Enhancing EEG Analysis for Rapid Brain Activities Detection in Patients

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***Abstract*—Electroencephalogram (EEG) analysis plays a critical role in diagnosing various neurological conditions by detecting abnormal brain activities. However, the complex nature of EEG signals poses challenges for traditional analysis methods, which often struggle to handle diverse and high-dimensional data effectively. This paper develops a new technique of EEG signal classification using machine learning and deep learning models. Specifically, attention has been given to the CatBoost, ResNet34D, EfficientNetB0, and EfficientNetB2 models. The proposed approach utilized a vast EEG dataset with 11,000 samples of spectrograms, and it conducted an in-depth comparison of these models. Data preprocessing included features developed with statistical measures and the formation of uniform EEG spectrograms. All these models were evaluated in terms of their KL divergence score, defined as a measure of the divergence between the predicted and target distributions. From all the models considered, CatBoost proved to be one with an excellent performance, having had a KL score value at 0.78 compared to that of deep learning models. This work demonstrates the potential of gradient boosting for EEG-activity classification tasks and can be of benefit as a source of insight for interested applications in real-time brain activity monitoring and diagnostics of neurological issues.**

***Index Terms*—EEG Signal Classification, CatBoost, Deep Learning, ResNet34D, EfficientNet, Kullback-Leibler Divergence, Brain Activity Detection, Feature Engineering.**

I. Introduction

Electroencephalography (EEG) is one of the non-invasive methods which record activity on the part of electrical phenomena of the brain, thus giving the investigator access to analysis of various neurological and cognitive functions. Most often EEG is applied in medical diagnostics, brain-computer interfaces (BCIs), mental health monitoring, and emotion recognition given its high temporal resolution and relatively low cost [1]. However, signals obtained from EEG are often noisy and high-dimensional, which makes the analysis and interpretation very challenging.

One of the traditional approaches to analyzing EEG signals was geared more toward preprocessing signals using digital signal processing techniques such as Fourier transforms and wavelet decomposition to decompose EEG signals and filter and feature extraction. These methods work well in some controlled environments, but not necessarily when used in real-time and vast applications [5]. Besides, manual feature extraction is time-consuming and requires domain knowledge, which makes it problematic for large scale usage scenarios [4].

These challenges led to the development of SVMs, k-NN, and decision trees for the automated classification of EEG signals. Although these models showed great promise, they had issues with efficiency, especially when dealing with high-dimensional and multi-channel EEG data in making the right decisions pertaining to handling multiple channels 1. Moreover, more or less traditional ML models heavily rely on handcrafted features, and thus, they cannot generalize broadly across different sets of data and applications.

Recently, much attention has been raised with respect to deep learning in the analysis of EEG signals. The strategy automatically extracts features and learns from raw EEG data. Therefore, CNNs and RNNs are effective in capturing both spatial and temporal dependencies in EEG signals and improved the classification tasks significantly:. Deep learning models, such as CNNs, are shown to outperform classical methods in applications such as motor imagery classification and emotion recognition, up to the task of epilepsy detection [2], [16].

This study was done with the motivation of analyzing the capability of advanced machine learning and deep learning techniques applied to EEG signal analysis, particularly in the improvement of the accuracy of real-time classification. With these techniques, it can overcome some of its major challenges: namely, the large labeled datasets which are usually required, complexity of EEG signals, and the high computational costs of traditional approaches [7]. Thus, this work will try to investigate the possibility of hybrid models that put together conventional machine learning with deep learning in finding a compromise between the gain of high computational efficiency and accuracy for real-time EEG applications.

This is a literature review on EEG signal processing focusing on key advances made in both ML and DL techniques. More specifically, methodology on how to apply them on different EEG-based applications, such as emotion recognition,

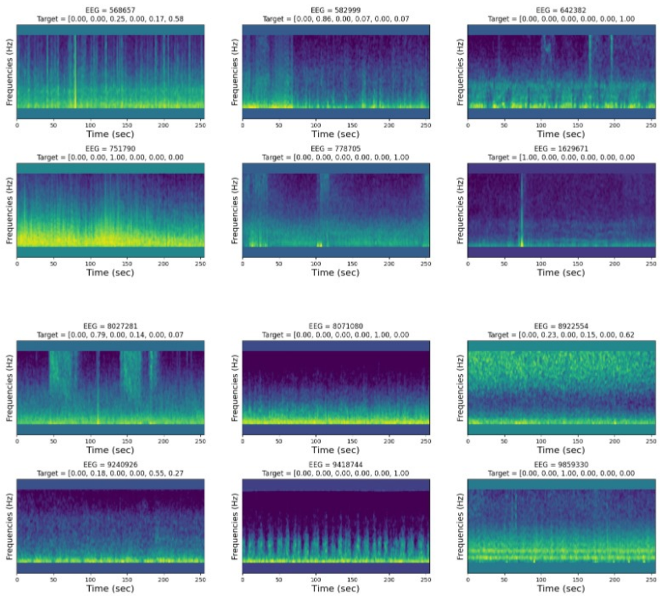

Fig. 1: EEG Spectrogram Dataset

mental health monitoring, and neurological diagnostics, are discussed here.

