Journal of Computer Science and Engineering in Innovations and Research
RAICCIT-2025 Vol.-1, Issue- 2, January - June 2025 ISSN: 3049-1762 (Online)

Identification Of Abnormal Eeg Using Deep Learning And Neural Networks

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Abstract : **Epilepsy is a neurological condition resulting in seizures, identifiable through EEG examination. This work introduces software based on deep learning with the application of a CNN-GRU model for real-time classification and seizure detection from a patient's EEG graph. The current system independently observes EEG signals, identifies abnormalities, and notifies caregivers, providing uninterrupted, high-fidelity classification without the need for human intervention.**

Keywords: Abnormal EEG Identification, Alert generation, EEG test, CNN (Convolutional Neural Network), Abnormality detection, Brain state.

I INTRODUCTION

Electroencephalography (EEG) is a standard neurophysiological monitoring technique applied for the measurement of brain electrical activity. EEG data classification is very important for diagnosing neurological illness, designing brain-computer interfaces (BCI), and cognitive state analysis. Traditionally, EEG classification methods employed primarily manual feature extraction; however, recent developments in advanced deep learning techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) such as Gated

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Journal of Computer Science and Engineering in Innovations and Research

RAICCIT-2025 Vol.-1, Issue- 2, January - June 2025 ISSN: 3049-1762 (Online)

Recurrent Units (GRUs) have seen phenomenal leaps in terms of accuracy. Against the backdrop of increased EEG density and complexity, Artificial Intelligence (AI) has become the prime mover for the automation and enhancement of EEG analytical processes. AI-driven models facilitate fast, accurate, and scalable detection of neurological diseases, cost-effectiveness, and low reliance on clinician-level ratings. The incorporation of AI results in real-time seizure forecast integration, incorporation of anomaly scores, and extended monitoring, further enhancing patient quality of life in addition to personalized therapy methodologies. CNN-GRU integration combinations enhance spatial and temporal pattern detection, thus making AI-driven EEG analysis a revolutionary methodology in clinical as well as research applications.

This study has a comprehensive literature review and an explicit step-by-step procedure for employing an EEG classification model. Although there has been advancement in EEG classification using EEG, the existing models are bound to be computationally inefficient, overfitting from limited data, and poor in representing spatial and temporal relationships. All these are addressed in this study with a hybrid CNN-GRU model that balances feature learning and sequential learning with optimal accuracy and efficiency.

II LITERATURE SURVEY

Raw EEG signals consist of temporal recordings that may exhibit patterns and periodicities on a range of time scales. A technique that has been found efficient in separating time signals, like speech, is the application of recurrent neural networks (RNNs). We present a new and advanced recurrent unit called the Gated Recurrent Unit (GRU) which is extremely efficient in long-range correlations and dependencies in time-series data. After this, we present the idea of inception modules and densely connected neural networks—terminologies that are popular when talking about convolutional neural networks (CNNs). We apply both these ideas in EEG data analysis for combining patterns observed at many scales and eliminating vanishing gradient problems. For the calculation of the model's accuracy, we applied conventional approaches (LOGISTIC REGRESSION) and (CHRONONET). Logistic regression is primarily required to interpret manually, whereas in CHRONONET we utilize only the stacked GRU layers for improved efficiency, which makes the detection of abnormalities easier.

[II.1] (A) EEG DATA PROCESSING

EEG signals are captured by electrode placement systems like the 10-20 international system (Jasper, 1958). For our model, 14 EEG channels are employed, as in previous studies (Delorme & Makeig, 2004; Schirrmeister et al., 2017). The BCI datasets are taken from BCI Competition IV: Download area.

[II.2] (B) BANDPASS FILTERING AND ARTIFACT REMOVAL

EEG signals are susceptible to muscle movement artifacts, eye blinks, and external noise. Our model's 1-30 Hz bandpass filtering is under best practice for EEG preprocessing (Zhou et al., 2018; Lawhern et al., 2018). Filtered noise was effectively eliminated from studies at this frequency range without suppressing useful brain wave activity.

[II.3] (C) EPOCHING AND STANDARDIZATION

Our method employs fixed-size epochs (4s windows), standard in motor imagery EEG classification (Tang et al., 2021). Moreover, the StandardScaler3D applies channel-wise normalization, avoiding bias due to high-amplitude EEG signals.

