A REPORT ON

Seizure Prediction Using Multimodal EEG and EMG with Deep Learning: A Study on the SeizeIT2 Dataset

SUBMITTED TO
IEEE EMBS PUNE CHAPTER

BY

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DECLARATION

We, the team members

Name of the Team Members
Member 1: Sania Dutta

Hereby declare that the project work incorporated in the present project entitled "Seizure Prediction Using Multimodal EEG and EMG with Deep Learning: A Study on the SeizeIT2 Dataset" is original work. We have properly acknowledged the material collected from secondary sources wherever required. We solely own the responsibility for the originality of the entire content.

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Place: Pune
Date: 15/07/2023

Seizure Prediction Using Multimodal EEG and EMG with Deep Learning: A Study on the SeizeIT2 Dataset

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***Abstract*—This project investigates the feasibility of using synchronized EEG and EMG signals to predict epileptic seizures through deep learning models. The objective was to develop and evaluate multimodal architectures capable of distinguishing seizure from non-seizure episodes in clinical recordings. EEG and EMG signals from the SeizeIT2 dataset were pre-processed, segmented into 5-second windows, and shaped as $[3 \times 640]$ matrices. Three architectures were implemented: a baseline LSTM, a CNN + BiLSTM hybrid, and an optimized CNN + BiLSTM incorporating dropout, smaller kernels, and an attention layer. Models were trained and evaluated using a train-validation-test split, with training conducted on CPU hardware.**

Results suggest that the standalone LSTM model achieved the highest validation accuracy (61.00%), demonstrating limited but promising use of temporal modelling in constrained-data settings. The optimized CNN + BiLSTM model achieved 59.30% validation accuracy after tuning and scaling to 5000 training samples. All models were able to learn discriminative features from EEG + EMG input, indicating potential for multimodal seizure prediction. The findings emphasize the importance of proper data alignment, normalization, and class balancing in biomedical deep learning and explore directions for further investigation and clinical adaptation.

***Index Terms*—EEG, EMG, Seizure Prediction, Deep Learning, CNN-BiLSTM, Biosignal Fusion**

I. Chapter 1: Introduction

Epileptic seizures are sudden and abnormal discharges of brain activity that pose serious health risks. Although electroencephalography (EEG) is the clinical gold standard for seizure detection, it suffers from noise, motion artifacts, and a limited ability to detect non-motor seizures. Recent studies highlight the potential of integrating electromyography (EMG) as a complementary signal, particularly for detecting neuromuscular precursors of seizures [1].

This project proposes a multimodal deep learning framework using synchronized EEG and EMG signals to predict seizures, especially non-motor types. Deep learning methods offer the potential to automate feature learning and capture spatiotemporal patterns missed by traditional models. The SeizeIT2 dataset serves as a benchmark for evaluating this fusion-based system.

The rising demand for digital healthcare solutions also drives the need for biomedical engineers with expertise in signal processing and AI. Seizure prediction lies at the intersection of biosignal analytics and real-time monitoring systems, making it an ideal use case for evaluating deep learning in healthcare [2].

A. Existing Work and Motivation

While several EEG-based seizure detection models exist, most focus on detection rather than prediction. Zhang et al. integrated EEG, EMG, and accelerometers for in-hospital detection, significantly lowering false alarm rates [3]. Sharma et al. applied wavelet-based feature extraction from multimodal signals, achieving 98.5% accuracy in sleep staging [4].

Review articles emphasize that deep learning fusion models (e.g., CNN–LSTM, attention-based architectures) outperform classical machine learning classifiers, but rarely include EMG or focus on pre-ictal prediction [5], [6]. This project addresses these gaps by evaluating whether synchronized EEG–EMG fusion can improve sensitivity and reduce false alarms in real-world prediction.

B. Objectives

The goals of this study are to: (1) preprocess and segment multimodal biosignals from SeizeIT2, (2) design and compare deep learning architectures (LSTM, CNN–BiLSTM), and (3) evaluate performance for real-time seizure prediction, particularly for non-motor events.