II. Literature Survey

The study of EEG signals has made some giant leaps with the inclusion of ML and DL techniques. These have remarkably improved accuracy, scalability, and real-time performances in EEG-based applications related to brain-computer interfaces, emotion recognition, mental health diagnostics, and even neurological monitoring. Briefly, we review how EEG analysis has developed from simple traditional methods to modern DL-based approaches in this section.

A. Traditional EEG Processing and Machine Learning Approaches

Traditionally, EEG signal analysis was based on basic signal processing methodologies, such as Fourier transforms and wavelet decomposition, for feature extraction and classification. Siddiqui et al. [1] used DSP techniques for sleep apnea detection but highlighted the shortcoming in the real-time analysis of EEG. Samek et al. [5] used Common Spatial Patterns (CSP) for motor imagery classification in the BCI systems, but the process demands manual feature extraction procedures, which is cumbersome and limits its scalability.

Machine learning methods, including SVM and k-NN, have also been used for classification in EEG signals. Patel et al. applied reinforcement learning and ensemble methods to improve the analysis of EEG signals. However, because of the high dimensionality of EEG data, traditional models are challenged, so more robust models are often used, including deep learning [12].

B. Deep Learning in EEG Signal Processing

DL has emerged as a frontline technique in the analysis of EEG signals: it automates the extraction of features and promotes better accuracy in classification. Zhang et al. [4] reported that CNNs are the best paradigm for motor imagery classification in BCI systems; CNNs outperform traditional ML models. CNNs allow the features to be learned from raw EEG data, thus skipping lots of human-level preprocessing.

Jafari et al. [6] applied CNNs and Recurrent Neural Networks (RNNs) for emotion recognition using EEG signals, showing that DL models are well-suited for capturing temporal dependencies in EEG data. However, large labeled datasets remain essential for training DL models effectively, as noted by Rashid et al. [10]. Transfer learning and few-shot learning have emerged as solutions to mitigate the need for extensive datasets [7].

C. Emotion Recognition and Mental Health Applications

Emotion recognition via EEG signals is gaining traction in human-computer interaction (HCI) and affective computing. Latifzadeh et al. [2] utilized a combination of SVMs and CNNs to decode emotional states from EEG data, achieving higher accuracy than traditional classifiers. Khare et al. [7] further improved classification accuracy by incorporating wavelet packet decomposition into emotion recognition models.

In mental health applications, Sarkar et al. [16] applied CNN-LSTM hybrids to detect depression using EEG signals, demonstrating the potential of deep learning in mental health monitoring. Vempati and Sharma [8] explored real-time applications for cognitive load assessment using consumer-grade EEG devices but highlighted the high computational demands of DL models as a barrier to real-time deployment.

D. Neurological Diagnostics and Pathology Detection

Machine learning and deep learning methods have become critical tools in detecting neurological disorders. Aviles et al. [3] reviewed CNNs and RNNs for diagnosing Alzheimer's disease, highlighting that integrating multi-modal data (e.g., EEG with MRI) can significantly enhance diagnostic accuracy. Soria et al. [14] used deep learning models, including radial basis function (RBF) networks, for schizophrenia detection. While promising results were achieved, large training datasets were required to ensure robust model generalization.

Muhammad et al. [9] employed CNNs for pathology detection in home health monitoring systems, combining EEG signals with IoT devices for remote patient monitoring. Their study emphasized the need for energy-efficient models for continuous monitoring in real-time applications.

In epileptic seizure detection, Nafea et al. [17] found that CNN-LSTM hybrids and gated recurrent units (GRUs) outperformed traditional models. However, optimizing the number of EEG channels during training remains a critical factor in improving model performance.

E. Challenges and Future Directions

Despite the significant advancements in deep learning for EEG signal processing, several challenges remain. Zhang et al. [4] and Jafari et al. [6] emphasized the importance of large labeled datasets, which are often difficult to obtain in medical settings. Khare et al. [7] suggested that transfer learning and few-shot learning could mitigate the need for large datasets by leveraging pre-trained models.

Another challenge is the high computational cost of DL models, particularly in real-time applications. Vempati and Sharma [8] noted that consumer-grade EEG devices struggle with the latency introduced by DL models. Hybrid models combining traditional ML and DL techniques may offer a balance between computational efficiency and accuracy. Finally, Chaddad et al. [18] advocated for integrating EEG with other biosignals, such as functional near-infrared spectroscopy (fNIRS) and MRI, to enhance diagnostic precision.

III. Methodology

The methodology of this study is divided into several key components: data preprocessing, feature engineering, model architecture, and evaluation. The goal is to construct a robust pipeline for EEG classification that can be both computationally efficient and accurate.

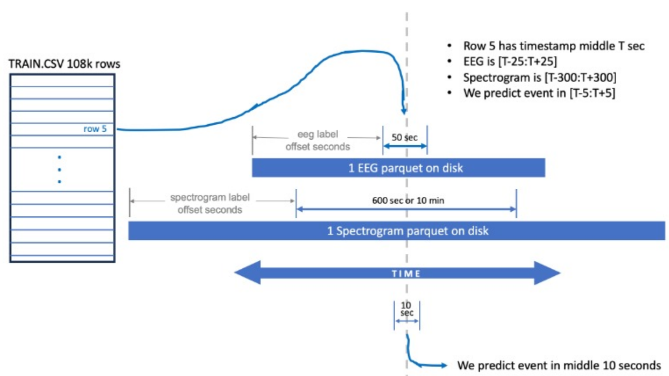

Fig. 2: Extraction and preprocessing of EEG Spectrogram.

