC, namely LTC-SE, which has been addressed by Bidollahkhani [14] and further extended from the foundational work of Hasani [7]. The enhancements in LTC-SE are intended to address the inherent constraints of embedded devices, where efficiency and performance are critical. LTC-SE provides full configuration options for Liquid Time Constant Cell (LTC cell), Continuous-Time Recurrent Neural Networks (CTRNNs), Neural Ordinary Differential Equations (NODEs), and CTGRU classes through a consolidated class library that is compatible with TensorFlow 2.x. This consolidation streamlines the implementation process and facilitates seamless integration into existing machine learning pipelines.

III. PROPOSED SYSTEM:

The CTN is designed to handle the irregularly sampled and variable-length nature of EEG data, while effectively capturing long-range temporal dependencies. The system includes a robust data preprocessing pipeline for cleaning and preparing the EEG datasets, followed by a detailed description of the CTN architecture, including the five layers, types of layers are input layer, convolutional layer, RNN layer with embedded LTC, average pooling layer and lastly dense layer. Finally, the Mental State is classified into three types states like Positive, Negative and Neutral. It also includes the training technique, optimization algorithms, and assessment metrics for evaluating the CTN model's performance on specific tasks, including EEG signal classification.

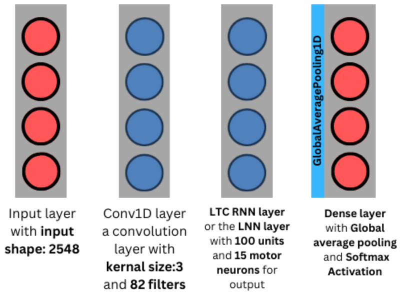

Figure: LNN Architecture

IV. METHODOLOGY:

Liquid Neural Network Architecture:

- Introduce and implement the Liquid Neural Network (LNN) architecture as the core of the proposed system.
- Explore the dynamics and capabilities of LNN for modelling temporal dependencies in EEG signals, specifically focusing on its noise resistance and adaptability.

Feature Extraction:

- Extract relevant features from the preprocessed EEG data to serve as input to the LNN model.
- Investigate features that align with the strengths of LNN, such as its ability to handle temporal dependencies and resistance to noise.

Training the LNN Model:

- Train the Liquid Neural Network using labelled datasets where EEG signals are associated with corresponding emotional states (e.g., Positive, Neutral, Negative).
- Leverage the adaptability and continuous learning capabilities of LNN to enhance the model's performance over time.

Emotion Classification:

- Utilize the trained LNN model to classify emotional states when presented with new, unseen EEG data.
- Assess the model's accuracy and effectiveness in comparison to existing LSTM-based systems and potentially other traditional architectures.

Generalization and Continuous Learning:

- Investigate the applicability of the proposed system to various participants, experimental circumstances, and continuous data streams.
- Emphasize the ability of LNN to adapt and learn continuously, addressing the evolving nature of EEG data.

V. SYSTEM ARCHITECTURE:

Dataset: The dataset is named as "EEG Brainwave Dataset: Feeling Emotions" by Jordan J. Bird. This is a dataset of EEG brainwave data processed using our initial statistical extraction approach. The data used has been recorded on Muse's headband. The data was obtained from two participants (1 male, 1 female) for three minutes per state: positive, neutral, and negative. We used a Muse EEG headband and recorded the TP9, AF7, AF8, and TP10 EEG locations using dry electrodes.

Data Transformation: In the preprocessing phase of the EEG data, several important procedures were done to prepare the dataset for appropriate training and testing in the proposed emotion detection system. Firstly, the Fast Fourier Transform (FFT), a mathematical technique for transforming time-domain EEG signals into their frequency domain representation, was applied to extract frequency components. This process, already performed by the author of the dataset, enables a more comprehensive analysis of the EEG data by capturing information across different frequency bands. Subsequently, label encoding was implemented, assigning numerical values to emotional states—0 for negative, 1 for neutral, and 2 for positive. This encoding facilitates the training process, enabling the model to interpret and learn from the categorical emotion labels. Additionally, a scaler transform was performed to standardize the feature values, ensuring that they all fall within a similar numerical range. Standardization is crucial for enhancing the convergence and efficiency of certain machine learning algorithms. Lastly, reshaping the training and testing data without altering its content preserves the integrity of the EEG signals while making them compatible with the chosen neural network architecture. These preprocessing steps collectively contribute to refining the EEG dataset, aligning it with the requirements of the proposed Liquid Neural Network for accurate and robust emotion classification. (see Figure 1 for reference)

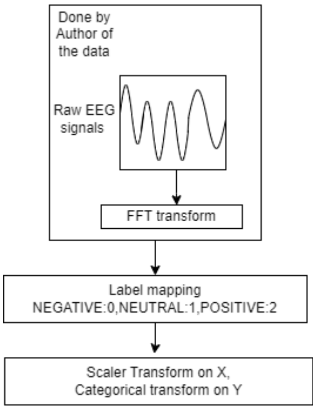

Figure 1: Data Transformation

Feature Representation:

- Temporal Dynamics: Time-domain parameters that capture changes in signal amplitude over time.
- Physiological Signals: Additional measures of arousal and emotional response.
- Artifact Removal: Independent Component Analysis is used to remove Artifacts or unwanted components.