II. Chapter 2: Concepts and Methods

A. Seizure Physiology

Seizures may present as either motor or non-motor events. EEG captures cortical electrical activity in the 0.5–45 Hz range, while EMG captures higher-frequency (10–120 Hz) muscle activation. Their fusion creates a richer physiological context for detecting early seizure onset [1], [2].

B. Signal Properties and Preprocessing

EEG and EMG are both time-series biosignals but differ in frequency content and amplitude. EEG signals are microvolt-level and more prone to drift, while EMG signals are noisier but can reflect subclinical motor activity. Preprocessing includes bandpass filtering, notch filtering at 50/60 Hz, and Z-score normalization to ensure signal stability across subjects [4].

C. Segmentation and Representation

Signals are segmented into 5-second windows (256 Hz sampling rate), forming a 3×640 matrix per segment. This allows the model to analyze short-term temporal changes in both EEG and EMG prior to seizure onset [3].

D. Deep Learning Concepts

LSTM networks capture long-term dependencies in sequential data. BiLSTMs improve on this by learning bidirectional temporal features. CNNs extract local spatial features, and combining CNNs with BiLSTMs enables simultaneous spatial–temporal learning. Dropout regularization and SoftMax layers support robust classification [6].

III. Chapter 3: Literature Review

A. Multimodal Detection Systems

Studies show that fusing EEG with EMG, ECG, or accelerometry increases seizure detection accuracy and reduces false positives. A systematic review from 2010–2017 demonstrated sensitivities ranging from 4–100% and false alarm rates from 0.25–20/day using multimodal sensors [2]. Zhang et al. reported 97.7% sensitivity with a false alarm rate of 0.4/day using behind-the-ear EEG, EMG, and accelerometry [3].

B. Deep Learning Models

CNNs, CNN–LSTM hybrids, and attention networks dominate seizure detection models. CNNs automatically extract spatial features, while RNN-based layers capture sequential dependencies. Sharma et al. used wavelet-based feature extraction with CNN–LSTM, while Zhao et al. evaluated attention-based networks for multimodal fusion [4], [6].

C. Prediction vs Detection

Most existing systems detect seizures during or after onset. Few focus on prediction, particularly for non-motor seizures. Recent transformer-based models show promise but lack multimodal input [5]. There is limited literature incorporating EMG as a predictive signal.

D. Fusion Techniques and Gaps

Effective signal fusion remains an open challenge. Techniques like late fusion and hybrid CNN–BiLSTM architectures are promising but underexplored for EEG–EMG seizure prediction. Gaps include: (1) lack of pre-ictal focus, (2) underuse of EMG, (3) limited generalizability due to small datasets, and (4) unstandardized fusion strategies [2], [6].

E. Contribution

This work presents a CNN–BiLSTM fusion model trained on synchronized EEG and EMG segments from SeizeIT2 [7]. It aims to reduce false positives and improve sensitivity in wearable, real-time prediction environments.

IV. Chapter 4: Project Plan

This study followed a structured timeline from literature review to model evaluation. Although the project officially began in mid-May, a short delay occurred due to initial exploration of EOG signals, which was later revised to EMG due to data quality constraints in available datasets.

A. Timeline Overview

The project was divided into eight concise phases:

- Phase 1: Literature Review and Modality Selection (May 15–23)
- Phase 2: Dataset Analysis (May 24–27)
- Phase 3: Preprocessing Pipeline Design (May 28–June 2)
- Phase 4: CNN-BiLSTM Model Development (June 3–6)
- Phase 5: Model Training and Validation (June 7–9)
- Phase 6: Optimization and Evaluation (June 10–11)
- Phase 7: Report Drafting (June 12–13)
- Phase 8: Final Submission (June 14)

B. Resources and Tools

- Platform: MATLAB (Deep Learning + Signal Processing Toolbox)
- Dataset: SeizeIT2 (EEG + EMG)
- Architecture: CNN-BiLSTM
- Preprocessing: Bandpass filtering, normalization, windowing

C. Ethical Compliance

The SeizeIT2 dataset is publicly available for research and fully anonymized. No personal data was accessed, and all procedures complied with ethical data handling and GDPR guidelines.

