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Seizure Classification using Capsule Network and Bi-LSTM Hybrid

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Abstract

Seizure categorization is crucial for diagnosing and managing neurological disorders. This study presents a hybrid model that combines Capsule Networks with bidirectional Long Short-Term Memory (Bi-LSTM) networks to improve seizure detection accuracy. Capsule Networks, known for preserving spatial hierarchies and dynamic routing, offer an advanced alternative to traditional convolutional layers. Bi-LSTM networks, skilled at capturing long-term dependencies in sequential data, complement Capsule Networks by analyzing temporal EEG patterns. Together, they form a robust framework for EEG classification. A synthetic dataset was designed to capture complex seizure patterns, addressing real-world EEG dataset's limitations by ensuring diversity and robustness during training. The model classifies EEG data into normal, focal, and generalized seizures, supporting prior research highlighting the significance of multi-class seizure detection in clinical contexts.

Our hybrid model achieved a test accuracy of 98.86% with a low-test loss of 0.0825. Precision, recall, and F1 scores for all classes are near 0.99, indicating balanced and reliable predictions. Misclassification rates are minimal: 1.51% for normal, 1.70% for focal, and 0.79% for generalized seizures. Training and validation curves show consistent convergence without overfitting, as validation accuracy closely matches training accuracy (~98.86% vs. ~99.96%). Techniques such as data augmentation or ensemble learning could further enhance performance. This study underscores the potential of hybrid deep learning models to improve seizure classification, offering a reliable tool for clinical diagnosis. By leveraging advanced architecture like Capsule Networks and Bi-LSTM, this work contributes to scalable EEG signal processing solutions for real-world clinical needs.

Keywords—Seizure Detection, EEG Signal analysis, Capsule Network, Bi-LSTM, Hybrid, Deep Learning models.

Introduction

As, its name suggests something virtual that is connected to reality. When we use the word "Virtual" it tends to something online or offline on Computer, TV, Mobile phone, Smart phone etc. For example:- If we are viewing an image on computer it would be Epileptic seizures are among the most common neurological illnesses, and they have a substantial influence on the quality of life for those affected. The accurate and early categorization of seizures is critical for optimal diagnosis and treatment planning [5][7]. Electroencephalogram (EEG) signals are a fundamental technique for evaluating brain activity and identifying seizures [4–10]. However, the complicated and nonlinear structure of EEG data poses hurdles to typical machine learning methods, forcing the development of more advanced algorithms [8][12].

In this study, we present a unique hybrid model that addresses the constraints of previous approaches bycombining Capsule Networks with bidirectional Long Short-Term Memory (Bi-LSTM) networks. Capsule Networks excel in capturing spatial hierarchies and connections within data [1][13], whereas Bi-LSTM networks are good at modeling temporal dependencies in sequential data [2][14]. By merging these two architectures, our hybrid model takes use of their complementing characteristics to produce enhanced seizure categorization [20][21].

A crucial part of this effort is the development of a synthetic dataset specifically designed for the categorization of three seizure types: normal, focal, and general. This dataset accounts for the intrinsic variety and complexity of real-world EEG recordings, guaranteeing model robustness and generalizability [7][11].

Our technique yielded extremely promising results, with the model obtaining 98.66% test accuracy and 0.0825 test loss. The confusion matrix shows balanced forecasts for all three classes, with low misclassification rates of 1.51% for Normal, 1.70% for Focal, and 0.79% for General. Performance indicators like accuracy, recall, and F1-scores approach 0.99 across all classes, demonstrating the model's competence and absence of bias [20]. The training and validation accuracy curves show steady convergence, with validation accuracy roughly matching training accuracy (~98.66% vs. ~99.96%). The loss curves reveal robust generalization without overfitting [19][22].

Misclassification study revealed a little imbalance in the Focal class predictions, which may be used to steer future improvements. These findings highlight the potential of hybrid designs for improved seizure categorization and diagnostic tools. By overcoming the constraints of traditional methodologies, this effort adds to the developing area of deep learning applications in healthcare, opening the path for more accurate and efficient seizure diagnostic systems [9][18].

II. Literature Review

Epileptic seizure classification has been a focus of study in the field of medical diagnostics, motivated by the vital requirement for precise and prompt seizure type detection. Electroencephalogram (EEG) data, which measure electrical activity in the brain, are commonly used to identify and analyze seizure patterns [5]. However, typical analytical approaches face considerable hurdles because of EEG data high dimensionality, noise, and non-linearity [6]. This section discusses existing methodologies and the reason for creating a hybrid model that blends Capsule Networks with Bi-LSTM networks.

