Case Study 3:
Seizure Detection Using EEG Data: Exploring the potential of Convolutional Neural Networks (CNNs)[1]

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[1]We recognize that the inspiration and selection of this topic were influenced by the DSDA 310: Senior Seminar course, under the guidance of Dr. Bergstrom and Dr. Disha. We also extend our gratitude to Dr.Bergstrom for providing us with the data to run our analysis.

I. INTRODUCTION[2]

Electroencephalography (EEG) is a method to record electrical activity in the brain and is commonly used to diagnose neurological conditions like epilepsy. This report highlights how we developed and tested a machine learning model to detect seizures using EEG data. Analyzing EEG data manually is slow and prone to errors, this study explores the challenges involved in researching computational methods to identify interictal spikes.

II. METHODOLOGY

A. DATA EXPLORATION[3]

The "Bonn dataset" is a widely used collection of Electroencephalography (EEG) data primarily used for research on epilepsy detection, originating from the University of Bonn, Germany; it contains EEG recordings from both healthy individuals and epilepsy patients, allowing researchers to analyze different brain states and identify potential seizure patterns.

Our dataset consists of:

- Full Signals: 500 signals, including 400 seizures and 100 non-seizures.
- Short Signals: 11,500 signals, including 2,300 seizures and 9,200 non-seizures.

B. DATA PROCESSING

To prepare the data for the model, we performed several steps which are as follow: -

- **Column Headers**: Headers were added to all columns to clearly define their contents.
- **Labels**: Labels were merged into the main dataset, providing a structured and unified format for analysis.
- **Signal Normalization**: All signals were normalized using row wise min-max scaling to handle differences in amplitude, ensuring consistency across the dataset and improvement in performance for model training.

C. DATA MODELING

We used a convolutional neural network (CNN) because it's great at recognizing translation invariance patterns in data. We believe that the repeated cycles in signal data can be considered to have the translational invariance property. Our model included layers for convolution, pooling, and activation functions like ReLU and Softmax to handle the complexity of the signals.

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[2] Pfammatter, J. A., Bergstrom, R. A., Wallace, E. P., Maganti, R. K., & Jones, M. V. (2018). A predictive epilepsy index based on probabilistic classification of interictal spike waveforms. *PLoS ONE*, *13*(11), e0207158–e0207158. https://doi.org/10.1371/journal.pone.0207158.

[3] Upadhyay, P., & Ujoodha, Y. (2024). *Case Study 3*. Google.com. https://colab.research.google.com/drive/1wGs71Z7wuN6JRldJAVcoDVc8VA62L_8V?usp=sharing.

TABLE I : CNN Architecture for full and short signals

Filters	Kernel Size	Pool Size	No. of Neurons	Activation Function	Loss Function	Optimizer
64	3	2	128	ReLU Softmax	Categorical Cross Entropy	Adam

Note: *This table outlines the Sequential CNN architecture for the full and short signals, specifying filters, kernel and pool sizes, neurons, activation functions (ReLU Softmax), loss function (categorical cross-entropy), and optimizer (Adam).* ***Categorical Cross-Entropy*** *is ideal for multi-class classification, penalizing incorrect confident predictions to improve accuracy.* ***ReLU*** *prevents vanishing gradients and speeds up training with its simplicity.* ***Softmax*** *ensures outputs are interpretable as probabilities.* ***Adam*** *offers fast, adaptive optimization, ideal for efficient and stable training.*

TABLE II : Training Parameters for CNN Model

Dataset	Training (%)	Validation (%)	Testing (%)	Batch Size	Epochs	Patience
Short Signals	90	5	5	16	6	5
Full Signals	80	10	10	32	12	5

Note: *This table presents the training parameters for the Sequential CNN model after several test runs, detailing datasets splits (training, validation, testing), batch size, number of epochs, and patience for early stopping. For full Signal because of insufficient data points, 80-10-10 split was preferred.*

III. RESULTS AND ANALYSIS

Our analysis showed an accuracy of 99% on short signals data and 90% on full signals dataset. This observation is expected as the short signals dataset provides more granular information on each signal pattern compared to the full signal dataset. Also, the small sample size of 500 signals might not be sufficient to achieve a high accuracy. It is also important to note that the Bonn dataset generally contains signals which are clean and do not contain noisy data.