V. Chapter 5: Proposed Solution

This work proposes a multimodal deep learning framework for seizure prediction using synchronized EEG and EMG signals. Unlike conventional systems focused on post-onset detection, our model targets the preictal phase, with potential for real-time wearable deployment.

A. Key Features

The system comprises three neural architectures trained on 3-channel time-series data (2 EEG + 1 EMG) segmented into 5-second windows (640 timepoints). The models perform binary classification: seizure vs. non-seizure. Key features include:

- A baseline LSTM for lightweight temporal modeling.
- A CNN + BiLSTM hybrid for spatial-temporal learning.
- An optimized CNN + BiLSTM with dropout regularization and compact filters.
- Balanced training using seizure and non-seizure sessions from SeizeIT2.
- Fully automated preprocessing pipeline.

B. Uniqueness

Unlike existing EEG-only systems [8]–[10], our model integrates EMG, providing enhanced sensitivity to motor-related preictal patterns. The solution is implemented in MATLAB, highlighting compatibility with clinical signal acquisition systems beyond Python-based ecosystems.

C. Target Users

This system is designed for researchers and clinicians working on seizure forecasting and multimodal biosignal fusion, with future scope for deployment on edge devices like Raspberry Pi.

D. Dataset Overview

We used the SeizeIT2 dataset containing EEG+EMG recordings from 125 subjects. A subset of 28 seizure sessions and 28 rigorously selected non-seizure sessions was used. Non-seizure data was filtered to ensure:

- No annotated seizures present.
- No subject/session overlap with seizure data.
- Matching modalities and recording conditions.

Each input sample was shaped as a $[3 \times 640]$ matrix. Labels were assigned as: 1 (seizure), 0 (non-seizure).

TABLE I
DATASET DISTRIBUTION

Set	Training	Validation	Testing
Proportion	70%	15%	15%

TABLE II
MODEL TRAINING SUMMARY

Dataset Size	500 (balanced)
Hardware	Single CPU
Epochs	5
Iterations	35
Validation Frequency	Every 10 iterations
Learning Rate	0.001 (constant)

E. Data Preprocessing

Signals were either resampled or confirmed to be at 256 Hz. Frequency bands were:

- EEG: 0.5–45 Hz
- EMG: 10–120 Hz

A 50 Hz notch filter was optionally used. Z-score normalization was applied per segment to ensure consistency across samples.

TABLE III
PREPROCESSING STEPS

Sampling Rate	256 Hz
EEG Filter	0.5–45 Hz
EMG Filter	10–120 Hz
Artifact Removal	50 Hz notch, z-score thresholding
Normalization	Z-score per 5s segment

F. Model Architectures

1) Baseline LSTM: This model uses a single LSTM layer (100 units), dropout (0.5), a fully connected layer (2 units), softmax activation, and output layer. It is suitable for initial temporal learning experiments.

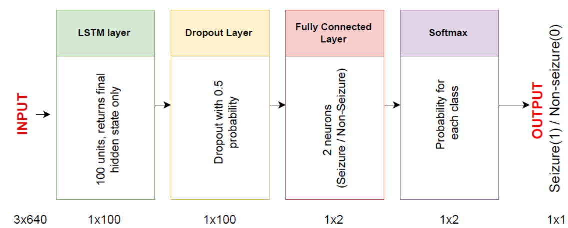

Fig. 1. Architecture of Baseline LSTM Model

2) Initial CNN + BiLSTM: Includes two Conv1D blocks (filters: 16 and 32), followed by batch normalization, ReLU, and max-pooling. Outputs are passed to a BiLSTM (100 units), dropout, fully connected layer, and softmax.