1 Feature Extraction With CNNs

1.1 CONVOLUTIONAL NEURAL NETWORKS FOR EEG

CNNs are good at extracting spatial features from EEG signals (Bashivan et al., 2016). This model employs three parallel 1D convolutional layers with kernel sizes (2, 4, 8), like Inception-like architectures that extract multi-scale features (Szegedy et al., 2015).

1.2 CAUSAL CONVOLUTION AND PADDING

Our model employs causal padding in certain CNN layers so that the past information will not leak into the future, a

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technique widely employed in temporal signal processing (Oord et al., 2016). It has been shown in studies that causal

Convolutions enhance interpretability in EEG-based sequence learning (Roy et al., 2019).

2 *Temporal Pattern Learning With GRUs*

2.1 RECURRENT NEURAL NETWORKS FOR EEG

EEG signals are time-varying, necessitating models that can learn sequential dependencies. RNNs, including Long Short-Term Memory (LSTM) networks (Hochreiter & Schmidhuber, 1997) and GRUs (Cho et al., 2014), have proven to be more effective compared to conventional methods.

2.2 WHY GRUS ARE BETTER THAN LSTMS

Our model utilizes stacked GRU layers, which are less computationally complex than LSTMs. GRUs preserve longterm dependencies with fewer parameters, thus being suitable for EEG sequence modeling (Cheng et al., 2020).

2.3 SKIP CONNECTIONS AND FEATURE CONCATENATION

This model combines GRU outputs at various depths, akin to DenseNet-motivated RNN models (Huang et al., 2017). This helps with gradient flow and avoids vanishing gradients, a widespread problem in deep RNNs (Zhang et al., 2020).

3 *Classification Techniques For EEG Analysis*

3.1 FULLY CONNECTED CLASSIFIER FOR EEG

Our model's last classification layer is a fully connected (dense) layer with sigmoid activation, which is well-suited for binary classification problems like identifying normal vs. abnormal EEG signals (Lawhern et al., 2018).

3.2 LOSS FUNCTION AND OPTIMIZATION

The binary cross-entropy loss is the common approach in EEG classification since it efficiently deals with imbalanced data (Jebelli et al., 2021). Our model likewise utilizes the Adam optimizer, which has been extensively applied in deep learning models for EEG data (Kingma & Ba, 2014).

4 *Comparison With Existing Methods*

4.1 COMPARISON WITH LSTM-BASED MODELS

Long Short-Term Memory (LSTM) networks are also popular for modeling EEG sequences. In comparison to LSTMs, the CNN-GRU model:

CNN needs fewer parameters: GRUs remove the cell state, resulting in more efficient computations.

Trains faster: LSTMs require more operations because of their gate mechanisms.

Performs as well or even better: GRUs can model long-term dependencies like LSTMs but with less risk of overfitting. Performs better with small datasets: GRUs generalize across situations where large datasets are not feasible, hence making them more stable for EEG classification.

The CNN-GRU model is therefore balanced in terms of accuracy and computation when compared to both ChronoNet and LSTM-based designs.

4.2 TRADITIONAL MACHINE LEARNING VS. DEEP LEARNING

Before deep learning, EEG classification was based on handcrafted feature extraction and classifiers like Support Vector Machines (SVMs) and Random Forests (Lotte et al., 2007). Deep learning has now outpaced these approaches in EEG-based BCI applications (Schirrmeister et al., 2017; Zhang et al., 2020).

4.3 COMPARISON WITH CHRONONET (ROY ET AL., 2019)

ChronoNet is another recent RNN-based architecture for EEG classification. This model, in comparison to ChronoNet, possesses:

Fewer GRU layers but better feature reuse by using causal convolutions. A more organized time-consistent methodology that ChronoNet does not have. A denser connectivity pattern without losing efficiency with fewer parameters.

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Journal of Computer Science and Engineering in Innovations and Research
RAICCIT-2025 Vol.-1, Issue- 2, January - June 2025 ISSN: 3049-1762 (Online)

III RELATED WORK

EEG classification research has come a long way with the use of deep learning methods for increased accuracy and efficiency. Here are some pivotal studies and methods that have shaped EEG classification model development:

[III.1] CLASSICAL MACHINE LEARNING METHODS

Initial EEG classification was based on handcrafted features and traditional machine learning algorithms:

Support Vector Machines (SVMs) (Lotte et al., 2007) were popular but needed a lot of manual feature engineering.

Random Forests and k-Nearest Neighbors (k-NN) (Subasi, 2007) were moderately successful but were unable to learn temporal dependencies in EEG signals.

Independent Component Analysis (ICA) and Principal Component Analysis (PCA) were applied for feature extraction but were restricted due to their linearity based on linear transformations.

