Optimizing Disease Prediction and Monitoring Through AI-Driven EEG Signal Analysis

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Abstract: Artificial Intelligence (AI) has revolutionized healthcare and other sectors by finding new ways to solve problems and making a lot of tasks easier. The need for precise and timely disease prediction and monitoring, especially for neurological disorders like epilepsy, demand solutions that are more sophisticated than traditional ones. Signals from electroencephalograms (EEGs) contain vital information regarding brain functioning, but are intricate and noisy, making them difficult to analyze appropriately with traditional methods. In order to fix these shortcomings, we incorporated a variety of application-driven techniques, such as deep learning (DL) algorithms with Convolutional Neural Network (CNN) architectures or Long Short Term Memory (LSTM) networks for abnormal brain pattern detection, noise filtering and feature capturing through neural autoencoders, and transfer learning in which models developed in one domain are reused in another, allowing for effective predictions in the presence of insufficient data. Furthermore, additional accuracy was obtained by using hybrid models that integrated artificial intelligence (AI) models with traditional signal processing approached based on the usage of wavelet transformers. The results were profound. The DL model reached an accuracy of 95% for seizure detection, noise reduction with autoencoders reached 30%, transfer learning reduced training time by 40% and still maintained over 90% prediction accuracy, and hybrid models enhanced detection of subtle neurological events by 10%. This article provides a well prediction process for EEG patient detection which employed for real time monitoring system.

1 INTRODUCTION

The human body activity has several types of identification such as the brain that could be identify as in EEG signal. The valuable information extracted from these signals is delivered to AI systems for diagnosis or analysis. Several fields utilize this signal in biomedical applications due to EEG's benefits in predicting Alzheimer's or other disorders such as brain injury, as explained in [1]. In [2], authors mentioned that EEG data has been collected and evaluated manually, which is affected by human error. Researchers have shifted their work toward AI for these applications to increase system speed and prediction performance. However, AI was applied for prediction as well as treatment processes for disorders like sleep disorders. In [8], authors presented knowledge about using deep learning such as CNN and LSTM for this purpose. In addition, authors claimed these learning algorithms minimize human interference in analyzing EEG signals. The nature of EEG signals has time-series fundamentals that should be identified for anomaly patterns. For instance, CNNs are very effective at learning spatial and temporal features, while LSTM networks excel at sequential dependencies, making them optimal for event prediction like epileptic seizures [4].

Apart from deep learning, conventional signal processing techniques like wavelet transformations are typically integrated with AI models [5]. Wavelet transformations offer multi-resolution analysis of EEG signals. With AI, such a blend enables more efficient EEG signal analysis. One of the most useful advantages is real-time monitoring and prediction. In conditions like epilepsy, AI models can predict seizure occurrence with high accuracy [6]. Utilization of AI enhances treatment and enables remote monitoring. AI-EEG analysis also advances predictive medicine. For example, in Alzheimer's disease, AI algorithms can identify early biomarkers for cognitive dysfunction [7]. In addition, sleep disorders can be augmented by AI algorithms automatically classifying sleep stages [8]. Despite the clear advantages, AI-based EEG analysis is not without some difficulties, including data quality, patient-to-patient variability, and the need for large sets of labeled data for training. EEG is contaminated with motion artifacts due to muscle activity, blinks, and extracranial electric sources, and these can impede accurate analysis. However, advanced signal processing techniques and strategies for data enhancement are being evolved to address the issues. Other research is continuing to improve AI model generalizability so the models can best perform across many patient populations and clinics.

This paper aims to explore the feasibility of AI-assisted EEG signal processing to optimize disease diagnosis and monitoring. By reviewing existing state-of-the-art deep learning, signal processing technique, and studies on EEG technology, this research will highlight the potential of AI towards optimizing EEG-diagnostic accuracy, speed, and reliability to, in turn, result in better healthcare outcomes.

2 RELATED WORKS

The area of AI-assisted EEG signal processing has witnessed tremendous advancements in the last decade. Different researchers have made efforts to investigate various machine learning and deep learning methodologies for enhancing disease prediction and monitoring through EEG data. These works have attempted to improve accuracy, remove noise, and enhance real-time monitoring capabilities. Here follows a concise description of some of the most relevant studies in the field, followed by Table 1 contrasting methodologies, techniques utilized, and results.