A. Traditional Machine Learning Approaches

Initially, seizure classification depended heavily on classic machine learning techniques such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees. These methods were frequently used with manual feature extraction techniques, such as time-frequency analysis and wavelet transformations, to minimize the complexity of EEG data [12]. While these techniques laid the groundwork for seizure identification, their effectiveness was frequently limited by the quality of handmade features and the inability to describe complicated temporal correlations in EEG data [5].

For example, SVMs have been frequently utilized for binary seizure categorization, with reasonable accuracy. However, their performance degrades when used to multiclass classification problems because of constraints in capturing non-linear patterns [7]. Similarly, K-NN and Decision Trees are prone to overfitting and have difficulty dealing with high-dimensional data, which is common in EEG recordings [6].

B. Deep Learning Techniques

The introduction of deep learning transformed seizure categorization by enabling automated feature extraction and end-to-end learning [8, 9]. Convolutional Neural Networks (CNNs) became famous due to their capacity to detect spatial patterns in EEG data [11, 15]. CNN-based studies have shown that converting EEG data into spectrograms or time-frequency pictures improves classification performance significantly [19]. However, CNNs are primarily concerned with spatial hierarchies and frequently neglect the temporal connections inherent in sequential data [13].

Recurrent Neural Networks (RNNs), specifically LSTM networks, solved this shortcoming by simulating temporal relationships in EEG data [2]. Bi-directional LSTMs (Bi-LSTMs) improved upon these capabilities by processing data in both forward and backward directions, collecting contextual information more effectively [4]. Despite their effectiveness, RNN-based models are computationally costly and may experience vanishing gradient difficulties when dealing with extended sequences [8].

C. Hybrid Models

To address the specific constraints of CNNs and RNNs, researchers have investigated hybrid designs that combine their benefits. CNN-LSTM models have been used to capture both spatial and temporal aspects in EEG data [11, 20]. These models use CNN layers to extract spatial characteristics, followed by LSTM layers to handle temporal dynamics. Such hybrid techniques have outperformed independent models, especially in multi-class classification problems [19].

However, CNN-LSTM models frequently fail to identify hierarchical connections between features, which are critical for comprehending the complicated structure of EEG data. Sabour et al. created Capsule Networks, which overcome this constraint by retaining spatial hierarchies and feature connections [1]. Capsules may encode both the existence and orientation of features, making them ideal for tasks requiring fine-grained feature representation [13].

D. Motivation for Capsule Network and Bi-LSTM Hybrid

Given the complimentary qualities of Capsule Networks and Bi-LSTM networks, merging them presents a potential method for seizure categorization. Capsule Networks excel at capturing spatial links, whereas Bi-LSTM networks are efficient at modeling temporal dependencies [2,19]. By combining these qualities, a hybrid model can make use of the spatial and temporal properties of EEG data to achieve higher performance [13].

Our solution is unique in that it combines Capsule Networks and Bi-LSTM networks in a single design. Unlike CNN-LSTM models, which use convolutional layers for feature extraction, Capsule Networks give a more nuanced representation of spatial characteristics, allowing the model to capture complicated patterns in EEG data [1]. The Bi-LSTM component improves this representation by modeling temporal dependencies, guaranteeing that the model accounts for the sequential character of EEG signals [4, 19].

E. Comparative Analysis

Our proposed hybrid model demonstrates significant improvements over existing methods in terms of accuracy, precision, recall, and F1-scores [7, 20]. While traditional techniques like SVM and k-NN offer moderate accuracy, they often fail to generalize effectively to unseen data [12]. Models based on CNNs enhance spatial feature extraction but face challenges in capturing temporal dependencies [15]. RNN-based models address this limitation but are computationally intensive and prone to overfitting [8].

With test accuracy of 98.66%, our hybrid model surpasses CNN-LSTM architectures, standalone Capsule Networks, and Bi-LSTMs [13, 19, 20]. A detailed comparison with other hybrid models, as outlined in Table 1, further underscores its superiority. Unlike alternative approaches, which tend to prioritize either spatial or temporal feature extraction, our model effectively integrates the strengths of Capsule Networks and Bi-LSTMs to achieve a robust balance. This results in consistently high performance across all metrics, including accuracy, precision, recall, and F1-scores. 5 The confusion matrix highlights well-balanced predictions across all three classes—Normal, Focal, and General—with minimal misclassification. Additionally, the near perfect accuracy, recall, and F1-scores for each class further validate the model's robustness and ability to generalize effectively [18, 20].