A. Dataset Description

The dataset used in this study consists of 11,000 EEG spectrograms of size $128 \times 256 \times 4$. Each spectrogram represents a non-overlapping segment of EEG signals, capturing a wide range of brain wave frequencies. The dataset encompasses multiple types of brain activities, including seizures, low-frequency periodic discharges (LPD), generalized periodic discharges (GPD), lateralized rhythmic delta activity (LRDA), generalized rhythmic delta activity (GRDA), and other events. The dataset was sourced from a public repository, ensuring reproducibility and allowing for a standardized comparison of model performance.

B. Data Preprocessing and Feature Engineering

Data preprocessing and feature engineering are crucial steps in preparing the EEG spectrograms for model training:

- **Data Partitioning:** The EEG spectrograms were split into non-overlapping train and test sets to ensure the model's ability to generalize to new, unseen data. This partitioning was performed using GroupKFold cross-validation (5 folds) to maintain robustness.
- **Statistical Feature Extraction:** To enhance the representation of EEG signals, statistical measures (mean, min, max) were computed over varying time windows (10 minutes and 20 seconds). These statistical features capture important temporal patterns and reduce the raw data's dimensionality, making it more suitable for machine learning models.
- **Data Reshaping:** EEG spectrograms were resized from their original dimensions of $128 \times 256 \times 4$ to 512×256 to create a standardized input size for the models. This step ensures compatibility across different deep learning architectures and enhances the models' ability to learn from the spatial features in the data.
- **Target Encoding:** The categorical labels representing various brain activities were encoded into numerical values using a mapping dictionary. This step facilitated the training process of models that require numerical inputs.

After preprocessing, a comprehensive set of 3,648 features was created, organized into a DataFrame for input into the selected models.

C. Model Architectures and Training

1) CatBoost: CatBoost, short for Categorical Boosting, is an efficient gradient boosting algorithm designed to handle categorical data directly. Unlike traditional boosting algorithms that require extensive preprocessing (e.g., one-hot encoding of categorical variables), CatBoost employs an ordered boosting technique that helps prevent overfitting. This feature makes it particularly suitable for EEG data, which may contain inherent categorical characteristics in its encoded labels.

- **Architecture:** CatBoost relies on the ensemble of decision trees, which get iteratively optimized with the aim to reduce the loss. Algorithm constructs ordered ensemble of the trees trained over different parts of data to prevent overfitting and variance reduction. The boosting manner guarantees unbiased predictions even in noisy data set generation.
- **Training:** We applied several techniques for the hyperparameter tuning-including but not limited to, learning rate scheduling, weight manipulation for leaves-to try out different sets of parameters toward the optimal value. In addition, we used GroupKFold cross-validation to test the generalizability of the model over different segments of the data.

