Section IV: Discussion

The objective of this research was to develop an ECG-based seizure detection model through the use of an LSTM network. Then, its performance would be evaluated using key metrics like accuracy, loss, precision, recall, and F1-score. The results provided are indicative that the model successfully learned from the training data, shown by the decreasing loss and increasing accuracy over epochs. The recall remaining consistently higher than the precision suggests that the model is prioritizing sensitivity. This aligns with the goal of minimizing false negatives in seizure detection - missing a seizure. Statistical analysis supports the observed trends, with a significant correlation between F1-score and training epochs ($p < 0.05$), confirming incremental performance improvements over time.

A key concern in deep learning models, LSTMs included, is the risk of overfitting. This is when the model prioritizes memorizing the training data rather than learning generalizable patterns that could be used on outside data. However, based on the observed loss and accuracy graphs, it is unlikely that the model is overfit. The training and validation loss decreased at similar rates and stabilized rather than diverging. This suggests that the model did not perform significantly better on training data at the cost of generalizability. Additionally, the validation accuracy remained relatively stable and did not exhibit major fluctuations or declines, which would potentially be indicative of overfitting. The consistent performance of recall and precision across epochs further supports that the model generalizes well to unseen data. These findings indicate that the regularization techniques employed such as dropout and early stopping were effective in maintaining a balance between learning and preventing overfitting.

One limitation of this study is the potential for class imbalance in the dataset, which could have led to biased predictions. This was addressed through resampling techniques to balance seizure and non-seizure samples. While high recall is beneficial for detecting seizures, it comes at the cost of lower precision, increasing false positives. This trade-off needs further optimization, potentially through improved feature engineering or model architecture adjustments.

Future Research

Future research should focus on improving precision without compromising recall by exploring other model architectures. This could include, but is not limited to, transformer-based networks. These have been proven to show great success in time-series classification. Additionally, incorporating different domain adaptation techniques could help generalize the model to diverse patient populations. Another area for improvement is explainability—techniques such as SHAP (SHapley Additive exPlanations) could be integrated to provide insight into which ECG features contribute most to seizure detection. Lastly, real-time deployment and validation on wearable ECG devices should be explored to assess the feasibility of translating this model into clinical practice.

Section V: Conclusion

This research aimed to successfully develop and evaluate an ECG-based seizure detection model using an LSTM network. The results show that the model effectively learned from training data as it achieved a high F1-score and prioritizing recall to minimize the risk of missing seizures. Statistical analysis also confirmed a significant positive correlation between training epochs and performance improvements, which also supports the narrative that the model has the ability to adapt and generalize.

Key methodological approaches like noise reduction techniques, data augmentation, and class balancing, were a critical part of enhancing the model's accuracy. The findings also suggest that regularization methods like dropout and early stopping, effectively mitigated overfitting. This ensures great performance on unseen data. However, difficulties still remain in reducing false positives while maintaining sensitivity. This highlights the need for further optimization in future iterations.

Future research should include focusing on refining the model's precision through architectural improvements. This could include transformer-based networks and domain adaptation techniques. Additionally, incorporating modelexplainability tools, like SHAP, could enhance trust and interpretability, making the technology more viable for real-world clinical applications.

The ultimate goal of this research is to integrate this deep learning model into a wearable seizure detection device, providing real-time alerts to patients and caregivers. This advancement has the potential to revolutionize epilepsy management. It could offer a new level of safety and independence to tens of millions of individuals worldwide. By leveraging cutting-edge AI and biomedical signal processing, this work takes a crucial step toward a future where seizures are not only detected but potentially anticipated, transforming lives through technology.