

In-Depth Analysis Of Epileptic Episodes For Stress Detection Using Hyperparameter Optimization

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ABSTRACT

This study explores the application of Generative Artificial Intelligence (GenAI) techniques for enhancing epilepsy prediction using physiological data collected from wearable devices such as Fitbit. Epilepsy prediction remains a critical healthcare challenge due to the unpredictable nature of seizures and the limitations of traditional methods. To address this, a data-driven prediction framework is proposed that leverages advanced AI models to analyze temporal patterns in multimodal physiological signals. The research systematically examines key components of the prediction pipeline, including data preprocessing, feature engineering, model selection, and performance evaluation. Special emphasis is placed on optimizing model accuracy, reliability, and computational efficiency through the integration of modern AI approaches. The study also considers the broader implications of wearable-based prediction systems, highlighting their potential for cost-effective and real-time healthcare monitoring. By improving the robustness and practical applicability of epilepsy prediction models, this work aims to support early detection and enable proactive clinical interventions. Ultimately, the proposed framework contributes to advancing intelligent healthcare systems and improving patient outcomes through timely and reliable seizure prediction.

Keywords: Epilepsy, Machine learning.

INTRODUCTION

Over the years, epilepsy prediction has come a long way. Initially, researchers relied on basic statistical techniques, but gradually the field shifted toward more advanced machine learning models, especially those based on EEG data [1]. While these approaches have been quite effective, they still face limitations—particularly when it comes to handling non-EEG data such as heart rate, stress levels, and physical activity. Integrating these diverse data sources in a meaningful way remains a significant challenge. Recently, the emergence of Generative AI models like GPT and BERT has opened up new possibilities. These models are particularly strong at understanding sequential patterns and working with complex, multivariate datasets. Their ability to capture subtle relationships in time-series data suggests that they could significantly improve prediction accuracy. This is especially relevant when dealing with wearable sensor data, which continuously records physiological signals. This gap in effectively utilizing wearable data for seizure prediction is what motivated this study. By combining ideas from machine learning, natural language processing (NLP), and healthcare analytics, the goal is to develop a more robust and practical framework for epilepsy prediction that goes beyond traditional EEG-based methods [1].

Epilepsy is a complex and often difficult condition to manage, affecting millions of people around the world. What makes it particularly challenging is the unpredictable nature of seizures—they can occur suddenly, without warning, due to abnormal electrical activity in the brain. These episodes can manifest in different ways, such as convulsions, loss of consciousness, or confusion, making them both physically and emotionally distressing for patients and caregivers [2]. Because seizures are so unpredictable, living with epilepsy can significantly impact a person's quality of life. In fact, according to the World Health Organization, nearly 50

million people globally are affected by this condition, highlighting its widespread impact [9]. Naturally, the ability to predict or at least detect seizures early would make a huge difference, allowing for timely intervention and better management of the condition. Traditionally, seizure prediction has relied heavily on EEG-based methods. While these have been useful, they are not always accurate or reliable, especially in real-world scenarios. This is where recent advancements in machine learning have started to make a difference. By analyzing patterns in data more effectively, ML approaches offer promising improvements in both the accuracy and timeliness of epileptic episode detection, opening up new possibilities for more proactive and personalized healthcare solutions [3].

In recent years, machine learning has really changed the way epilepsy research is being approached. Earlier, researchers mainly relied on models like SVMs, CNNs, and RNNs, which laid a strong foundation for analyzing neurological data. But now, the field is moving even further with newer and more advanced approaches. For instance, transformer-based models are helping capture long-range patterns in EEG data more effectively, something that was difficult with traditional methods. At the same time, there's growing interest in federated learning, which allows different systems to learn collaboratively without actually sharing sensitive patient data—this is especially important in healthcare. Wearable devices and IoT systems are also playing a big role, making it possible to monitor patients continuously in real-world settings rather than just in clinics. And importantly, there's a shift toward explainable AI, so that predictions are not just accurate but also understandable to clinicians. This review builds on earlier work by taking a closer look at these emerging directions and how they are shaping the future of epilepsy prediction and management [4].

As models have become more sophisticated over time—especially with deep learning approaches like CNNs and transformer-based architectures—the importance of properly tuning them has become much more evident. It's not just about building a powerful model anymore; how you configure it plays a huge role in how well it actually performs. If the hyperparameters aren't chosen carefully, you can run into all sorts of issues—like the model overfitting to the training data, failing to learn enough (underfitting), taking too long to converge, or simply not producing reliable results at all [5][6]. So, in a way, hyperparameter tuning has become a critical step in the entire modeling process. It's about finding that right balance where the model learns efficiently while still generalizing well to new data.