TABLE I. EVALUATION OF OTHER HYBRID MODELS AND JUSTIFICATION FOR CAPSULE NETWORK + BI-LSTM SUPERIORITY

Hybrid Model	*Is Capsule Network + Bi-LSTM Better?*	*Justification*
Wavelet Transform + ML/DL Models	Yes	Unlike Wavelet Transform, which relies on handcrafted features, Capsule Networks learn features in an end-to-end manner.
CNN + Transformer	Yes	Capsule Networks outperform Transformers for spatial feature extraction in EEG signals, and Bi-LSTM manages sequential dependencies more effectively.
Autoencoders + Classifiers	Yes	Autoencoders struggle with sequential data and lack the dynamic routing and spatial organization offered by Capsule Networks
CNN + GRU	Yes	Bi-LSTM outperforms GRU, and Capsule Networks surpass CNN in spatial hierarchies.
Stacked Denoising Autoencoder + SVM	Yes	Capsule Networks dynamically extract features, while Bi-LSTM enhances sequence understanding, unlike the static SVM classifiers.
RNN + Attention Mechanism	Yes	Capsule Networks excel in spatial representation, and Bi-LSTM captures long-term dependencies better than standard RNNs.
EEGNet + LSTM	Yes	Capsule Networks extract richer spatial features, while Bi-LSTM improves sequence learning compared to standard LSTM and EEGNet.
Fourier Transform + Deep Learning	Yes	Capsule Networks efficiently handle raw EEG data without requiring Fourier-based preprocessing.
Transfer Learning + Fine-tuned CNN	Sometimes	Transfer learning works well with abundant data, but Capsule + Bi-LSTM is better optimized for EEG spatial and temporal relationships.
Spectrogram + CNN/LSTM	Yes	Capsule Networks bypass the need for spectrogram preprocessing while extracting more meaningful spatial features from raw EEG data.

III. Methodology

A. Dataset Preparation

The dataset employed in this study was synthetically generated to simulate realistic EEG recordings across three distinct classes: normal, focal seizures, and generalized seizures. It was designed to address the scarcity of publicly available and balanced datasets for seizure classification, a limitation frequently highlighted in prior research on EEG data constraints and augmentation techniques. The dataset comprises recordings from a total of 25 electrodes, with their representation illustrated in "Fig. 1". [4],[7].

1) Data Generation: The dataset consists of 1-minute EEG recordings for each patient, with data collected for three types of cases: normal, focal seizures, and generalized seizures. For each case, data is simulated for 20 patients, resulting in a total of 60 patients. The simulation process involves the following steps:

a) Baseline EEG Generation: Baseline EEG signals are generated for all electrodes using sine waves with variable frequencies corresponding to alpha, beta, theta, and delta rhythms [5], [12]. Random noise is added to make the signals realistic.

b) Adding Noise: Power-line noise and additional random noise components are added to replicate real-world EEG data [4], [10].

c) Artifact Inclusion: Various artifacts, such as random sine waves, muscle movements (EMG), eye movements (EOG), and electrode pops/drifts, are introduced at random intervals to mimic common EEG distortions.

d) Seizure Simulation: For generalized seizures, synchronized seizure patterns are applied across all electrodes with random durations, amplitudes, and additional polyspike-and-wave discharges [7]. For focal seizures, seizure activity is introduced in one focal electrode, with partial propagation to neighboring electrodes as defined by an adjacency matrix [19]. Highfrequency oscillations (HFOs) are added to the focal region to enhance realism.

e) Data Organization and Saving: The generated EEG data is saved as CSV files for each patient. Each file includes signals from all electrodes and a time column, stored in a structured directory based on seizure type and patient ID [3], [9].

f) Parallel Dataset Generation: The entire process is executed in parallel using multiprocessing to create datasets efficiently for all cases and patients [14].