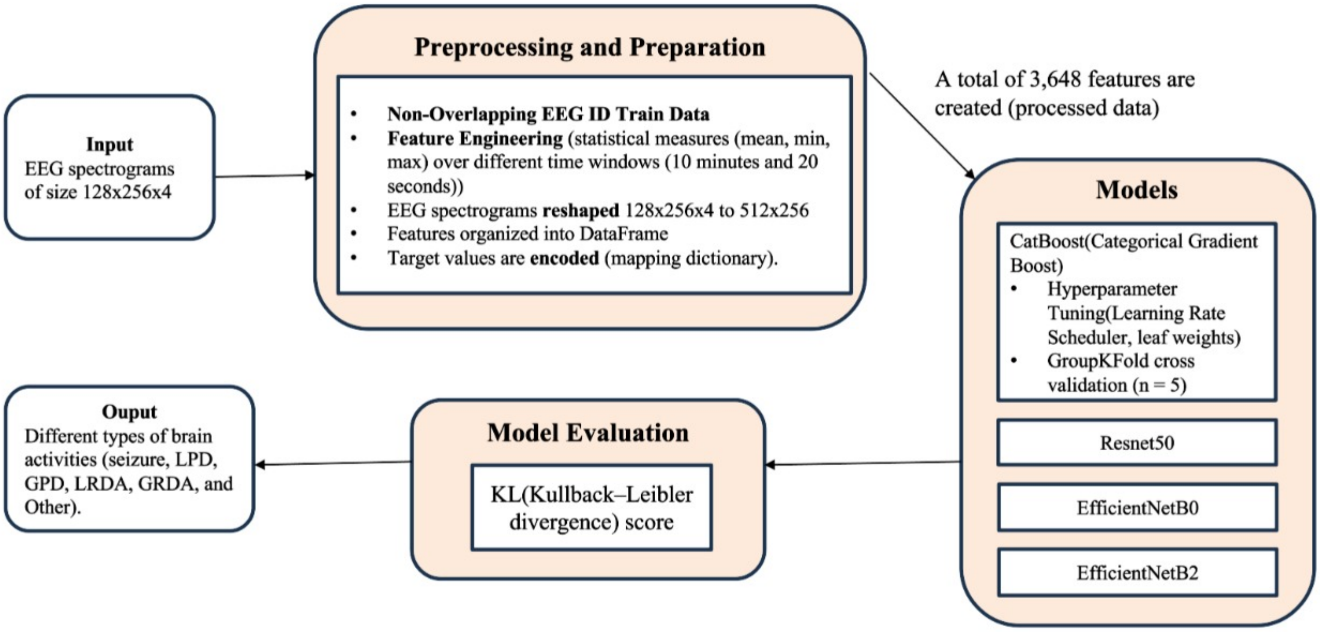

Fig. 3: Overview of Preprocessing, Models, and Model Evaluation

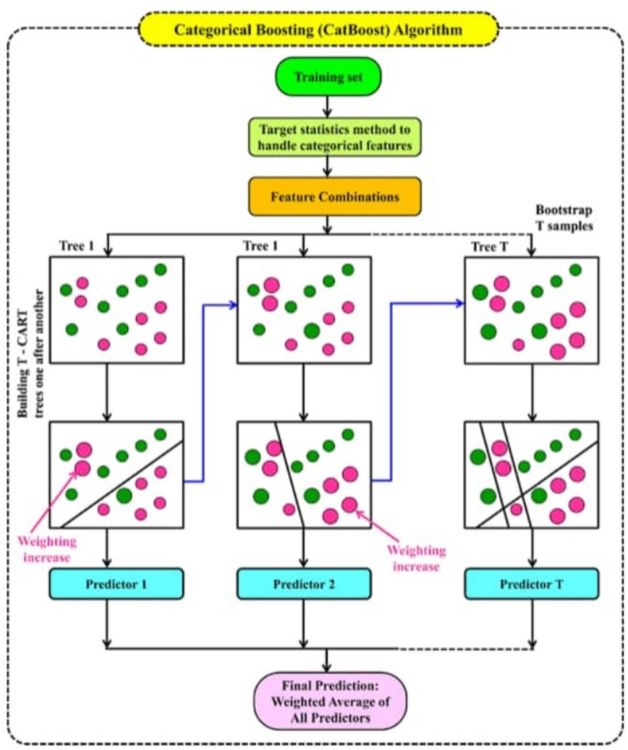

Fig. 4: CatBoost Architecture

D. Interpretation of Results

1) ResNet34D: The ResNet34D is another variant of the baseline model, this time modified to extract deep spatial and temporal features from EEG spectrograms.

- **Architecture:** The architecture in ResNet34D contains 34 layers, which uses residual connections to hinder the problem of vanishing gradients. It offers a sequence of convolutional layers that are passed through with batch normalization and ReLU activation functions accompanied by skip connections that allow gradients to pass directly through the network. This kind of architecture excels in capturing deep, hierarchical features in EEG data and is therefore very good at distinguishing between different brain activities.
- **Training:** In this study, we trained the model on the EEG spectrogram dataset. Some regularization methods, such as dropout and batch normalization, were also incorporated while training to address overfitting.