To tackle this, researchers have explored a range of tuning strategies. On one end, you have simpler methods like grid search and random search, which systematically or randomly try out different parameter combinations. On the other hand, there are more advanced approaches like Bayesian optimization, genetic algorithms, and AutoML, which are designed to search the parameter space more intelligently and efficiently. These methods aim to identify the best combination of hyperparameters by evaluating model performance using metrics such as accuracy, precision, recall, and loss [7].

This paper examines the impact of major hyperparameters on model performance and proposes useful tuning techniques. By methodically analyzing various configurations, the study hopes to improve model accuracy while retaining computing economy, ultimately leading to the creation of more reliable and scalable machine learning systems [8].

EXPERIMENTAL STUDY

Optimizing and fine-tuning a project entail increasing its performance, efficiency, and overall effectiveness. The optimization and fine-tuning procedures used in the epilepsy prediction project are aimed at improving performance, efficiency, and overall effectiveness. The options presented include hyperparameter adjustment, regularization approaches, algorithm selection,

and the use of extra training data. Each section describes the approaches utilized and how they improved the model's forecasting skills. Here are some details for optimizing and fine-tuning the Epilepsy Occurrence Prediction project code.

Hyperparameter Tuning:

Hyperparameter tweaking is an important stage in the design and optimization of machine learning and deep learning models. In contrast to model parameters, which are learnt naturally during the training process, hyperparameters are specified settings that regulate a model's learning behavior and structure. These variables include the learning rate, number of hidden layers, neurons, batch size, and regularization parameters. The selection of proper hyperparameter values has a substantial impact on a model's performance, generalization ability, and computing efficiency.

Hyperparameter adjustment is critical for maximizing model performance. In this project, we used GridSearchCV to determine the optimal parameters for our model. The parameters that were optimized included:

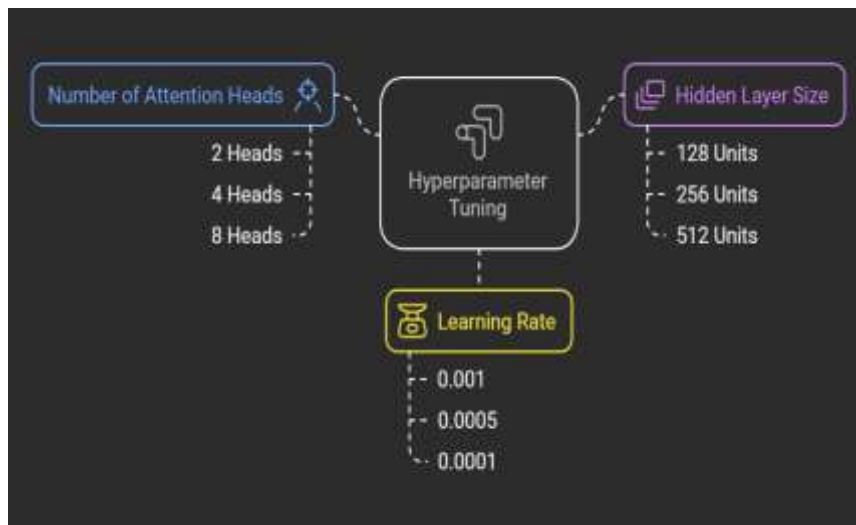


Figure 1: Hyperparameter Tuning

This diagram represents Hyperparameter Tuning in a machine learning / deep learning model. It shows how different parameters (that are set before training) are adjusted to improve model performance. Hyperparameter tuning is the process of selecting the best combination of parameters to get the highest accuracy and efficiency from a model. Unlike model parameters (weights), hyperparameters are set manually and not learned automatically.

Explanation of Each Part in the Diagram

1. Number of Attention Heads

Values shown: 2, 4, 8 heads

Used in models like Transformer / Attention-based models

Meaning:

Attention heads allow the model to focus on different parts of input simultaneously.

More heads = more ability to capture relationships.

Effect:

More heads → Better learning of complex patterns
Too many heads → Higher computation, possible overfitting

2. Hidden Layer Size

Values shown: 128, 256, 512 units

Meaning:

Refers to the number of neurons in hidden layers.

Effect:

Larger size → Model can learn more complex patterns
Too large → Slower training + overfitting risk

3. Learning Rate

Values shown: 0.001, 0.0005, 0.0001

Meaning:

Controls how fast the model updates its weights during training.