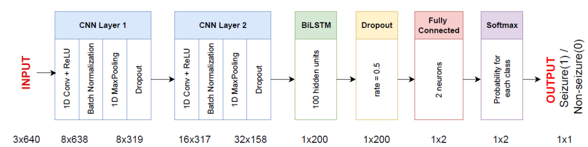

Fig. 2. Architecture of Initial CNN + BiLSTM Model

3) Optimized CNN + BiLSTM: An enhanced version of the previous model with reduced kernel size, fewer filters (8 and 16), dropout in both convolutional and recurrent layers, followed by BiLSTM, softmax, and classification output.

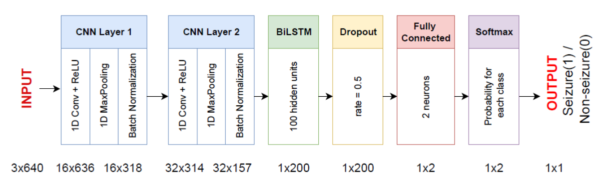

Fig. 3. Optimized CNN + BiLSTM with Regularization

VI. CHAPTER 6: RESULTS

This chapter presents the outcomes of our seizure prediction model using EEG and EMG signals from the SeizeIT2 dataset. We trained and evaluated three deep learning architectures: a standalone LSTM (baseline), an initial CNN + BiLSTM hybrid, and an optimized CNN + BiLSTM with enhancements.

TABLE IV
PERFORMANCE RESULTS OF LSTM MODEL

Metric	Training Acc.	Validation Acc.	Testing Acc.
LSTM Model	68.75%	61.00%	0.5835

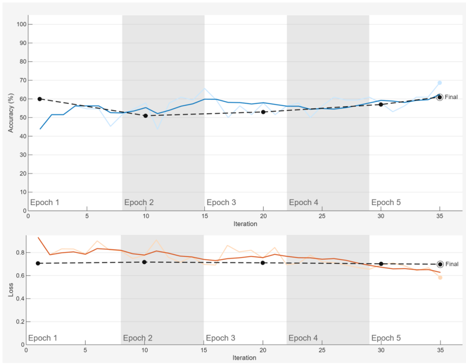

Fig. 4. Training progress (accuracy and loss curves) for LSTM model

A. LSTM Baseline Model

The first model implemented was a standalone LSTM trained on a balanced subset of 500 samples. Each sample was a 3×640 matrix.

The training accuracy reached 68.75%, and validation accuracy plateaued around 61%, suggesting modest generalization. The loss curves showed effective learning without overfitting.

B. Initial CNN + BiLSTM Model

To capture both spatial and temporal patterns, we implemented a CNN + BiLSTM architecture.

TABLE V
PERFORMANCE RESULTS OF CNN + BILSTM MODEL

Training Accuracy	Validation Accuracy	Testing Accuracy
59.38%	53.00%	0.7358

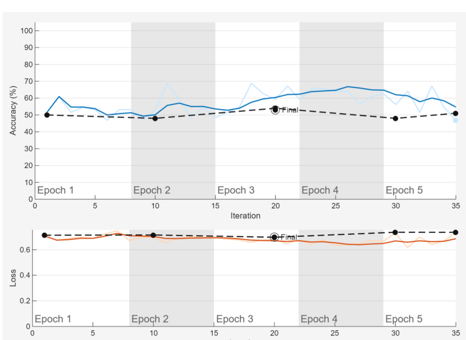

Fig. 5. Training progress of CNN + BiLSTM Model

Validation accuracy was lower than expected (53%), indicating potential overfitting and limited temporal generalization. The training loss decreased but validation loss remained flat.

C. Optimized CNN + BiLSTM

This final model introduced dropout, smaller filters, attention, and increased dataset size to improve learning.