Architecture:

Here the most important layer is the LNN layer also known as Liquid Time Constant Layer

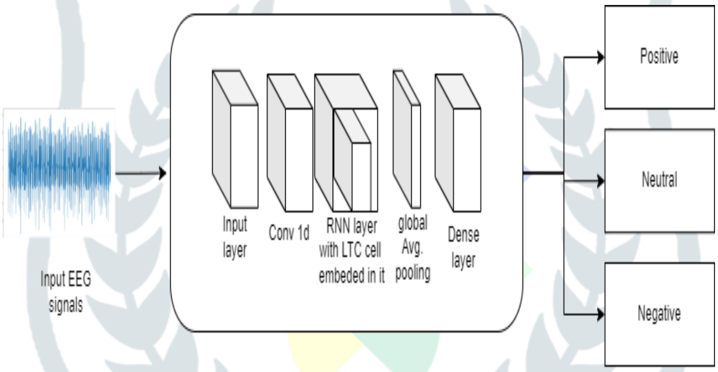

Figure 2: System Architecture

This architecture is available in NCPS toolkit in python and also made available recently in both PyTorch and Tensorflow.kera s.

There are 2 methods possible to implement this layer i.e.

keras.layers.RNN(rnn_cell,return_sequences=True)

Where, rnn_cell = LTC(wiring)

Available in NCPS or

LTC(wiring,return_sequences=True), This would be a direct approach and have a LTC layer instead of embedding LTC in RNN layer

VI. PERFORMANCE EVALUATION:

The proposed LTC based model was developed and trained on Google Colab using core Python programming, enabling efficient training even on EEG datasets. Additionally, in the context of EEG-based emotion recognition, the evaluation metrics can be interpreted as follows:

True Positive: TP indicates instances in which the model properly detects a positive emotional state using EEG inputs.

False Negative: FN refers to cases in which the model wrongly fails to detect a positive emotional state from EEG inputs.

True Negative: TN denotes situations in which the model properly detects a negative emotional state or the lack of a positive emotional state from EEG data.

False Positive: FP denotes cases in which the model mistakenly identifies a positive emotional state that is not present in the EEG signals.

To offer a full evaluation of the model's efficiency, a detailed categorization report was generated. This report includes essential metrics such as F1 score, precision, recall, macro average, and weighted average, offering insights into the model's performance across different emotion categories.

VII. RESULT ANALYSIS:

Potential Impact and Promising Application:

- The LTC and the Implementation of this project is a promising application.
- The proper utilization of this project could bring about significant changes in the field of Neurotechnology, psychology, and other brain-related domains.

During the testing phase of our model, an impressive test accuracy of 97.190% (table 1) was achieved, showcasing the robust performance of the proposed system in accurately classifying emotional states from EEG signals. To further evaluate the model's efficacy, a comprehensive classification report was generated. This report covers key measures like as F1 score, precision, recall, macro average, and weighted average, which provide a detailed overview of the model's performance across many emotion categories.

	Precision	Recall	F1 Score	Support
Negative	0.99	0.98	0.98	136
Neutral	0.99	0.96	0.97	141
Positive	0.95	0.98	0.96	150
Accuracy			0.97	427
Macro Avg	0.97	0.97	0.97	427
Weighted Avg	0.97	0.97	0.97	427

Table 1: Performance Evaluation metrics of Model

Furthermore, a confusion matrix was constructed, providing a visual depiction of the model's capacity to accurately categorize examples and identify potential regions of misclassification. These evaluation metrics collectively demonstrate the system's high accuracy and provide insights into its precision, recall, and overall performance across the emotional categories, affirming the effectiveness of the Liquid Time Constant (LTC) layer in enhancing emotion detection from EEG data.

VIII. CONCLUSION:

In conclusion, the proposed system introduces and implements the Liquid Neural Network (LNN) architecture to model temporal dependencies in EEG signals, extracting relevant features and training the LNN model using labeled datasets to classify emotional states. The system also emphasizes the adaptability and continuous learning capabilities of LNN, while exploring its generalizability across different subjects and experimental conditions. our proposed system achieved outstanding performance in accurately detecting emotional states from EEG data. The accuracy underscores the efficacy and reliability of our model in capturing subtle nuances in EEG patterns associated with positive, negative, and neutral emotions with a single layer of LTC Cell.

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