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Optimized EEG Signal Classification for Accurate Neurological Disorder Prediction

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Abstract: *The neurological disorders have been a significant cause of physical and cognitive disability globally that has afflicted approximately 15 percent of the population. This project will analyze how machine learning (ML) and deep learning (DL) methods are applied to the study of Electroencephalography (EEG) responses in the context of various neurological conditions, including Epilepsy, Autism Spectrum Disorder (ASD), Schizophrenia , Dementia and Alzheimer disease, to identify a similarity between the disorders. The given workflow consists of the EEG data acquisition using a headset, preprocessing by means of Finite Impulse Response (FIR) filters and Independent Component Analysis (ICA) to eliminate noise and artifacts. Data coloring is further broken to extract important features such as Bandpower and Shannon entropy and enhance the classification performance. These features will be easily accessed in an offline database and assist during the further analysis. This project compares the performance of the ML and the DL models and conclude that the random forest model attains 99.85 percent in the process of classifying autism and healthy individuals and the Support Vector Machines (SVM) attains 100 percent in the process of distinguishing between healthy individuals and those with dementia. As well, Convolutional Neural Networks (CNN) or ChronoNet, were also considered such deep learning models that displayed accuracy rates of up to 98 percent. The use of the XGBoost model in the analysis demonstrates the effectiveness of the methodology .In the result, this project indicates the potential of ML and DL approaches within the context of EEG signal processing and presents significant contributions to the creation of brain computer interfaces and enhancing the accuracy of the process of classifying and diagnosing neurological disease.*

Keywords: Electroencephalography (EEG), neurological disorders, machine learning, deep learning

I. INTRODUCTION

Electroencephalography (EEG) signals play an important role in helping us understand how the brain works, especially in relation to thinking, movement, and sensory experiences, and they are widely used in brain computer interfaces (BCIs) for diagnosing neurological disorders. The brain is made up of billions of neurons, which communicate with each other through electrical impulses called action potentials that travel along structures known as axons and dendrites. EEG signals mainly arise from the synchronized activity of pyramidal neurons in the cerebral cortex and can be recorded non invasively from the scalp using electrodes. Because these electrical signals are very weak, advanced methods are needed to capture and analyze them accurately. EEG signals vary over time, frequency, and location, and are grouped into different frequency bands .To record these signals, electrodes are placed on the scalp following standard systems like the 10–20 method, allowing researchers and clinicians to monitor brain activity. EEG data can be collected using invasive techniques, which involve placing electrodes directly in the brain for more precise readings but require surgery, or non invasive techniques, which are safer, painless, and more commonly used in both research and medical practice.

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II. LITERATURE REVIEW

Electroencephalography (EEG) combined with machine learning and deep learning has become a powerful tool for diagnosing neurological disorders such as Alzheimer's disease, autism spectrum disorder (ASD), and epilepsy. EEG is widely used because it is non invasive and provides high temporal resolution, making it effective for analyzing brain activity. Zheng et al. [1] studied changes in time frequency functional connectivity in patients with Alzheimer's disease and frontotemporal dementia using EEG signals. Their results showed that connectivity based features can significantly improve classification accuracy between these disorders. For ASD classification, Al-Qazzaz et al. [2] developed a hybrid deep learning model using transfer learning and convolutional neural networks (CNNs). Their approach improved performance by adapting pre trained models to EEG data. Similarly, de Oliveira Silva et al. [7] demonstrated that low density EEG systems, when combined with machine learning, can still provide reliable and cost effective diagnosis. In epileptic seizure detection, various methods have been explored. Skaria and Savithriamma [3] proposed a system based on phase space reconstruction features, showing that nonlinear techniques are effective in distinguishing seizure and non seizure signals. Rivera et al. [4] evaluated CNN based models and found that deep learning methods generally perform better than traditional techniques when enough data is available.Singh et al. [6] further improved seizure prediction by proposing a hybrid deep learning model suitable for real time applications. Their approach showed promising results for early detection. Abdulghani et al. [5] introduced a method combining multi wavelet feature extraction with a support vector machine (SVM) for inner speech decoding, achieving higher classification accuracy and highlighting the importance of feature extraction. Cao et al. [8] proposed a graph neural network (GNN) based approach for dementia classification using brain connectivity data. Their work emphasizes the value of graph based models in improving classification performance. Finally, Jaipriya and Sriharipriya [9] provided a detailed review of brain computer interface (BCI) based EEG techniques for motor imagery classification.