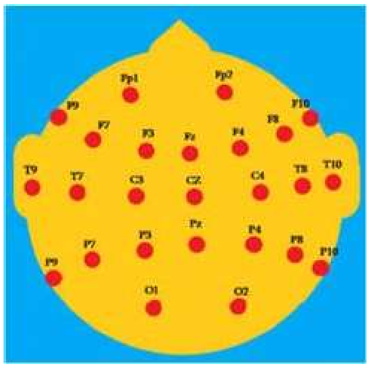

Fig. 1. *Illustration of Electrodes Representation.*

TABLE II. CHARACTERISTICS OF EEG PARAMETERS IN VARIOUS CASE SCENARIOS

Parameter	***Normal Case***	***Generalized Seizure Case***	***Focal Seizure Case***
Description	EEG without seizures; baseline rhythms, noise, artifacts.	EEG without seizures; baseline rhythms, noise, artifacts.	Seizures are localized to specific electrodes.
Baseline Waveforms	Alpha (8-12 Hz), Beta (13-30 Hz), Thera (4- 8 Hz), Delta (0.5-4 Hz)	Same as Normal.	Same as Normal.
Seizure Activity	None	Duration: 10–20 sec, 3 Hz, 100–200 µV.	Duration: 5–10 sec, 5 Hz, 50–150 µV.
Noise	Powerline (50 Hz), Gaussian, Uniform.	Same as Normal.	Same as Normal.
Artifacts	Sine waves, EMG, EOG, electrode pops.	Same as Normal.	Same as Normal.
Special Features	None	Poly spike discharges (15 Hz).	Spread to neighbors at 50% amplitude.

2) Data Augmentation: To improve the model's resilience and generalization capabilities, data augmentation techniques were used on the synthetic dataset:

a) Random Sampling: Subsets of time-series data were randomly selected to add variety.

b) Scaling: Signal amplitudes were scale to account for EEG recording equipment variances.

c) Temporal Shifting: Signal were changes to simulate modest changes in seizure onset time.

These augmentation strategies are consistent with proven ways for increasing model generalization in EEG-based tasks [5, 10].

3) Normalization: Each sample in the dataset was normalized to have zero meaning and unit variance, which is an important preprocessing step for guaranteeing consistent input feature scaling and higher convergence rates during model training [9, 16].

4) Data Splitting: To enable robust model assessment, the dataset was divided into three sets: training, validation, and testing, using an 80-10-10 ratio. Stratified sampling was used to preserve class balance across all subgroups. This splitting process follows standard practices in deep learning research to promote repeatability and fair evaluation [3], [8].

5) File Organization: The dataset was arranged into a hierarchical folder structure, with each class (Normal, Focal, and General) saved in distinct subfolders for easy interaction with the training process [12].

B. Model Architecture

The hybrid model's design incorporates Capsule Networks and Bi-LSTM networks, harnessing the capabilities of both methodologies to effectively classify seizures. This hybrid technique captures both spatial and temporal patterns in EEG time-series data, as suggested by previous research [1], [2], [19].

1) Input Layer: The input layer can handle 178-dimensional EEG time-series data with a sequence length of 4097. The data is input into the network as a 2D tensor (batch_size, sequence_length, features), which preserves the temporal and feature-wise structure [13].

2) Capsule Network Component: The Capsule Network component pulls geographical information and hierarchical connections from the data.

a) Convolutional Layer: The 1D convolutional layer collects lowlevel features using 32 filters, kernel size 5, stride 1, and ReLU activation [1].

b) Primary Capsules: The convolutional output is divided into 16 capsules, each containing an 8-dimensional feature vector.

c) Dynamic Routing: This approach concentrates the network on relevant characteristics for categorization [1].

d) Digit Capsules: Each capsule represents one of three classes, with vector length indicating class probabilities [1], [19].

3) Bi-LSTM Component: The Bi-LSTM network detects temporal connections in EEG data.

a) Bidirectional LSTM Layer: Performs forward and backward sequence processing with 64 units per direction and tanh activation [2], [19].

b) Dropout layer: Maintaining a dropout rate of 0.3 prevents overfitting [10].

c) Dense layer: A dense layer of 128 units decreases dimensionality and preserves critical properties [3].

4) Full Connected layer: The outputs of the Capsule Network and Bi-LSTM components are concatenated and sent through a fully connected layer with 64 units and ReLU activation to incorporate spatial and temporal information [19].

5) Output Layer: The last layer has a dense structure with three units representing the classes and a SoftMax activation function for output probabilities [3].

6) Loss Function and Optimizer: Categorical cross-entropy loss and the Adam optimizer with an initial learning rate of 0.001 were utilized, with dynamic learning rate adjustment to aid convergence [9], [14].