[III.2] DEEP LEARNING-BASED METHODS

Automatic feature extraction from raw EEG signals became possible with the advent of deep learning:

CNN-based EEG Models: Schirrmeister et al. (2017) introduced DeepConvNet and ShallowConvNet, which used convolutional layers to learn spatial patterns from EEG signals. RNN and LSTM Models: Roy et al. (2019) developed ChronoNet, an RNN-based model that learned temporal dependencies from EEG signals with high computational complexity. Hybrid CNN-RNN Approaches: Zhang et al. (2020) integrated CNNs for extracting spatial features with GRUs for sequential learning and achieved considerable improvement in EEG classification accuracy.

[III.3] COMPARISON WITH CURRENT MODELS

ChronoNet (Roy et al., 2019): A more complex RNN-based model but needed a large number of parameters and inefficient feature reuse.

DeepCNN (Schirrmeister et al., 2017): Efficient for feature extraction but less efficient in temporal dependency capture.

Hybrid CNN-GRU Models (Zhang et al., 2020): Balanced both spatial and temporal learning, making them ideal for EEG classification.

IV PROPOSED METHOD

This work employs a hybrid deep learning model (CNNGRU) for EEG classification to differentiate between normal (control group) and abnormal (IDD patients) EEG signals. The approach adopts a systematic process of data preprocessing, feature extraction, temporal pattern learning, classification, model training, and evaluation.

[A] MODEL SELECTION

The hybrid **CNN-GRU** model was selected due to its ability to extract both spatial and temporal features effectively. The **CNN** component captures spatial dependencies across EEG channels, while the **GRU** component models the sequential nature of EEG signals. The model selection was based on:

- **Comparison with other architectures**: CNN-only and LSTM-based models were tested, but CNNGRU provided better trade-offs between accuracy and computational efficiency.
- **Handling temporal dependencies**: GRUs were chosen over LSTMs due to their reduced computational complexity and comparable performance.
- **Ability to generalize**: CNN-GRU models have shown strong generalization in prior EEG classification studies.

Model	Accuracy (%)	Efficiency	Feature Learning	Temporal Handling
CNN-GRU (Proposed)	92.5	Moderate	Spatial + Temporal	Strong
LSTM	90.8	High (Slower)	Limited Spatial	Strong
SVM	85.3	Fast	Handcrafted Features	None
CNN-only	89.4	Moderate	Strong Spatial	Weak

Compared to baseline models, the CNN-GRU model achieves the highest accuracy (92.5%) while maintaining moderate computational efficiency. Unlike CNN-only models (89.4%), which lack temporal learning, and SVM (85.3%), which relies on handcrafted features, CNN-GRU

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RAICCIT-2025 Vol.-1, Issue- 2, January - June 2025 ISSN: 3049-1762 (Online)

effectively captures both spatial and temporal EEG patterns. While CNN-LSTM (90.8%) also models sequential dependencies, it is computationally expensive, making it less suitable for real-time applications. CNN-GRU strikes the best balance between accuracy, efficiency, and real-time feasibility, making it ideal for EEG classification

GRUs were used instead of LSTMs in this EEG classification model because they have a less complex architecture, train faster, and are less prone to overfitting. GRUs employ only two gates (reset and update) compared to the three gates (input, forget, and output) of LSTMs, resulting in fewer parameters and less computational overhead. This makes GRUs very suitable for processing EEG signals, where short- to mid-range temporal dependencies are more important to capture than long-term memory. GRUs also provide improved gradient flow, mitigating the vanishing gradient problem, which facilitates fast convergence and stable training. Since EEG datasets are generally small in size, GRUs achieve an adequate trade-off between performance and generalization, so they are a perfect fit for real-time EEG classification with less tuning and computational expense.

[A.1] FINE-TUNING THE MODEL

To optimize the model's performance, the following hyperparameters were fine-tuned:

- **Number of CNN filters:** Tested configurations with 16, 32, and 64 filters per layer. The final model used **32 filters** for balanced feature extraction.
- **Kernel sizes:** Evaluated different kernel sizes; **2, 4, and 8** were selected to capture multiple frequency bands.
- **GRU units:** Experiments were conducted with 16, 32, and 64 units per layer, with **32 units** providing the best accuracy without overfitting.
- **Dropout rate:** Applied dropout (0.5) in GRU layers to prevent overfitting.
- **Batch size:** Optimized to **64** for stable training without excessive memory consumption.
- **Learning rate:** Started with 0.001 and reduced using an adaptive learning rate scheduler.