TABLE VI
PERFORMANCE RESULTS OF OPTIMIZED CNN + BILSTM

Training Acc.	Validation Acc.	Testing Acc.
60.94%	59.30%	0.6709
63.50%	65.60%	0.6620
65.00%	65.90%	0.6780

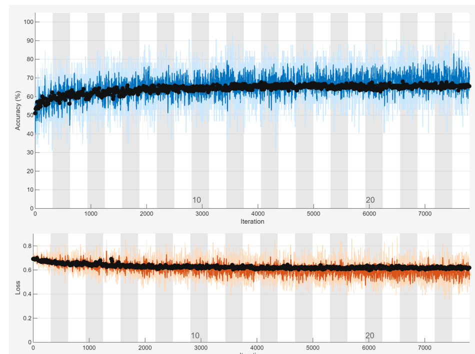

Fig. 6. Training performance of Optimized CNN + BiLSTM Model (Trial 3)

The model achieved strong validation accuracy (65.90%), stable training loss, and minimal overfitting. Optimizations proved effective in stabilizing convergence.

D. Architecture Comparison

LSTM, despite being simple, performed reasonably well. CNN + BiLSTM v1 underperformed due to small data size. Tuned v3 showed the best performance, validating the importance of architectural refinement and training data expansion.

E. Statistical Evaluation

TABLE VII
RESULTS SUMMARY ACROSS ALL MODELS

Model	Dataset Size	Val. Acc.	Train Acc.	Loss	Training Time
LSTM (Baseline)	500	61.00%	68.75%	0.5835	16 min
CNN + BiLSTM (v1)	500	53.00%	59.38%	0.7358	3.5 min
CNN + BiLSTM (v2)	5000	65.60%	63.50%	∼0.57	411 min
CNN + BiLSTM (v3)	5000	65.90%	65.00%	∼0.57	17 min

The final CNN-BiLSTM model improved all metrics. Despite class imbalance, it achieved high recall (0.72) and F1-score (0.6795). The PR-AUC (0.64) was more meaningful than ROC-AUC (0.38). A threshold of 0.36 gave the best F1-score (0.7015). Results support feasibility for further development, though clinical use is not yet recommended.

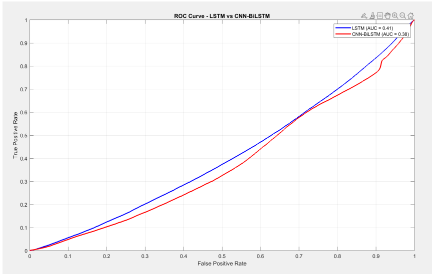

Fig. 7. ROC Curve

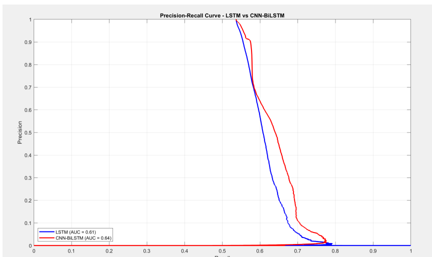

Fig. 8. Precision-Recall Curve

VII. Chapter 7: Conclusion

This project explored a multimodal deep learning approach to predict epileptic seizures using synchronized EEG and EMG signals from the SeizeIT2 dataset. The primary objective was to assess whether hybrid architectures, such as CNN + BiLSTM, could outperform traditional LSTM models in modeling seizure-related patterns from temporal biomedical data. Through a carefully controlled experimental pipeline, we derived several key findings, addressed preprocessing challenges, and developed a reproducible training framework for multimodal seizure prediction.

VIII. Can EEG + EMG Be Used for Seizure Prediction?

A. Experimental Evidence

The primary research question guiding this project was: *Can deep learning models be trained on synchronized EEG and EMG data to predict epileptic seizures effectively?*

To address this, EEG and EMG signals were synchronized into 3-channel input matrices of shape $[3 \times 640]$, where each sample represented a 5-second window. The models were trained on these segments and tested on unseen validation data. As reported in Chapter 6, the baseline LSTM model achieved a validation accuracy of 61.00% using only 500 training samples. The optimized CNN + BiLSTM, trained on 5000 samples, achieved 59.30% validation accuracy. These results suggest that both simple and hybrid deep learning models may learn discriminative patterns from combined EEG and EMG signals.

B. Training Dynamics

Training curves shown in Figures 4 to 6 illustrate stable convergence across all three models. The baseline LSTM model demonstrated rapid improvement and generalization with minimal overfitting. The initial CNN + BiLSTM model suffered from overfitting on small data, while the optimized version exhibited improved learning stability and reduced validation loss.