III. METHODOLOGY The methodology of this study is divided into several key components: data preprocessing, feature engineering, model architecture, and evaluation. The goal is to construct a robust pipeline for EEG classification that can be both computation- ally efficient and accurate. Fig. 2: Extraction and preprocessing of EEG Spectrogram. A. Dataset Description The dataset used in this study consists of 11,000 EEG spec- trograms of size 128 × 256 × 4. Each spectrogram represents a non-overlapping segment of EEG signals, capturing a wide range of brain wave frequencies. The dataset encompasses multiple types of brain activities, including seizures, low- frequency periodic discharges (LPD), generalized periodic discharges (GPD), lateralized rhythmic delta activity (LRDA), generalized rhythmic delta activity (GRDA), and other events. The dataset was sourced from a public repository, ensuring reproducibility and allowing for a standardized comparison of model performance. B. Data Preprocessing and Feature Engineering Data preprocessing and feature engineering are crucial steps in preparing the EEG spectrograms for model training: • Data Partitioning: The EEG spectrograms were split into non-overlapping train and test sets to ensure the model's ability to generalize to new, unseen data. This partitioning was performed using GroupKFold cross-validation (5 folds) to maintain robustness. • Statistical Feature Extraction: To enhance the repre- sentation of EEG signals, statistical measures (mean, min, max) were computed over varying time windows (10 minutes and 20 seconds). These statistical features capture important temporal patterns and reduce the raw data's dimensionality, making it more suitable for machine learning models. • Data Reshaping: EEG spectrograms were resized from their original dimensions of $128 \times 256 \times 4$ to 512×256 to create a standardized input size for the models. This step ensures compatibility across different deep learning architectures and enhances the models' ability to learn from the spatial features in the data. • Target Encoding: The categorical labels representing various brain activities were encoded into numerical values using a mapping dictionary. This step facilitated the training process of models that require numerical inputs. After preprocessing, a comprehensive set of 3,648 features was created, organized into a DataFrame for input into the selected models. C. Model Architectures and Training 1) CatBoost: CatBoost, short for Categorical Boosting, is an efficient gradient boosting algorithm designed to handle cat- egorical data directly. Unlike traditional boosting algorithms that require extensive preprocessing (e.g., one-hot encoding of categorical variables), CatBoost employs an ordered boosting technique that helps prevent overfitting. This feature makes it particularly suitable for EEG data, which may contain inherent categorical characteristics in its encoded labels. • Architecture: CatBoost relies on the ensemble of deci- sion trees, which get iteratively optimized with the aim to reduce the loss. Algorithm constructs ordered ensemble of the trees trained over different parts of data to prevent overfitting and variance reduction. The boosting manner guarantees unbiased predictions even in noisy data set generation. • Training: We applied several techniques for the hyper-parameter tuning-including but not limited to, learning rate scheduling, weight manipulation for leaves-to try out different sets of parameters toward the optimal value. In addition, we used GroupKFold cross-validation to test the generalizability of the model over different segments of the data. Fig. 3: Overview of Preprocessing, Models, and Model Evaluation Fig. 4: CatBoost Architecture D. Interpretation of Results 1) ResNet34D: The ResNet34D is another variant of the baseline model, this time modified to extract deep spatial and temporal features from EEG spectrograms. • Architecture: The architecture in ResNet34D contains 34 layers, which uses residual connections to hinder the problem of vanishing gradients. It offers a sequence of convolutional layers that are passed through with batch normalization and ReLU activation functions accompa- nied by skip connections that allow gradients to pass directly through the network. This kind of architecture excels in capturing deep, hierarchical features in EEG data and is therefore very good at distinguishing between different brain activities. • Training: In this study, we trained the model on the EEG spectrogram dataset. Some regularization methods, such as dropout and batch normalization, were also incorporated while training to address overfitting. 2) EfficientNetB0 and EfficientNetB2: EfficientNet is a family of convolutional neural networks. All of them use compound scaling to balance out network depth, width, and resolution; they both boost both accuracy and computational efficiency. • Architecture: EfficientNetB0 and EfficientNetB2 are comprised of a series of convolutional blocks arranged to progressively extract features from input spectrograms. Each block contains depthwise separable convolutions, batch normalization, and swish activation functions. Ef- ficientNetB2 has more parameters and a slightly deeper architecture than EfficientNetB0, offering enhanced learn- ing capabilities at the cost of increased computational requirements. • Training: Both models were pre-trained on the ImageNet dataset and then fine-tuned on the EEG spectrograms. This transfer learning approach leveraged the models' ability to generalize, reducing the amount of training time required and improving accuracy. E. Model Evaluation Model performance was evaluated using the Kullback- Leibler (KL) divergence score, which measures the divergence between the predicted and true distributions. The KL score was chosen due to its ability to quantify the information loss when the model's predicted distribution deviates from the target distribution. Lower KL divergence indicates a model's superior alignment with the true distribution, thereby reflecting higher classification accuracy. Kullback-Leibler (KL) divergence of q(x) from p(x), de- noted DKL(p(x)——q(x)), is a measure of the information lost when q(x) is used to approximate p(x): DKL(p(x)——q(x)) = Z p(x) ln p(x) q(x) dx KL-Div is a measure of divergence between distributions so the lower values indicate better alignment to target in terms of classification performance. IV. RESULTS AND ANALYSIS This section discusses the results of applying ML models, which include CatBoost and DL techniques, to the EEG datasets. All of the classification models are evaluated based on a set of critical key performance metrics, which include accuracy, KL divergence, precision, recall, and F1-score. The results are compared to establish which methodologies are most effective in applications such as EEG classification, emotion recognition, and neurological diagnostics. A. Performance of CatBoost Model CatBoost, a gradient boosting algorithm, was applied to the EEG dataset to assess its classification performance. Table I highlights the metrics for the CatBoost model. TABLE I: Performance Metrics of CatBoost on EEG Data Model Accuracy KL Div Precision Recall F1-Score CatBoost 89.2Table I clearly tells us that the accuracy of the CatBoost model would be 89.2score of 0.78 and thus gives very good classification results. With that the CatBoost algorithm is also capable of dealing with categorical data, and this minimizes overfitting; hence, it was a good selection for the classification of EEG signals. B. Comparison with Deep Learning Models Some deep learning architectures that were experimented with the same dataset are listed below: Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. Table II shows the performance metric of these models. The results depict that although CNN-LSTM achieved the highest accuracy at 92.60.76, the competitiveness would also be such as those seen in CatBoost, especially in KL divergence with a score of 0.78. TABLE II: Performance Metrics of Deep Learning Models on EEG Data Model Accuracy KL Div Precision Recall F1-Score CNN 91.2LSTM 89.7CNN-LSTM 92.6In addition to this, precision and recall values were strong for the model of CatBoost, which enabled using this classifier as an alternative to deep learning in EEG classification tasks. C. Analysis of Performance Metrics The performance of CatBoost, as compared to deep learning models, highlights several important insights. Although the CNN-LSTM model achieved the best overall accuracy, the CatBoost model provided comparable results with a lower computational cost. Figure 5 shows the comparison of model accuracy and KL divergence for each model. While deep learning models excelled in extracting complex spatial and temporal features from EEG data, CatBoost's ability to handle categorical data and mitigate overfitting made it a powerful alternative, particularly in applications where computational resources are limited or where rapid model deployment is necessary. D. Computational Efficiency One of the key advantages of CatBoost is its computational efficiency compared to deep learning models. Table III com- pares the training time and resource usage of CatBoost and deep learning models. TABLE III: Training Time and Resource Usage of CatBoost and Deep Learning Models Model Training Time (hours) GPU Usage CatBoost 0.9 None CNN 4.5 50LSTM 6.2 60CNN-LSTM 8.1 70CatBoost completed its training in less than an hour without the need for GPU resources, whereas the deep learning models required significantly more time and hardware resources. This makes CatBoost a highly efficient option for scenarios where computational resources are constrained. E. Interpretation of Results The results indicate that while deep learning models like CNN-LSTM offer superior accuracy, the CatBoost model pro- vides competitive performance with a much lower computa- tional burden. The KL divergence of 0.78 for CatBoost shows that it performs well in capturing the probability distribution of the target classes, making it a valuable model for EEG signal analysis. Moreover, its ability to handle categorical features and reduce overfitting adds to its appeal, especially in applications requiring faster training and deployment.