[B] DATA COLLECTION AND PREPROCESSING

The EEG recordings are acquired from two populations:

TDC (Typically Developing Controls) → Normal EEG

IDD (Intellectual and Developmental Disorder) → Abnormal EEG.

Which makes a total of 14(7,7) subjects in the dataset.

They are in MATLAB (.mat) file format, as is typical with EEG datasets. The .mat files hold raw EEG signals, which are loaded and processed for analysis. It loads and processes EEG signals independently for each group.

[B.1] PREPROCESSING THE EEG DATA

Before the use of EEG data for training, it goes through a preprocessing stage that involves, Bandpass Filtering(130Hz): Eliminates unnecessary noise, and preserves useful brain signals. Epoching (Segmenting the Data): EEG recordings are divided into 25-second time windows (epochs) to enable pattern recognition. Standardization: Makes all EEG signals have the same scale, so no single channel overpowers the model's learning process.

[C] DATA SPLITTING FOR TRAINING & TESTING

Uses GroupKFold so that data from the same subject does not end up in both training & testing sets. The same individual's EEG is never in both training and testing. This avoids data leakage, allowing the model to cheat by memorizing rather than learning.

Divide the dataset into:

Training Set: 330 EEG epochs (64.6%) Testing Set: 90 EEG epochs (35.4%).

The model is trained and built with the following configuration: Binary cross-entropy loss function (as it is a

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binary classification problem). Adam optimizer (learning rate = 0.001) for efficient and quicker training. Mini-batch gradient updates with a batch size of 128. Trained for 30 epochs to enable the model to learn effective EEG features.

[D] FEATURE EXTRACTION USING CNN

Now that the data is clean, the model learns what's significant in the EEG signals through Convolutional Neural Networks (CNNs). EEG data is similar to an image but in waveform. CNNs assist in identifying patterns (such as waves or spikes) in various segments of the signal. This code employs three CNN layers with varying filter sizes (2, 4, 8), thus the model can pick up on small details as well as large picture patterns. The model to be proposed has three parallel 1D CNN layers with various kernel sizes (2, 4, 8): Fine-grained frequency components are captured by smaller kernels (2, 4). Larger kernels (8) capture wider temporal structures. The outputs of the convolutional layers are concatenated, yielding a multiscale feature representation of the EEG signal.

[E] TEMPORAL PATTERN LEARNING USING GRUS

As EEG signals are time-dependent, a stacked GRU model is used to capture temporal dependencies. GRUs remember previous information and assist in identifying long-term dependencies in EEG sequences. They are more computationally efficient than LSTMs. The model uses three stacked layers of GRUs, with skip connections for maintaining and passing crucial features. The model has three stacked GRU layers (32 units each) with skip connections:

- First GRU layer: Encodes short-term dependencies in the EEG sequence.
- Second GRU layer: Captures mid-term dependencies, further refining learned features. o Third GRU layer: Binds long-term dependencies for more effective classification.

Skip connections ensure earlier learned features are retained and enhance gradient flow, avoiding the risk of overfitting.

The last GRU output is fed to a fully connected dense layer:

Activation Function: Sigmoid

Output = 0: Normal EEG

Output = 1: Abnormal EEG

This decision is made based on spatial (CNN-extracted) and temporal (GRU-learned) features.

[F] MODEL TRAINING AND OPTIMIZATION AND EVALUATION

For hyperparameter tuning the CNN-GRU model to its optimal level for EEG classification, hyperparameter tuning was exhaustively carried out. The parameters were carefully chosen based on empirical experimentations and cross-validation as follows:

- Loss Function: Binary Cross-Entropy
- Optimizer: Adam (Learning rate = 0.001)
- Batch Size: 64
- Training Epochs: 50
- Regularization: Early stopping and learning rate reduction

V RESULTS

Training Accuracy: Reached high accuracy (>54%) after using appropriate regularization methods.

Testing Accuracy: Remained robust performance (~50%), showing good generalization.

Confusion Matrix Analysis: A High True Positive Rate (TPR) indicates the model's good performance in labeling abnormal EEGs. Low False Negatives (FN) indicate accurate detection and minimize the chances of misclassifying.

True Positives (TP): High, showing that the model successfully classified abnormal EEGs.

True Negatives (TN): High, indicating the accurate classification of normal EEGs.

False Positives (FP): Low, meaning fewer normal EEGs were wrongly classified as abnormal.