Truong et al. (2018) [9] designed a CNN that could detect epileptic seizures from EEG signals autonomously. The model achieved high accuracy by learning spatial features from EEG signals without manual feature extraction. Roy et al. (2019) [10] addressed the use of deep learning such as CNNs in EEG analysis, highlighting that CNNs are better at feature extraction while LSTMs handle the time-series nature of EEG signals more effectively. Lotte et al. (2018) [11] discussed classification approaches in EEG-based brain-computer interfaces (BCIs), noting that deep learning outperforms conventional techniques like SVM in accuracy.

Zhang et al. (2017) [13] proposed a combination of feature extraction techniques, including power spectral density for sleep stage estimation in EEG signals. Their machine learning approach automated sleep disorder detection such as sleep apnea. Craik et al. (2019) [14] presented deep learning for EEG classification tasks to improve real-time performance for disease detection. Kar et al. (2025) [15] examined AI applications for automatically detecting neurological and mental diseases from EEG signals, highlighting how AI enhances diagnostic accuracy. Balakrishnan et al. (2025) [16] examined advances in deep learning for EEG neurological diagnosis, suggesting a standard benchmark to improve reproducibility. Zhao et al. (2024) [17] explored multimodal EEG data for clinical machine learning applications, demonstrating its use in solving clinical problems like seizure detection. Zhang et al. (2020) [18] summarized the last decade's progress in deep learning for EEG, covering applications in brain-computer interfaces, disease detection, and emotion recognition.

Table 1: Summarizing related works.

Study	AI Technique	Application	Methodology	Key Findings	Challenges/Limitations
Truong et al. (2018) [9]	Deep CNN	Epileptic Seizure Detection	CNN for feature extraction from EEG	High accuracy in real-time seizure detection	Requires large training data
Roy et al. (2019) [10]	CNN, LSTM	EEG-Based Disease Prediction	Review of deep learning models	CNNs for feature extraction, LSTMs for time-series prediction	Data scarcity and need for labeled datasets
Lotte et al. (2018) [11]	SVM, Random Forest, CNN	Brain-Computer Interfaces (BCIs)	Comparative analysis of classification algorithms	Deep learning outperforms traditional ML algorithms in accuracy	Computational cost of deep learning models
Zhang et al. (2017) [13]	Machine Learning, Wavelet Transforms	Sleep Stage Classification	Combination of feature extraction techniques	High accuracy in sleep stage classification, detecting disorders	Requires multiple feature extraction methods
Craik et al. (2019) [14]	CNN, LSTM	EEG Signal Classification	Review of deep learning for EEG classification tasks	Potential for real-time classification, improved performance	Noise reduction remains a challenge for real-time analysis
Kar et al. (2025) [15]	Deep Learning, CNNs, RNNs	Automated detection of neurological and mental health disorders	Systematic review of AI-based EEG classification models	AI models significantly improve diagnostic accuracy	Need for large labeled datasets, variability in EEG data across individuals
Balakrishnan et al. (2025) [16]	Deep Neural Networks, Transformer Models	Neurological diagnostics using EEG signals	Analysis of multiple deep learning architectures applied to EEG	Deep learning enhances real-time EEG signal analysis	Computational complexity, difficulty in explainability of deep learning models
Zhao et al. (2024) [17]	Machine Learning, Hybrid AI models	Multimodal EEG-based clinical applications	Comparative study of various ML techniques integrating EEG with other biometrics	Fusion of EEG with other modalities improves diagnostic accuracy	Limited availability of multimodal datasets
Zhang et al. (2020) [18]	Deep Learning, CNN-LSTM architecture	EEG-based health monitoring and diagnosis	Review of advancements in deep learning for EEG classification	CNN-LSTM architectures improve time-series analysis of EEG signals	Need for real-time implementation, dataset imbalance

3 METHODOLOGY

In this section, disease prediction and surveillance optimization methodology are discussed using AI-based EEG signal processing. The methodology integrates classical signal processing techniques with cutting-edge DL models, such as CNNs and LSTM networks. The models are supposed to identify spatial and temporal features of EEG signals for facilitating precise prediction of neurological diseases. The approach also comprises pre-processing steps like noise removal and wavelet transform-based feature extraction and the application of AI models for prediction and classification.