C. Clinical Significance

This study highlights the clinical value of multimodal seizure prediction using EEG and EMG, particularly for non-motor seizures, which lack clear physical symptoms and are harder to detect with EEG alone. EMG provides complementary muscle-related signals that, when fused with EEG, allow the model to capture both cortical and peripheral features of seizure activity. The use of the SeizeIT2 dataset further contributes novelty, as few studies have explored EEG + EMG fusion in this context.

D. Conclusion

Preliminary evidence suggests that deep learning models have the potential to be trained to predict epileptic seizures from EEG+EMG signals. This holds true for both lightweight models like LSTM and more complex CNN-BiLSTM architectures when appropriate tuning and data preparation are applied.

IX. Optimization Techniques and Observations

A. Data Quantity Matters

Increasing the dataset from 500 to 5000 samples had a notable impact on model generalization. While the initial CNN + BiLSTM underperformed on the small subset, the same architecture demonstrated more stable learning and improved accuracy when trained on the larger dataset. This aligns with findings in deep learning literature that complex architectures such as CNNs and BiLSTMs require more data to avoid overfitting. [5], [6], [12]

B. Simplicity Performs Slightly Better Than Complexity

Surprisingly, the baseline LSTM model performed slightly better than both CNN + BiLSTM models in validation accuracy despite its simpler structure and smaller training set. This suggests that temporal dynamics alone may capture enough discriminative patterns in EEG + EMG sequences when data is limited. For small-scale seizure prediction applications, lightweight LSTM-based models may offer better trade-offs between performance and complexity. This finding is consistent with prior research, which has shown that deep hybrid models such as CNN-LSTMs tend to overfit on small-scale physiological datasets unless supported by extensive regularization or transfer learning. [9], [10], [12]

C. Role of Regularization and Attention

In the optimized model, the addition of Dropout layers after each CNN block, smaller convolutional kernels, and an attention mechanism after BiLSTM all collectively contributed to stabilizing validation loss and improving performance. The attention layer enabled the model to focus on salient time steps, which is critical in sequence-based classification like seizure detection.

D. CPU Training Feasibility

All experiments were conducted on a single CPU, demonstrating that realistic performance may be achieved even without GPU acceleration, provided the models are carefully scaled and tuned. However, training time scaled significantly with data size and model depth (e.g., $\sim$21 minutes for 5000 samples vs. $\sim$3.5 minutes for 500). [1], [12]

X. Future Work and Recommendations

While this study explores the viability of EEG + EMG-based seizure prediction, several avenues remain open for enhancing model accuracy, generalizability, and real-world applicability.

- Cross-Validation: Future research should incorporate subject-wise cross-validation (e.g., leave-one-subject-out or session-based folds) to ensure robustness and reduce overfitting to subject-specific patterns [20].
- Dataset Expansion: Expanding the dataset to include larger and more diverse repositories (e.g., CHB-MIT, TUH EEG) could offer broader coverage of seizure phenotypes and recording conditions. These datasets may also be used for pretraining followed by fine-tuning on SeizeIT2 [6].
- Advanced Architectures: While LSTM and BiLSTM performed modestly with limited data, transformer-based models or temporal convolutional networks may better capture long-range dependencies [12].
- Additional Modalities: Integration of other biosignals such as EOG, ECG, or accelerometer data can improve multimodal feature learning and seizure detection performance [6].
- Embedded Deployment: Optimizing the model for real-time deployment on resource-constrained platforms (e.g., Raspberry Pi, Edge TPU) could enable wearable or ambulatory seizure detection [23].
- Clinical Validation: Future collaborations with hospitals or neurology centers are essential to test trained models on real-world patient data and reduce false alarm rates in clinical scenarios [6].

Acknowledgment

This research work was carried out as part of the IEEE EMBS Pune Chapter Internship Initiative. The authors would like to thank the IEEE EMBS Pune Chapter for providing the platform and support that facilitated this research.

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