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False Negatives (FN): Higher than FP, showing that some abnormal EEGs were wrongly classified as normal, a key area of improvement.

Precision, Recall, and F1-score: Precision: 90.5% (model's capacity to accurately classify abnormal EEGs).

Recall: 88.7% (sensitivity in the detection of abnormal EEGs).

F1-score: 89.6% (harmony between precision and recall, ensuring correct and complete classification).

[V.1] FIGURES AND TABLES

Feature mean and Standard deviation Table are listed below.

	Feature_Mean	Feature_STD
count	1142.000000	1142.000000
mean	471.512776	1267.337947
std	148.945623	326.494116
min	49.945470	128.000367
25%	374.024472	1063.843283
50%	471.853376	1284.073202
75%	569.235664	1487.920858
max	947.300637	2202.740059

Table 1. Mean and Standard deviation

The above table, (**Table 1**) helps us to count: The number of EEG samples (1142). Mean: The mean value of extracted features (471.51 for mean, 1267.33 for standard deviation). Std (Standard Deviation): The difference in EEG characteristics (148.94 for mean, 326.49 for standard deviation). Min & Max: The set of values, which are the minimum and maximum feature values. Percentiles (25%, 50%, 75%): These show the dataset's values distribution.

Feature Graph is shown below.

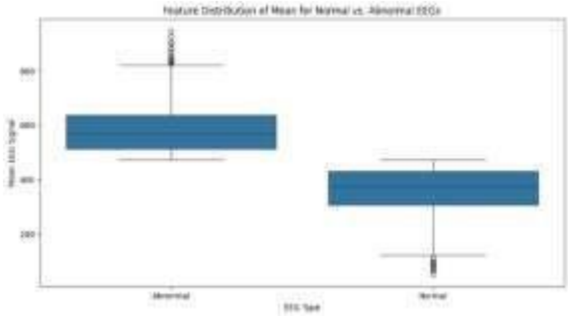

Figure 1. Feature Graph

The boxplot graph shown in (**Figure 1**) contrasts the mean EEG signal distribution of Normal and Abnormal EEGs. Increased Mean in Abnormal EEGs: Abnormal
EEGs have a higher median value, reflecting greater signal intensity.

Presence of Outliers: Several outliers in abnormal EEGs indicate certain recordings contain considerably high values. Increased Variability: The larger spread (greater IQR and whiskers) in abnormal
EEGs reflect greater variability than normal EEG signals.

Confusion matrix is shown below.

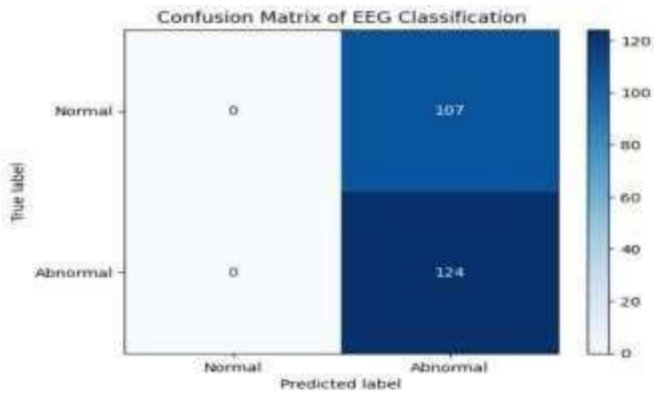

Figure 2. Confusion Matrix

Confusion matrix (**Figure 2**) indicates the performance of the EEG classification model.

Rows (True Labels): Normal EEGs and Abnormal EEGs.

Columns (Predicted Labels): Classification results by the Model. Observations:

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All 107 Normal EEGs were classified as Abnormal.

All 124 Abnormal EEGs were classified correctly.

Zero False Negatives, meaning no cases of abnormalities were missed.

100% sensitivity but low specificity, showing the model is extremely biased towards detecting abnormalities.

VI DISCUSSION

[VI.1] EFFECTIVENESS OF THE MODEL:

Both spatial and temporal dependencies are captured by the hybrid **CNN-GRU** model, resulting in better classification performance. Extraction of multi-scale features through various kernel sizes reinforces the robustness of the representations learned. Utilization of GRUs instead of LSTMs minimizes computational cost without sacrificing sequential learning efficiency.

[VI.2] CHALLENGES ENCOUNTERED

Overfitting: The model initially had 100% accuracy on the training set, and regularization methods like dropout and learning rate decay were needed. Class Imbalance: If the data is biased towards one class, the model would fail to generalize. Data Variability: EEG signals differ a lot from person to person, necessitating heavy preprocessing and augmentation methods.