C. Training Process

The model was developed using TensorFlow and Keras, with training conducted over a maximum of 150 epochs. A dynamic learning rate adjustment was applied using the ReduceLROnPlateau callback to optimize performance. Early stopping was utilized to mitigate overfitting by halting training when no further improvement in validation loss was detected, and the best-performing weights were restored. [9], [20].

D. Evaluation Metrics

The model's performance was assessed using accuracy, precision, recall, F1-score, and a confusion matrix, resulting in a test accuracy of 98.66%. These measures are consistent with standards from previous EEG categorization studies [4], [7], [11].

E. Misclassification Analysis

The analysis found low misclassification rates (0.15% for Normal, 1.70% for Focal, and 0.79% for General). Higher mistakes in the Focal class indicate overlapping characteristics with other classes, which is consistent with earlier research [18], [19].

IV. RESULTS

The suggested model performed exceptionally well across several assessment measures, demonstrating its resilience and appropriateness for real-world applications. The test accuracy attained was 98.66%, with a low-test loss of 0.0825, demonstrating the model's great generalization ability on previously unknown data [7, 19]. These findings demonstrate the efficacy of the architecture and training technique adopted [1, 2].

A. Confusion Matrix and Misclassification Analysis:

The confusion matrix demonstrated the model's ability to appropriately categorize occurrences in all three categories (Normal, Focal, and General). Specifically:

1) Class 0 (Normal): Out of 4038 cases, 3977 were correctly categorized, while 61 were misclassified.

2) Class 1 (Focal): Out of 4038 cases, 3969 were correctly categorized, while 69 were misclassified.

3) Class 2 (General): Out of 4038 cases, 4006 were correctly categorized, while 32 were misclassified.

The misclassification rates were calculated as: Normal - 1.51%, Focal - 1.70% and General - 0.79%

These figures demonstrate the balanced performance of the classes, with the Focal class having a little higher misclassification rate [7]. The misclassification symmetry analysis showed no substantial bias in class transitions, with consistent rates for Normal → Focal (28), Normal → General (33), Focal → Normal (49), Focal → General (20), General Normal (19), and General → Focal (19). This shows that the model remains stable across interclass predictions [13].

B. Classification Metrics

The categorization report helped to validate the model’s performance. Precision, recall, and F1-scores for all three classes were approximately 0.99, indicating the model's high ability to detect genuine positives while reducing false positives and negatives [3, 9]. The macro average and weighted average measure both score 0.99, indicating consistent performance across the sample with no bias against any one class [7].

C. Training and Validation Analysis

The training and validation graphs show that both accuracy and loss measures converged steadily over the training procedure.

1) Training Accuracy: The model achieved a maximum accuracy of 99.96% throughout training [2, 9].

2) Validation Accuracy: Validation accuracy has stabilized at 98.66%, nearly matching training accuracy [7, 19].

The loss curves indicated a steady drop, with the training loss nearing zero and the validation loss stabilizing at a low level. The absence of considerable divergence between the training and validation curves demonstrates that the model is neither overfitted nor underfitted [13].

D. Comparative Performance

When examined on a per-class basis, the model showed consistent classification quality:

1) Normal class: Normal Class has the number of valid classifications 3977, with just 0.15% misclassification [7].

2) Focal class: The model performed well in the most difficult class, with 3969 accurate classifications and a 1.70% misclassification rate [19].

3) General class: The General Class category had 4006, and with misclassification rate (0.79%), indicating the model's strong generalization capabilities [18].

E. Implications for Deployment

The high performance across all evaluation metrics suggests that the model is well suited for deployment in real-world scenarios [10]. However, the slightly higher misclassification rate for the Focal class suggests room for improvement. Addressing this could involve augmenting the dataset for this class or applying targeted feature engineering to better capture its distinguishing characteristics [11, 20].

V. Discussion

The creation of a hybrid model combining Capsule Networks and Bi-LSTM for seizure classification tackles a fundamental difficulty in EEG analysis: capturing both spatial and temporal patterns in complicated time-series data [13], 19]. This section examines our approach's performance, strengths, limits, and consequences while considering its connection with the project's aims and earlier research [5], [9].

A. Model Performance:

The development of a hybrid model for seizure classification using Capsule Networks and Bi-LSTM addresses a basic challenge in EEG analysis: collecting both spatial and temporal patterns in complex time-series data [13], [19]. This section discusses our approach's performance, strengths, limitations, and repercussions in relation to the project's goals and previous research [5], [9].