Confusion Matrix and Classification Report for both signals

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Confusion Matrix:
 [[459   1]
 [  2 113]]
Classification Report:
              precision    recall  f1-score   support

 Non-Seizure       1.00      1.00      1.00       460
     Seizure       0.99      0.98      0.99       115

    accuracy                           0.99       575
   macro avg       0.99      0.99      0.99       575
weighted avg       0.99      0.99      0.99       575
```

Figure 1a: Short Signal Results

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Confusion Matrix:
 [[37  3]
 [ 2  8]]
Classification Report:
              precision    recall  f1-score   support

 Non-Seizure       0.95      0.93      0.94        40
     Seizure       0.73      0.80      0.76        10

    accuracy                           0.90        50
   macro avg       0.84      0.86      0.85        50
weighted avg       0.90      0.90      0.90        50
```

Figure 1b: Full Signal Results

The confusion matrices and classification reports illustrate the model's ability to classify EEG signals as seizure or non-seizure. The confusion matrix presents the breakdown of actual and predicted labels, while the classification report provides precision, recall, F1-score, and accuracy metrics. For short signals, the model achieved 90% accuracy, with higher performance on non-seizure predictions. For full signals, the accuracy improved to 99%, showcasing near-perfect classification. This highlights the robustness of the model in detecting seizure patterns across different signal types and datasets.

Examples of Misclassified Signals: -

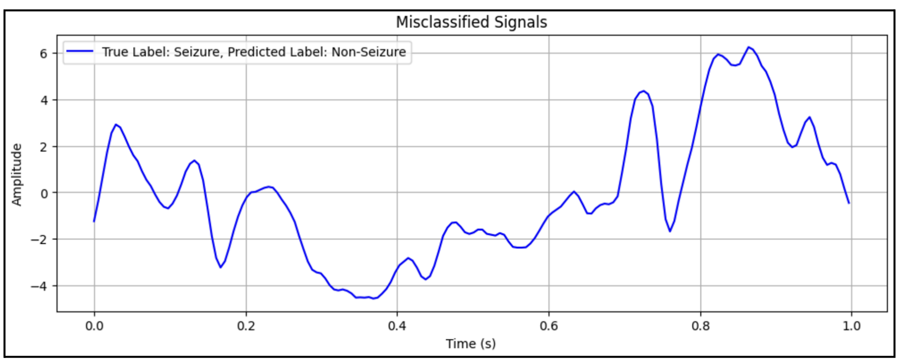

Figure 3: Short Signal Misclassified as Non-Seizure.

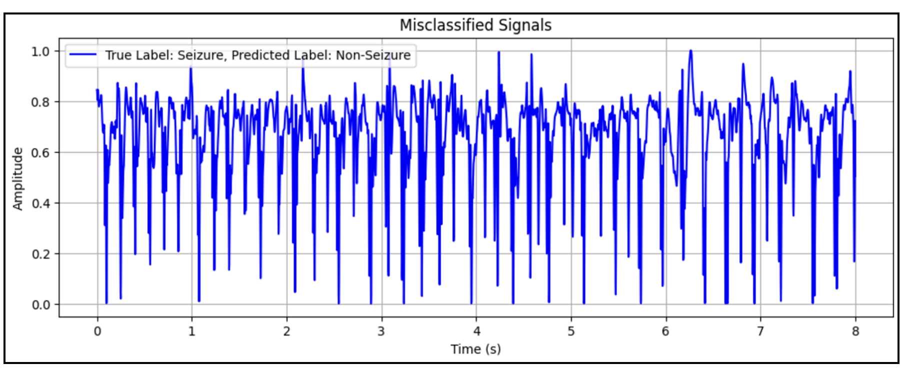

Figure 4: Full Signal Misclassified as Non-Seizure.

IV. CONCLUSION AND RECOMMENDATIONS

This study shows that Sequential CNNs can accurately detect seizures in EEG data. The high accuracy makes it a strong candidate for clinical use for formatted clean data. Moving forward we recommend:

- Fine tuning the model for both full and short signal data.
- Testing model performance on noisy, real-world dataset.
- Creating an easy-to-use interface for doctors and clinicians.

V. FUTURE WORK

Future work can be directed toward the development of prediction models on these datasets to enable early detection of seizures and, hence, better patient care. These models will be much more powerful if they incorporate various factors such as patient history and environmental influences. Testing the model on more datasets, for example, the CHB-MIT dataset, to establish its robustness, using transfer learning to enhance the results on smaller datasets, and collaboration with medical professionals for the integration of the model into practical diagnostic tools are also areas that need attention.