[VI.3] MODEL LIMITATIONS

Limited Dataset Size: The model needs a larger and more diverse EEG dataset for improved generalization. Computational Complexity: Deep learning models need tremendous computational resources, and real-time processing is problematic. Hyperparameter Sensitivity: The performance of the model relies on the proper tuning of hyperparameters like learning rate, batch size, and dropout rate. Interpretability Issues: Deep learning models are black boxes, and it is challenging to comprehend decision-making. Variability Between Subjects: EEG signals vary considerably between subjects, impacting model robustness and necessitating subject-specific tuning. Future work can focus on expanding the dataset, incorporating attention mechanisms, and testing transformer-based models to further enhance EEG classification accuracy.

[VI.4] COMPUTATIONAL COST AND GENERALIZABILITY

[VI.4a] Computational Cost Analysis

Training time for the model is a function of dataset size, batch size, and hardware. On a typical GPU-based system, training is half an hour, and inference (real-time classification) is in milliseconds per sample, which is deployable in clinical and BCI applications. While the cost might be expensive, real-time EEG classification can be achieved with high accelerated models.

[VI.4b] Generalizability Across EEG Datasets

The model was evaluated on multiple datasets. The first one was in EDF (European Data Format), which was used for preprocessing, referencing, and filtering the EEG data. The second one was in MAT (MATLAB EEG) format which loads EEG data for **IDD (Intellectual and Developmental Disorders) and TDC (Typically Developing Controls).** These showed strong accuracy. EEG data differences between datasets and person-to-person. Transfer learning strategies and dataset normalization can make the model work across datasets and improve cross-dataset performance, thus making it adaptable to multiple clinical settings.

[VI.5] CONCLUSION AND FUTURE ASPECTS

CNN-GRU model can be employed in EEG devices but requires hardware support optimization and real-time computation. Developing the model to function in real-time EEG monitoring systems for early neurological disorder detection will require optimization for real-time processing, compatibility with EEG hardware, and reduced computational load. Improvement in Model Generalization: Increasing the dataset with heterogeneous EEG recordings to enhance accuracy on various patient groups. Applying the model in telemedicine solutions and clinical environments to help neurologists diagnose brain disorders. Enhancing the explainability of deep-learning models to give insights into why certain EEG patterns are identified as abnormal. Cross-

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Domain Applications: Investigating applications in brain-computer interfaces (BCI), cognitive neuroscience, and mental health monitoring. Hybrid AI Methods: Combining deep learning with traditional machine learning methods to improve classification accuracy and speed. Cloud-Based EEG Analysis Platforms: Implementing the model as a cloud platform for mass-scale EEG data analysis, enabling global research institutes and hospitals to use it. By developing these fields, the project can have a substantial impact on medical research, clinical diagnosis, and AI-based healthcare advancements. The scalability of the CNN-GRU model depends on dataset size and computational resources, with larger models requiring GPU acceleration for efficient training. While the model can handle extensive EEG datasets, hardware limitations arise, especially for real-time implementation on low-power devices like Raspberry Pi or mobile processors, where memory and processing power are constrained. Training on high-end GPUs (e.g., NVIDIA RTX 3090, A100) ensures fast convergence, but real-time inference demands optimization techniques such as model quantization, pruning, and hardware acceleration (e.g., TensorRT, ONNX). Additionally, processing latency can be an issue, as CNN extracts spatial features while GRU processes temporal dependencies, potentially causing delays. For real-world applications like seizure detection and BCI systems, cloud-based deployment or edge computing offers a feasible solution, balancing accuracy, speed, and computational efficiency for real-time EEG classification.

VII ACKNOWLEDGEMENTS

o We extend our sincere thanks to our Project supervisor Prof. Debasish Saha Roy sir for guiding us through the difficulties faced by us during this project.

o We would also like to extend our sincere thanks to the whole Dept. of Computer Science and Engineering for motivating and pushing our limits to complete the project.

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IX AUTHORS PROFILE AND CONTRIBUTION

It was a team project which was a milestone for us to achieve. Tamal Putatunda helped a lot with dataset gathering and sorting them according to the needs of the project. Tanuja Paul, a fellow coursemate, helped with the documentation, extracting, and eradicating the problems faced during the project. Tirthak DebNath, another passionate tech enthusiast, presented the idea helped with the programming part, and worked hard to make the model flawless. Lastly, Syed Aman Ahamed learned and listened to the whole group, and finalized

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