SYSTEM ARCHITECTURE

The system architecture shows how different parts of the model work together and how data flows through each stage. It includes steps such as input, preprocessing, feature extraction, model training, and output. First, raw data is collected in the input stage. This data is then cleaned and normalized during preprocessing to remove noise and errors. Next, the feature extraction stage identifies the most important patterns in the data. These features are passed to a machine learning or deep learning model, where training and validation are carried out to improve accuracy. Finally, the output stage produces the predicted results, which can be displayed or stored for further use.

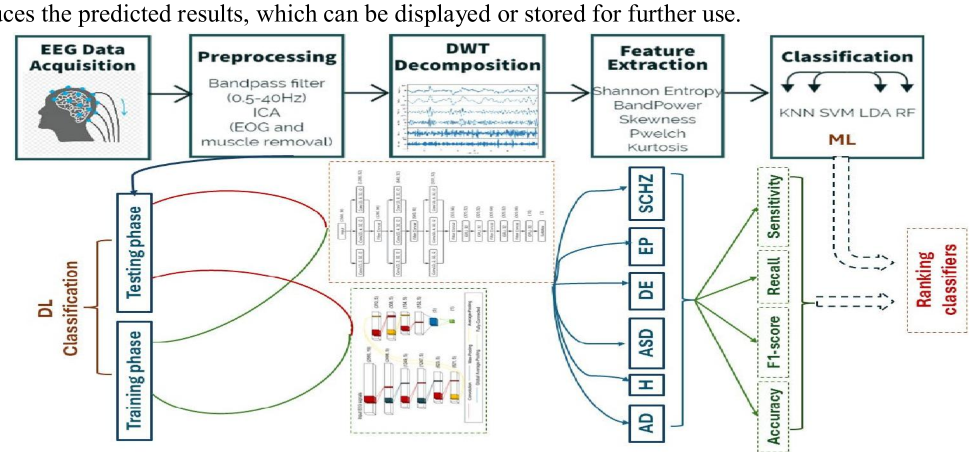

Fig 1: System Architecture

Architecture of our CNN model

Our CNN model comprises five convolutional layers, each utilizing five filters with a kernel size of 3, followed by LeakyReLU activations to enhance gradient flow. To reduce dimensionality and extract salient features, we incorporate

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MaxPooling 1D and AveragePooling 1D layers with pool sizes and strides of 2. The architecture further includes a Global Average Pooling 1D layer to aggregate features into a single value per feature map, culminating in a dense layer with a sigmoid activation function for binary classification.

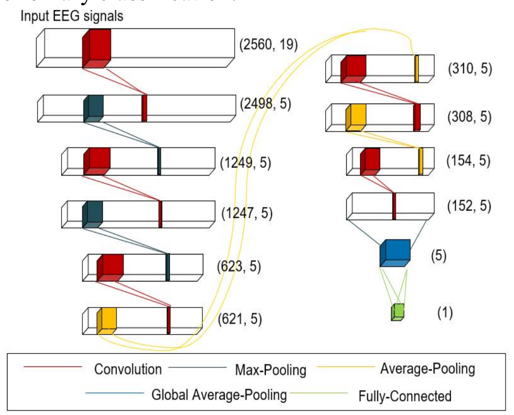

Fig 2: Architecture of our CNN model

Architecture of our chrononet model.

The ChronoNet model processes 3D input tensor data using 1D convolutional layers followed by batch normalization and ELU activation to extract features, which are then processed by GRU layers to capture temporal dependencies.