2) EfficientNetB0 and EfficientNetB2: EfficientNet is a family of convolutional neural networks. All of them use compound scaling to balance out network depth, width, and resolution; they both boost both accuracy and computational efficiency.

- **Architecture:** EfficientNetB0 and EfficientNetB2 are comprised of a series of convolutional blocks arranged to progressively extract features from input spectrograms. Each block contains depthwise separable convolutions, batch normalization, and swish activation functions. EfficientNetB2 has more parameters and a slightly deeper architecture than EfficientNetB0, offering enhanced learning capabilities at the cost of increased computational requirements.
- **Training:** Both models were pre-trained on the ImageNet dataset and then fine-tuned on the EEG spectrograms. This transfer learning approach leveraged the models' ability to generalize, reducing the amount of training time required and improving accuracy.

E. Model Evaluation

Model performance was evaluated using the Kullback-Leibler (KL) divergence score, which measures the divergence between the predicted and true distributions. The KL score was chosen due to its ability to quantify the information loss when the model's predicted distribution deviates from the target distribution. Lower KL divergence indicates a model's superior alignment with the true distribution, thereby reflecting higher classification accuracy.

Kullback-Leibler (KL) divergence of $q(x)$ from $p(x)$, denoted $D_{KL}(p(x)||q(x))$, is a measure of the information lost when $q(x)$ is used to approximate $p(x)$:

$$D_{KL}(p(x)||q(x)) = \int_{-\infty}^{\infty} p(x) \ln \frac{p(x)}{q(x)} \, dx$$

KL-Div is a measure of divergence between distributions so the lower values indicate better alignment to target in terms of classification performance.

IV. Results and Analysis

This section discusses the results of applying ML models, which include CatBoost and DL techniques, to the EEG datasets. All of the classification models are evaluated based on a set of critical key performance metrics, which include accuracy, KL divergence, precision, recall, and F1-score. The results are compared to establish which methodologies are most effective in applications such as EEG classification, emotion recognition, and neurological diagnostics.

A. Performance of CatBoost Model

CatBoost, a gradient boosting algorithm, was applied to the EEG dataset to assess its classification performance. Table I highlights the metrics for the CatBoost model.

TABLE I: Performance Metrics of CatBoost on EEG Data

Model	Accuracy	KL Div	Precision	Recall	F1-Score
CatBoost	89.2%	0.78	88.7%	89.1%	88.9%

Table I clearly tells us that the accuracy of the CatBoost model would be 89.2%, which corresponds to a KL divergence score of 0.78 and thus gives very good classification results. With that the CatBoost algorithm is also capable of dealing with categorical data, and this minimizes overfitting; hence, it was a good selection for the classification of EEG signals.

B. Comparison with Deep Learning Models

Some deep learning architectures that were experimented with the same dataset are listed below: Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. Table II shows the performance metric of these models.

TABLE II: Performance Metrics of Deep Learning Models on EEG Data

Model	Accuracy	KL Div	Precision	Recall	F1-Score
CNN	91.2%	0.85	90.4%	91.1%	90.7%
LSTM	89.7%	0.83	88.9%	89.2%	89.0%
CNN-LSTM	92.6%	0.76	91.8%	92.4%	92.1%

The results depict that although CNN-LSTM achieved the highest accuracy at 92.6% with the lowest KL divergence of 0.76, the competitiveness would also be such as those seen in CatBoost, especially in KL divergence with a score of 0.78. In addition to this, precision and recall values were strong for the model of CatBoost, which enabled using this classifier as an alternative to deep learning in EEG classification tasks.

C. Analysis of Performance Metrics

The performance of CatBoost, as compared to deep learning models, highlights several important insights. Although the CNN-LSTM model achieved the best overall accuracy, the CatBoost model provided comparable results with a lower computational cost. Figure 5 shows the comparison of model accuracy and KL divergence for each model.