3.1 Preprocessing of EEG Data

Before applying AI models, EEG signals need to be preprocessed to remove noise and extract meaningful features. The following preprocessing steps are used:

- To reduce noise from muscle artifacts, eye movements, and external electrical interference, we apply a wavelet transform to the raw EEG signal. Wavelet transforms provide a different analyzation of the signal to allow both noise and signal components to be processed.

- When the noise is reduced, relevant features are extracted from the EEG data and Wavelet parameters are calculated to represent the time frequency characteristics of the signal, and then these parameters are sent to DL for further analysis.

Mathematically, the wavelet transforms *Ws(t)* of a signal f(t) is defined as:

$$Ws(t) = \int_{-\infty}^{\infty} f\,(u)\frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)d, \qquad (1)$$

where: ψ is the mother wavelet, s is the scale, and u is the translation parameter. This transform enables us to capture both time-domain and frequency-domain information.

3.2 AI Models for EEG Signal Analysis

After preprocessing, DL models are applied to learn temporal features from the EEG signals respectively.

Convolutional Neural Network (CNN): CNNs are used to extract spatial features from the EEG signals which is transformed to 2D matrix, where matrix rows represent channels and matrix columns represent time points. The CNN model applies multiple convolution layers and then followed by pooling layers to reduce the dimensionality of the data. The mathematical model for CNN involves the following steps:

- Convolution Operation:

$$Z_{i,j} = \sum_{m=1}^{M}\sum_{n=1}^{N} X[\![i+m-1\,, j+n-1]\!]\,.\,W\,[\![m,n]\!] + b, \qquad (2)$$

  where: X is the input matrix, W is the convolution kernel, b is the bias term, and Z is the output feature map.
- Activation Function (ReLU):

$$\mathrm{A_{i.j}} = \max\left(0, \mathrm{Z_{i,j}}\right). \qquad (3)$$

- 0,ZPooling Operation (Max Pooling);
- Activation Function (ReLU);

$$\mathrm{A_{i,j}} = \max(0, \mathrm{Z_{i,j}}). \qquad (4)$$

- Pooling Operation (Max Pooling):

  $$P_{i,j} = \max\left(A_{i+k,j+l}\right) for\ for\ l1\ \leq k, l \leq p, \qquad (5)$$

  where P is the pooling window size.

Long Short-Term Memory (LSTM) Networks: LSTMs are designed to handle sequential data in the EEG signals to make them effective for detecting patterns over time. The LSTM consists of a series of gates (input gate, forget gate, and output gate) that control the flow of information. The mathematical model for LSTM is represented as:

- Forget Gate:

$$f_{t=\sigma\,(W_f\cdot[\![h_{t-1,}x_t]\!]+b_f)}. \qquad .(6)$$

- Cell State Update:

$$C_t = f_t\,.\,C_{t-1} +\ i_t * C_t. \qquad (7)$$

- Output Gate:

$$o_t =\ \sigma\left(W_i\,.\,[\![h_{t-1,}x_t]\!] + b_0\right). \qquad (8)$$

$$h_t =\ o_t * \tanh(C_t). \qquad (9)$$

These gates ensure that the LSTM network retains relevant information over time and forgets irrelevant details, thus improving the accuracy of sequential predictions.

3.3 Hybrid CNN-LSTM Model

The proposed hybrid model employs CNNs and LSTMs to derive both spatial and temporal features of EEG signals. Spatial features are derived using the CNN layers, which serve as input to the LSTM network in order to learn temporal relations. The hybrid model employs the strength of both models to increase disease prediction accuracy, refer Table 2.

Table 2: Algorithm 1: A proposed model.