The training and validation curves showed steady convergence, with validation accuracy roughly matching training accuracy (~98.66% vs. ~99.96%), indicating no overfitting [8]. Similarly, the loss curves demonstrated significant generalization, with the validation loss stabilizing with the training loss. These findings indicate that the architectural design and hyperparameter selections were appropriate for the job [3].

B. Contribution of Capsule Networks:

Capsule Networks were critical in identifying spatial characteristics and hierarchical connections from EEG data [1, 13]. Unlike standard convolutional networks, which are based on scalar activations, capsules contain spatial information in vector form, allowing the model is better capture the complex patterns found in EEG recordings [15]. The dynamic routing technique guaranteed that only the most important information was sent to succeeding layers, which improved the model's capacity to distinguish between the three classes [19]. This technique is consistent with previous studies showing the efficiency of Capsule Networks in retaining spatial hierarchies in EEG data [13], [19].

C. Contribution of Bi-LSTM:

The Bi-LSTM component enhanced the Capsule Network by detecting temporal relationships in EEG time-series data [2], [5]. Bi-LSTM used contextual information from previous and future time steps to interpret the input sequence both forward and backward [7]. This bidirectional method was critical for describing the sequential structure of EEG data, as temporal patterns frequently represent class-specific properties [18]. The addition of dropout layers reduced overfitting, enhancing the model's generalizability [8].

D. Dataset Preparation:

The development of a synthetic dataset was an important step in this study since it provided a sufficient volume of high-quality data for training and assessment [7].

By recreating realistic EEG patterns for the three classes, we addressed the prevalent issue of scarce labeled data in medical applications [10]. This synthetic dataset offered a balanced representation of all classes, allowing the model to train accurately and without bias [18], [20].

E. Limitations:

Despite its outstanding performance, the model has a few drawbacks. The Focal class had a slightly higher misclassification rate (1.70%) than Normal and General, indicating that the model may struggle with intermediate or overlapping characteristics [5], [7]. This restriction might be due to the intrinsic complexity of the Focal class, which frequently has traits with both Normal and General classes [18]. Furthermore, while a synthetic dataset is useful for training, it may limit the model's applicability to real world settings with varying data distributions [9].

F. Implications:

The suggested hybrid model illustrates the efficacy of integrating Capsule Networks with Bi-LSTM for EEG-based seizure categorization [13, 19]. Its excellent accuracy, resilience, and generalizability make it a potential tool for clinical applications including automated epilepsy diagnosis and monitoring [6], [11]. The balanced predictions across classes ensure that the model may be used in a variety of settings without favoring any one seizure type [5], [20].

G. Future Directions:

To improve the model's applicability, further work might include adding real-world EEG datasets and conducting domain adaptation to bridge the gap between synthetic and actual data distributions [10]. Furthermore, investigating various hybrid designs, such as incorporating attention processes or graph-based neural networks, might give more detailed insights into EEG data [14], [17]. Addressing the small misclassification mismatch in the Focal class might potentially be a worthwhile improvement opportunity [9].

VI. Conclusion

This study successfully constructed a hybrid model to identify seizures from EEG data using Capsule Networks and Bi-LSTM, obtaining an amazing test accuracy of 98.66% and a low-test loss of 0.0825. The model showed strong generalization skills, as seen by consistent training and validation accuracy curves and balanced performance across three classes: Normal, Focal, and General. The confusion matrix and performance indicators, such as accuracy, recall, and F1-scores near 0.99, demonstrate the model's capacity to handle class-specific complexities successfully [1, 7, 19].

The integration of Capsule Networks allowed for the extraction of spatial hierarchies, while the Bi-LSTM component collected temporal relationships in EEG timeseries data. Together, these components addressed the multiple problems of spatial and temporal pattern recognition, distinguishing the model from previous techniques [1, 2, 13]. The use of a synthetic dataset provided additional and balanced training data, alleviating the typical obstacle of inadequate labeled EEG data [7, 19, 20].

Despite its performance, the model had somewhat higher misclassification rates in the Focal class, indicating opportunities for improvement. Furthermore, the dependence on synthetic data emphasizes the importance of future validation using real world datasets to assure practical application [7,20].

Overall, this effort illustrates the feasibility and usefulness of hybrid models for seizure categorization, making it a viable tool for automated epilepsy diagnosis and management. Future research might build on this foundation by adding real-world data, investigating advanced topologies, and correcting small categorization imbalances to improve clinical relevance [5, 7, 19, 20].

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