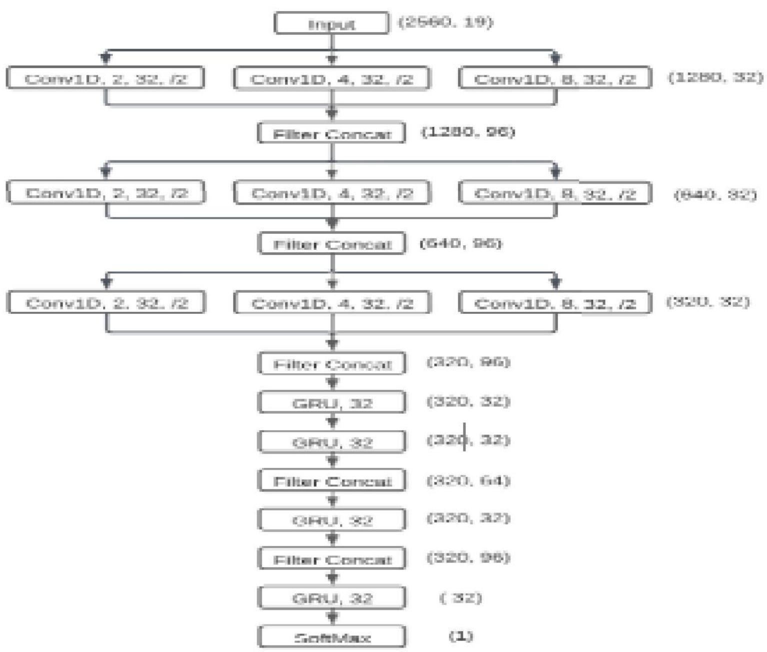

Fig 3: Architecture of our Chrononet model

III. PROPOSED METHODOLOGY

The proposed system is divided into interdependent modules, each addressing a specific aspect of signal processing, feature engineering, and neural modeling. The pipeline from data acquisition to performance evaluation establishes a reliable framework for automated EEG based neurological disorder classification. The modular architecture promotes scalability, enabling integration with real time EEG streams and transfer learning for unseen disorders. The project's results highlight the synergy between domain specific preprocessing and modern deep learning in computational neuroscience.

EEG Data Acquisition Module

The EEG Data Acquisition Module collects and organizes brain signals for analysis. It uses open source datasets for disorders like epilepsy, schizophrenia, autism, Alzheimer's, and dementia, with multi channel recordings sampled between 250–512 Hz. The module standardizes the data and stores patient details like ID, age, and diagnosis. It ensures accuracy by checking signal quality and alignment, and it can support real time recording with EEG devices. All data is stored securely for easy access, and continuous recording allows monitoring changes in a patient's condition over time.

Preprocessing Module

EEG signals often have noise from eye movements, muscles, or the environment, so they need cleaning before analysis. In this module, filters keep only the important brainwave frequencies (0.5–45 Hz), including delta, theta, alpha, beta, and gamma waves, while removing unwanted noise. Independent Component Analysis (ICA) is then used to separate and remove non brain activities like blinks or muscle movements. After cleaning, the EEG data is split into 10 second segments, called epochs, making it easier to work with and label for different disorders or healthy subjects. This preprocessing ensures the data is clear, stable, and ready for accurate analysis. The process is implemented using Python tools like MNE and SciPy, making it reliable and easy to reproduce.

Feature Extraction Module

The Feature Extraction Module turns raw EEG signals into meaningful numbers that machine learning models can use. It analyzes the signals in three ways: over time (looking at mean, variance, skewness, and kurtosis), in frequency (measuring power in different brain waves like delta, theta, alpha, beta, and gamma), and by complexity (using entropy to see how irregular the signal is). Wavelet techniques are also used to capture short, changing patterns in the data. Each EEG segment (epoch) is converted into a feature vector and stored for training models. To keep the data simple and useful, less important features can be removed with techniques like PCA or RFE, and all features are normalized so they're on the same scale. Adding small variations, like noise or shifting time windows, can increase data variety and reduce bias.