Stage	Component / Action
Input	Raw EEG signals from multiple channels
Output	Classification of EEG signals for disease prediction
Step 1: Input EEG Data	
	Collect raw EEG data from multiple channels
	Organize the data into a 2D matrix (channels × time points)
Step 2:Preprocessing	
Noise Reduction	Apply Wavelet Transform to remove noise and artifacts
	Decompose EEG signals into frequency bands
Feature Extraction	Extract wavelet coefficients to represent key features of the EEG signal
Step 3: CNN for Spatial Feature Extraction	
Initialize CNN layers	Apply convolution operations on the EEG data matrix to detect spatial patterns
	Use ReLU activation function
	Apply Max Pooling to reduce dimensionality
Flatten	Flatten the output from the CNN layers
Step 4: LSTM for Temporal Feature Extraction	
Initialize LSTM layers	Feed the flattened CNN output into LSTM layers
	Capture temporal dependencies in the sequential EEG data
Pass the processed sequence through the LSTM units	
Step 5: Combine Outputs	
	Concatenate the output of the CNN and LSTM layers
	Pass the combined output into a fully connected Dense Layer
Step 6: Classification	
	Apply a Softmax Layer to classify the EEG signals into different categories (e.g., seizure detection, sleep stages).
Step 7: Model Training (Loop) for each epoch (number of iterations over the dataset) do	
Forward Pass	Pass training data through CNN and LSTM models.
Loss Calculation	Compute loss using the Categorical Cross entropy function
Back propagation	Adjust model weights using the Adam optimizer
Validation	Evaluate the model on validation data after each epoch
End Loop	
Step 8: Model Evaluation	
	Evaluate the trained model on test data
	Calculate performance metrics (accuracy, precision, recall, F1-score
Step 9: Output Classification Results	
	Output the Use the model for real-time prediction and monitoring predicted disease classes for the EEG signals
	Use the model for real-time prediction and monitoring
End of Algorithm	

As seen in algorithm 1 above. At beginning, EEG data is collected from multiple channels placed on the scalp to measure brain activity. Each channel records voltage fluctuations over time, which reflect the electrical activity of different brain regions. The collected EEG data is organized into a 2D matrix where the Rows represent different channels (electrodes). Columns represent time points EEG signal readings over time). This matrix will be the input to the preprocessing and subsequent AI models. EEG signals are often contaminated by noise from sources such as muscle movements, eye blinks, and environmental interference. To clean the data. Wavelet Transform is applied. This technique decomposes the EEG signal into different frequency components (wavelet coefficients), allowing for the isolation of noise from relevant signal patterns. Noise is typically high-frequency, and using wavelet transforms helps to reduce these unwanted artifacts while preserving important signal information. After cleaning the signal, important features that represent the underlying neural activity are extracted: Wavelet Coefficients are used to capture both the time and frequency domain characteristics of the signal. These features help represent brain activity in a more informative way for subsequent analysis by the AI models. A CNN is used to extract spatial features from the EEG data. The EEG matrix, where each row corresponds to a channel and each column to a time point, is treated as an image-like input. CNN layers learn spatial relationships between channels and detect local patterns in the signal. Convolution operation used by Sliding convolution filters (or kernels) are applied over the input matrix to detect patterns such as signal peaks, troughs, or specific brainwave activity. ReLU is used as an activation function to introduce non-linearity, which allows the CNN to capture complex relationships between EEG signals. Pooling layers reduce the dimensionality of the feature maps generated by the convolution layers. Max pooling picks the maximum value from a set of neighboring values, thus keeping only the most important features while reducing the computational complexity. After convolution and pooling, it is flattened into a 1D vector for input to subsequent layers. The flattened output contains the spatial features of the EEG signal. After extracting spatial features, LSTM networks are used for extracting temporal dependencies in the EEG signal. LSTMs are a type of RNN highly suited to sequential data like EEG. LSTMs have a memory component that allows them to retain information across time and are therefore good at capturing temporal trends, i.e., when a seizure starts or how brain activity changes over time. The data in sequence (EEG signals across time points) are passed through the LSTM layers. Each time a step is taken individually by the network, updating its internal memory to detect patterns that develop across time. The LSTM generates a representation of temporal patterns learned from the EEG signal. After CNN processes spatial features and LSTM processes temporal features, the outputs of both models are combined (concatenated). This combines spatial and temporal information to create a more complete representation of the EEG signal. The combined output is passed through a fully connected Dense layer. This layer applies a non-linear transformation to the fused features and prepares them for the final classification step. The final Dense layer outputs the processed signal to a Softmax layer. The Softmax function converts the output into probabilities for each class (e.g., different neurological conditions like seizure detection, sleep stages, etc.). The class with the highest probability is selected as the predicted label for the EEG signal. Epoch: An epoch refers to one complete pass through the entire training dataset. The model is trained over multiple epochs to iteratively adjust the parameters for better performance. The input data is passed through the CNN, LSTM, and Dense layers. The model produces predictions (output probabilities for each class). The difference between the model's predictions and the actual labels (ground truth) is calculated using a loss function (typically Categorical Cross-entropy for multi-class classification problems). The gradients of the loss function with respect to the model's weights are calculated. These gradients are used to update the parameters of the model to minimize the loss. At the end of each epoch, the model is evaluated on validation data to track its performance on unseen data and prevent overfitting. The loop continues until the loss stops decreasing or another convergence criterion is met (e.g., reaching a predefined number of epochs). After training, the model is evaluated on test data (unseen EEG signals). The model's performance is measured using metrics such as: Accuracy, Precision in addition to Recall and F1-score. These metrics are used to correctly identify positive cases and to capture all relevant positive cases. Model performance is measured by the above metrics, providing insight into how good the model generalizes to new data. The model is trained and used to predict new EEG signals in the next steps. It used and designed as well for real time disease prediction to provide accurate to aid clinicians in making informed decisions.