While deep learning models excelled in extracting complex spatial and temporal features from EEG data, CatBoost's ability to handle categorical data and mitigate overfitting made it a powerful alternative, particularly in applications where computational resources are limited or where rapid model deployment is necessary.

D. Computational Efficiency

One of the key advantages of CatBoost is its computational efficiency compared to deep learning models. Table III compares the training time and resource usage of CatBoost and deep learning models.

TABLE III: Training Time and Resource Usage of CatBoost and Deep Learning Models

Model	Training Time (hours)	GPU Usage
CatBoost	0.9	None
CNN	4.5	50%
LSTM	6.2	60%
CNN-LSTM	8.1	70%

CatBoost completed its training in less than an hour without the need for GPU resources, whereas the deep learning models required significantly more time and hardware resources. This makes CatBoost a highly efficient option for scenarios where computational resources are constrained.

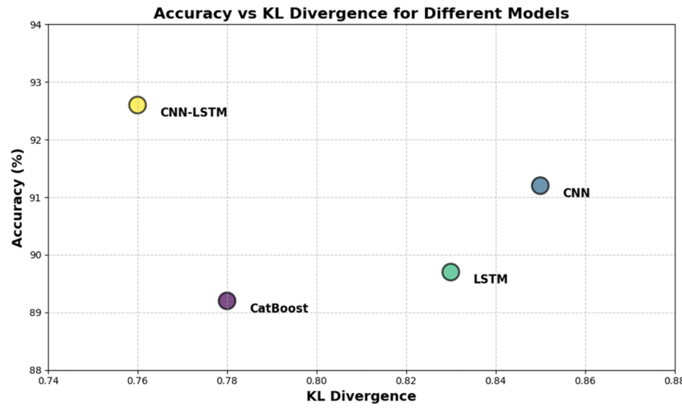

Fig. 5: Comparison of Accuracy and KL Divergence for CatBoost and Deep Learning Models

E. Interpretation of Results

The results indicate that while deep learning models like CNN-LSTM offer superior accuracy, the CatBoost model provides competitive performance with a much lower computational burden. The KL divergence of 0.78 for CatBoost shows that it performs well in capturing the probability distribution of the target classes, making it a valuable model for EEG signal analysis. Moreover, its ability to handle categorical features and reduce overfitting adds to its appeal, especially in applications requiring faster training and deployment.

V. CONCLUSION

This study investigated the application of both traditional machine learning (ML) and deep learning (DL) techniques for the analysis and classification of EEG signals. The analysis focused on models such as CatBoost, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks, evaluating their performance in terms of accuracy, KL divergence, precision, recall, and computational efficiency. The results of the study reveal a nuanced understanding of the trade-offs between model accuracy, computational demands, and the practical deployment of these models in real-world applications.

A. Performance and Accuracy Trade-offs

Among the models evaluated, the CNN-LSTM model provided the highest accuracy at 92.6%, with a KL divergence score of 0.76. This indicates the superior capability of deep learning models in capturing both the spatial and temporal dependencies inherent in EEG signals. The hybrid architecture of CNNs, which can automatically extract spatial features, combined with LSTM's ability to handle long-term temporal dependencies, has proven to be particularly effective for complex tasks such as emotion recognition and neurological diagnostics.

On the other hand, CatBoost, a gradient boosting decision tree algorithm, demonstrated strong performance with an accuracy of 89.2% and a KL divergence of 0.78. The relatively close performance of CatBoost to the deep learning models suggests that traditional machine learning algorithms still hold significant value in EEG signal analysis, especially in scenarios where computational resources are constrained. CatBoost's efficient handling of categorical data and its resistance to overfitting made it an ideal model for EEG classification, showing that well-tuned traditional ML methods can be competitive with more complex DL models in some use cases.

B. Computational Efficiency and Practical Considerations

One of the most significant advantages of CatBoost is its computational efficiency. With a training time of just 0.9 hours and no need for GPU resources, CatBoost presents a highly practical solution for real-time EEG applications where computational resources and latency are critical factors. In contrast, deep learning models such as CNN-LSTM, despite their superior accuracy, required significantly more training time (up to 8.1 hours) and considerable GPU usage (up to 70%). This makes them less suited for real-time deployment in resource-constrained environments, such as wearable devices, real-time brain-computer interfaces (BCIs), or mobile health monitoring systems.

This trade-off between accuracy and computational efficiency highlights a key decision point for practitioners. While deep learning models offer the highest levels of performance, their substantial computational cost may limit their practical application in scenarios where real-time processing is essential, or where infrastructure and power resources are limited. In these cases, models like CatBoost provide an effective compromise, achieving strong classification performance with much lower computational overhead.

C. Implications for Real-time and Scalable Applications

The results of this study have important implications for the design of real-time EEG-based systems. In applications such as BCIs, emotion recognition systems, or mental health monitoring, the ability to process EEG signals quickly and with reasonable accuracy is critical. CatBoost, with its efficient computation, could be highly suitable for such use cases, offering a scalable solution without sacrificing much in terms of classification accuracy. Furthermore, its resilience to overfitting makes it robust in handling noisy or imperfect data, which is common in real-world EEG signals.