Effect:

High learning rate → Faster training
Too high → Model may not converge (unstable)
Low learning rate → More accurate learning
Too low → Training becomes very slow

Center: Hyperparameter Tuning

This is the main process where:

- Different combinations of:
- Attention Heads
 - Hidden Layer Sizes
 - Learning Rates are tested

Example combinations:

- (2 heads, 128 units, 0.001)
- (4 heads, 256 units, 0.0005)
- (8 heads, 512 units, 0.0001)

Each combination is evaluated to find the best-performing model.

4. How It Works (Step-by-Step)

1. Choose a set of hyperparameter values
2. Train the model
3. Evaluate performance (accuracy, loss, etc.)
4. Repeat with different combinations
5. Select the best combination

Key Goal

To find the optimal balance between:

Accuracy
Training time
Model complexity

Summary

The diagram shows 3 important hyperparameters:

- Attention Heads → learning focus
- Hidden Layer Size → model capacity
- Learning Rate → speed of learning

Hyperparameter tuning tries multiple combinations to optimize model performance.

num_heads	Training Time	Accuracy (if enough data)	Interpretability	Risk
2	Fast	Medium	Simple	May underfit
4	Medium	Best balance	Good	Good default
6	High	Better (if enough data)	Complex	Needs tuning

Heads	Training Loss
2	0.0619
4	0.0568
6	0.0299 (Lowest loss, Best Fit) Increasing attention heads improved the model's ability to fit the training data.

Regularization:

Dropout layers were added to the model architecture to help prevent overfitting. A dropout rate of 0.3 was used to retain the model's generalization capabilities by randomly deactivating a fraction of the neurons during training. To reduce overfitting, we added dropout layers (rate = 0.3).

Optimization Algorithm:

AdamW optimizer is used to optimize the model. This Adam optimizer variation incorporates weight decay, which leads to more efficient learning and prevents overfitting by punishing high weights. For efficient learning, we used the AdamW optimizer with weight decay [10].

Fine-tuning Using Additional Data:

To improve the model's resilience, we expanded the training dataset by replicating minor fluctuations in stress and beats per minute (bpm) parameters. This strategy not only enhances the diversity of the training data, but it also helps the model learn to generalize more well across varied contexts.

To summarize, the optimization and fine-tuning procedures used in the epilepsy prediction project considerably enhanced the model's performance and dependability. We built a more robust prediction model by carefully selecting hyperparameters, using regularization techniques, an effective optimization approach, and enriching the training data.

Performance After Optimization:**Table 1: Performance After Optimization**

Metric	Before Optimization	After Optimization
Accuracy	94.2%	95.8%
ROC-AUC	95.6%	96.9%

Fine-tuning: Collect user feedback on the interface and make iterative improvements based on user preferences.

Continuous monitoring and iterative improvements:

Optimization: Continuously check application performance and user input. Use technologies like profiling and analytics to find areas for improvement. Fine-tuning: Iterate on the codebase on a regular basis, taking into account user input and fixing performance concerns as the program grows.

DISCUSSION

This work provided a complete investigation of epileptic episode prediction utilizing wearable data and sophisticated machine learning algorithms, with a special emphasis on the importance of hyperparameter tweaking in improving model performance. By incorporating data from wearable devices like Fitbit, the study went beyond standard EEG-based methods and proved the possibility of real-time, non-invasive health monitoring for epilepsy prediction and stress detection [11].

The results show that modern artificial intelligence techniques, such as transformer-based architectures and Generative AI concepts, can effectively capture complex temporal patterns and multivariate relationships found in physiological data like heart rate and stress levels. However, the study underlines that the effectiveness of such models is greatly dependent on good hyperparameter selection and optimization. Key hyperparameters such as the number of attention heads, hidden layer size, and learning rate were tuned via rigorous testing using approaches such as GridSearchCV. The findings clearly show that effective tuning leads to meaningful increases in model correctness and dependability [12].

In addition to hyperparameter tweaking, the study included regularization techniques like as dropout, sophisticated optimization algorithms like AdamW, and data augmentation tactics to increase generalization and resilience. These integrated techniques reduced overfitting, stabilized training, and ensured consistent performance under shifting data circumstances [13]. Furthermore, the system's implementation as a web-based application proves its practicality and promise for real-world use [14]. The ability to continually monitor user input and iteratively modify the model based on feedback and performance statistics adds to the system's usefulness in healthcare settings [15].

CONCLUSION

This study shows that hyperparameter tweaking is an important step in constructing high-performance machine learning models for epilepsy prediction. The combination of wearable data, powerful AI approaches, and systematic optimization methodologies can dramatically improve early detection capabilities, allowing for proactive healthcare treatments and improved patient quality of life. Future work should focus on combining bigger and more diverse datasets, studying automated hyperparameter optimization approaches such as AutoML, and improving model interpretability to enhance clinical decision-making.

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