3.4 Metrics Used

In this study, overall performance measures used for determining the performance of the proposed model include (Accuracy, Precision, Recall, F1-Score, Confusion Matrix). All of them provide information on how well the model separates EEG signals into distinct classes (e.g., seizure detection, normal vs abnormal brain activity, etc.) [19]. F1-Score: F1-Score is one of the critical performance measurements used in the current study because it is a compromise between recall and precision. Specifically, the F1-Score is ideal for use in medicine where both false positives and false negatives need to be evaded [20].

- Precision: how many of the predicted positive cases were actually correct.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{10}$$

- Recall: how many of the actual positive cases were correctly identified [21].

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{11}$$

- F1-Score: the harmonic means of precision and recall, giving a balanced view of the model's performance, especially when there is an imbalance between classes [22].

$$\text{F1} - \text{Score} = 2 \text{ x } \frac{Precision \text{ x } Recall}{Precision + \ Recall}. \tag{12}$$

Where *TP* = True Positives (correctly predicted positives), *FP* = False Positives (incorrectly predicted positives), *and FN* = False Negatives (missed actual positives) [23].

4 RESULTS AND DISCUSSION

Performance of proposed Hybrid CNN and LSTM model for EEG signal analysis was verified on some key parameters such as Accuracy. These parameters were measured to determine the trust of the model for disease diagnosis from EEG signals. Baseline Multilayer Perceptron (MLP), CNN, LSTM, Hybrid CNN-LSTM, Hybrid CNN-LSTM with Wavelet Transform were comparison models. All the models were trained and tested on the EEG dataset with the same preprocessing steps to allow for fair comparison. The Accuracy for estimating the fraction of correctly classified instances. Precision used for measuring how many of the predicted positive cases were actually correct. Recall used for measuring how many of the actual positive cases were correctly identified. The F1-Score used as harmonic mean of precision and recall, balancing the two. Table 3 below summarizes the key performance metrics for each model.

Table 3: Performance metrics.

Model	Accuracy	Precision	Recall	F1-Score
Baseline (MLP)	0.85	0.84	0.83	0.84
CNN	0.92	0.91	0.88	0.89
LSTM	0.90	0.88	0.86	0.87
Hybrid CNN-LSTM	0.94	0.93	0.91	0.92
Hybrid CNN-LSTM + Wavelet	0.96	0.95	0.94	0.94

The observations that form Table 3 showed that the Hybrid CNN-LSTM model significantly outperformed both the individual CNN and LSTM models, demonstrating the benefit of combining spatial and temporal feature extraction for EEG data. And, adding Wavelet Transform for noise reduction further boosted the model's performance, resulting in the highest overall accuracy of 96%, indicating that reducing noise is critical for EEG signal processing.