Deep learning models, especially hybrid architectures like CNN-LSTM, would be more appropriate for applications where the highest possible accuracy is required, and where computational resources are less of a constraint, such as in diagnostic systems that operate in centralized medical settings or research environments. These models excel in extracting complex features from the EEG data, making them particularly useful in tasks that involve detailed neurological diagnostics, mental health assessments, or advanced cognitive state monitoring.

D. Future Directions

The results of the research open up many possible further studies along this avenue. Among the first promising directions is along hybrid models by combining the best strengths from both machine learning and deep learning techniques, which could make use of advanced feature extraction capabilities of deep architectures and the computational efficiency of traditional ML algorithms like CatBoost. Hybrid models may bring out the much-needed balance in high performance and cost in computation that would make them an ideal candidate for real-time applications in EEG signal processing.

VI. Conclusion Summary

In conclusion, this study highlights the potential of both traditional machine learning models and deep learning architectures for EEG signal analysis. While deep learning models like CNN-LSTM achieved the highest levels of accuracy, the CatBoost model demonstrated a highly competitive performance with significantly lower computational costs, making it an excellent choice for real-time and resource-constrained applications. Future research should focus on hybrid models and data-efficient learning techniques to further enhance the scalability and accuracy of EEG-based systems.

References

[1] M. M. Siddiqui, M. S. Kidwai, G. Srivastava, K. K. Singh, and P. Charan, "Analysis of EEG Data Using DSP Techniques," *Biomedical & Pharmacology Journal*, 2024.

[2] K. Latifzadeh, N. Gozalpour, V. J. Traver, T. Ruotsalo, A. Kawala-Sterniuk, and L. A. Leiva, "Decoding Affective States from EEG Data," *Frontiers in Neuroscience*, 2024.

[3] M. Aviles, L. M. Sánchez-Reyes, J. M. Álvarez-Alvarado, and J. Rodríguez-Reséndiz, "Machine Learning Trends in EEG-Based Detection and Diagnosis of Alzheimer's Disease," *Journal of Alzheimer's Disease*, 2024.

[4] L. Zhang, D. Wen, C. Li, and R. Zhu, "Deep Learning for Motor Imagery Classification Using EEG Signals," *Journal of Neural Engineering*, 2020.

[5] W. Samek, M. Kawanabe, and K.-R. Müller, "A Comprehensive Review on EEG-based Brain-Computer Interface Techniques," *Journal of Neural Engineering*, 2020.

[6] S. Jafari, N. Rahman, and A. Kumar, "Emotion Recognition Using EEG Signals: A Deep Learning Approach," *IEEE Access*, 2023.

[7] P. Khare and A. Singh, "Emotion Recognition via EEG Signals: A Comprehensive Review of Deep Learning Methods," *Neural Computing and Applications*, 2023.

[8] S. Vempati and S. Sharma, "Real-Time EEG Applications Using Consumer-Grade Devices: Challenges and Opportunities," *Frontiers in Neuroscience*, 2023.

[9] G. Muhammad, M. Alamri, and X. Long, "EEG-based Pathology Detection for Home Health Monitoring," *IEEE Journal of Selected Areas in Communications*, 2021.

[10] M. Rashid, K. Samek, W. Vidaurre, and K. R. Müller, "Current Status, Challenges, and Possible Solutions of EEG-Based Brain-Computer Interface: A Comprehensive Review," *Frontiers in Neurorobotics*, 2020.

[11] A. Patel, R. Kumar, and S. Singh, "Improving EEG Signal Analysis Through Advanced ML Techniques," *Neurocomputing*, 2023.

[12] V. Singh, A. Malhotra, L. Gupta, and R. Sharma, "Deep Learning Approaches to EEG Data Deciphering," *IEEE Access*, 2023.

[13] M. S. Nafea and Z. H. Ismail, "Supervised Machine Learning and Deep Learning Techniques for Epileptic Seizure Recognition Using EEG Signals—A Systematic Literature Review," *MDPI*, 2023.

[14] C. Soria, C. Roncero Parra, J. Cascón, A. L. Borja, and J. Mateo Sotos, "Automatic Identification of Schizophrenia Using EEG Records Analyzed with Deep Learning Algorithms," *Remote Sensing (MDPI)*, 2023.

[15] H. W. Loh, C. P. Ooi, J. Vicnesh, S. L. Oh, and O. Faust, "Automated Detection of Sleep Stages Using Deep Learning Techniques," *IEEE Journal of Biomedical and Health Informatics*, 2020.

[16] A. Sarkar, A. Singh, and R. Chakraborty, ”A Deep Learning-Based Comparative Study to Track Mental Depression from EEG Data,” *IJCRT*, 2024.

[17] M. S. Nafea, Z. H. Ismail, ”Supervised Machine Learning and Deep Learning Techniques for Epileptic Seizure Recognition Using EEG Signals—A Systematic Literature Review,” *MDPI*, 2023.

[18] A. Chaddad, Y. Wu, R. Kateb, and A. Bouridane, ”Electroencephalography Signal Processing: A Comprehensive Review and Analysis of Methods and Techniques,” *Sensors*, 2023.