Machine Learning Classification Module

The Machine Learning Classification Module uses several algorithms to find patterns in EEG data and classify neurological disorders. Models like SVM, KNN, Logistic Regression, LDA, and Random Forest each have their strengths SVM separates classes clearly, KNN predicts based on nearby points, Logistic Regression and LDA are simple and interpretable, and Random Forest boosts accuracy by combining multiple decision trees. To achieve the best results, key settings like the number of neighbors in KNN or the number and depth of trees in Random Forest are carefully tuned. The data is also normalized so all features are treated equally, and cross validation is used to ensure reliable, unbiased evaluation. This module shows that wellprepared features like band power, entropy, and power spectral density can deliver very high accuracy, providing a strong and interpretable baseline for comparison with more advanced deep learning methods.

Deep Learning Classification Module

The Deep Learning Module automatically finds patterns in EEG data without needing manual feature extraction. It uses models like Convolutional Neural Networks (CNN) and ChronoNet to understand both spatial patterns across channels and temporal patterns over time. CNNs use layers like convolution, pooling, and dropout to extract important features and avoid overfitting, while ChronoNet combines CNN layers with GRUs to capture both short and long term brain signal patterns.These deep learning models achieve very high accuracy (around 98%) and often outperform traditional machine learning methods. Built with TensorFlow and Keras, this module shows how deep learning can automatically detect meaningful EEG patterns, making the system more powerful and efficient.

Performance Evaluation and Visualization Module

This module evaluates how well both machine learning (ML) and deep learning (DL) models perform and makes sure the results are reliable and easy to understand. Tools like SHAP and Grad CAM show which EEG channels or brainwave frequencies influenced the model's decisions, helping doctors verify that the results match real brain activity. Simple statistical tests are also used to compare models and check that performance differences are meaningful. The system tracks metrics like accuracy, precision, recall, F1 score, sensitivity, and specificity, and uses confusion matrices to highlight where mistakes occur. It also creates visualizations such as learning curves, comparison charts, and brain activity maps to make results easier to interpret. All outputs are saved for future reference and reproducibility. Overall, this module ensures the models are accurate, trustworthy, and clinically useful, with deep learning models often performing better on complex EEG data than traditional approaches like Random Forest.

IV. CONCLUSION

This project demonstrates that both Machine Learning (ML) and Deep Learning (DL) models can effectively classify EEG signals for diagnosing brain disorders such as schizophrenia, autism, epilepsy, dementia, and Alzheimer's disease. The study found that combining features like power spectral density (Pwelch), Shannon entropy, and band power, along with using 10 second signal segments, plays a key role in achieving high accuracy, as shorter segments better capture important brain signal patterns. Traditional models like Support Vector Machine (SVM) and Random Forest performed consistently well, especially when enhanced with techniques like Discrete Wavelet Transform (DWT) and feature optimization. Deep learning models especially Convolutional Neural Networks (CNN) and ChronoNet demonstrated superior performance by automatically capturing complex patterns from the data, including the temporal dynamics present in EEG signals.

V. FUTURE SCOPE

Future research on EEG based detection of neurological disorders can explore several exciting directions. Combining EEG with other data sources like fMRI, MEG, or clinical information could give a fuller picture of brain activity and improve diagnosis. Real time EEG monitoring could allow continuous tracking of patients, helping detect seizures or cognitive changes as they happen. Personalized models that include age, genetics, or long term data could make predictions more accurate and tailored to each patient. New deep learning approaches, such as attention networks, transformers, or graph neural networks, could better capture complex patterns in EEG signals. Making systems more robust to noise and using affordable, wearable EEG devices would make them easier to use in clinics or at home. Improving explainability with AI tools would help doctors understand and trust the models' decisions. Finally, testing these models on diverse populations and over long periods could ensure they are reliable, useful, and capable of detecting early signs of neurological disorders.

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