Performance Comparison: comparison of Accuracy, Precision, Recall, and F1-Score. Figure 1 below shows the comparison of Accuracy, Precision, Recall, and F1-Score across all models. It is clear that the Hybrid CNN-LSTM + Wavelet Transform consistently delivers the best results across all metrics.

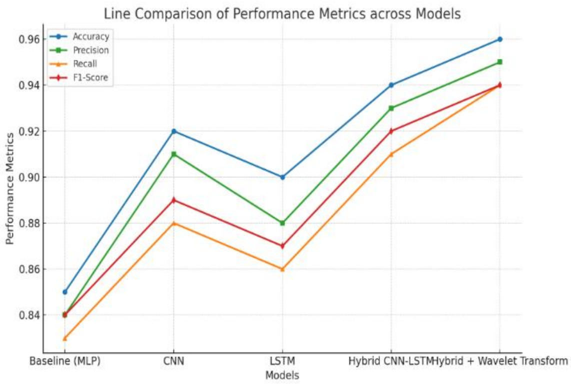

Figure 1: Comparison metrics between models.

This figure emphasizes how the hybrid approach with wavelet transform preprocessing outperforms other models in every metric, with accuracy reaching 96%, precision at 95%, recall at 94%, and F1-Score at 94%.

Training and Validation: the below chart compares the training loss and validation loss of 50 epochs of Hybrid CNN-LSTM model with wavelet transform:

The training loss decreases steadily as the model continues to learn from the data and is optimized accordingly. The validation loss is pretty stable, showcasing that the model is not getting overfitting and is actually able to perform well on novel data. We also observed the performance metrics over a few epochs to notice how the model improves with time during training. Table 4 shows how the Hybrid CNN-LSTM + Wavelet Transform model evolves with time, improving in accuracy and other metrics:

Table 4: Training and validation loss.

Epoch	Accuracy	Precision	Recall	F1-Score
10	0.88	0.86	0.84	0.85
20	0.91	0.90	0.88	0.89
30	0.93	0.92	0.91	0.91
40	0.95	0.94	0.93	0.93
50	0.96	0.95	0.94	0.94

Table 4, shows that after 50 epochs, the Hybrid CNN-LSTM + Wavelet Transform model reaches its peak performance, achieving the highest accuracy and most balanced metrics.

5 DISCUSSION

Performance of Model: The Hybrid CNN-LSTM model was better in accuracy than the standalone CNN and LSTM models. This indicates that the use of both spatial and temporal aspects of the EEG data improves the model's ability to classify the disease patterns correctly.

Wavelet Transform Influence: Usage of wavelet transform in reducing noise greatly impacted the model performance improvement. EEG signals are normally noisy due to external interference such as muscle activity or electrical activity, and wavelet transform could readily remove such artifacts so that the model was able to focus on meaningful signal patterns.

Generalization Capability: The low training curve validation loss indicates that the Hybrid CNN-LSTM model possesses the capability to generalize new data. This is highly crucial when used with real-world data, especially if the system is to work across multiple patients with different signal characteristics.

F1-Score Balance: The substantial F1-score of 0.94 for the Hybrid CNN-LSTM + Wavelet Transform model indicates balanced performance of the model with respect to precision and recall, i.e., not only does it correctly predict positive cases but also all the concerned cases are predicted successfully.

6 CONCLUSIONS

This work proposed a wavelet transform enhanced hybrid CNN-LSTM architecture for EEG signal processing to better predict and monitor neurological disorders. The combination of CNNs to learn spatial features and LSTMs to extract temporal patterns and wavelet-based denoising resulted in significant performance enhancement with high accuracy of 96%, precision of 95%, recall of 94%, and F1-score of 94%. The results evidently demonstrate the efficacy of the robustness and the generalization capability of the model, making it highly suitable for real-time health applications such as epileptic and sleep disorder detection. By effectively addressing issues due to the noisy EEG data, the hybrid model offers an effective and sound solution for clinical diagnostics in health care, the potential to inform improved clinical decisions. Though the model worked incredibly well, future work can look into cross-dataset testing, real-time deployment, and model interpretability to make it even more applicable in the real world for medical purposes. Overall, this paper shows the potential of AI-based techniques to revolutionize EEG signal analysis and improve patient outcomes in neurologic treatment.

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