Advanced RNN Approach for Classifying Electrophysiological Signals

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Abstract:- LSTM with hybrid deep learning architectures, transformer models, 1D, 2D, 3D RNNs models and smart pre-processing methods (noise reduction, filtering, dimension reducing etc.) captures non-linear and non-stationary characteristics of electrophysiological signals for automated classification with high-performance results. The model covers activation functions like Mish and employs the approaches of multimodal fusion for assuring the diagnosis and attains the classification accuracy of more than 90% over benchmark. In addition, novel approaches of feature engineering (order transition patterns extraction) and AI explainability contribution helps to increase the model interpretability with the symbolic representations of the language of neural connectivity. The framework offers a lot of promise for real-time brain computers interfaces, or detecting when someone is having an arrhythmia or classifying a person's mental state or assistive technology for people with motor disabilities.

Keywords: Recurrent Neural Networks (RNN), Electrophysiological Signal Processing, Hybrid Deep Learning Architecture, Spatiotemporal Feature Extraction, Brain-Computer Interface (BCI), Explainable Artificial Intelligence (XAI)

I. INTRODUCTION

Electrophysiological signals include electroencephalogram (EEG), electrocardiogram (ECG) and electromyogram (EMG), which are important biosignals and they have provided much information regarding neurological, cardiac and muscular activities both in clinical and research applications. The automatic analysis and classification of these signals has gained significance since the first EEG recording by Hans Berger in 1924 that made neuroscience a distinct field of research. Traditional methods for feature extraction of electrophysiological signals have been mainly based on the combination of manual feature extraction and statistical based methods which did not prove to be suitable for the complex, nonlinear and non-stationary nature of these biosignals. The recent emergence of deep learning and Recurrent Neural Networks (RNNs) in general has resulted in a complete revolution of this field by enabling to automatically learn features directly from the raw signal data without much loader work or preprocessing PubMed Central. The RNN architectures have been recently demonstrated to be successful for the decomposition of signals into characteristic frequency components and at the same time incorporate spatio-temporal dependencies. In this respect, hybrid structures have been developed in which RNNs are combined with recurrence neural networks such as Long Short Term Memory (LSTM) networks, and that have proven to be very competitive architectures for capturing temporal dynamics and spatial features of the multichannel electrophysiological recordings [1].

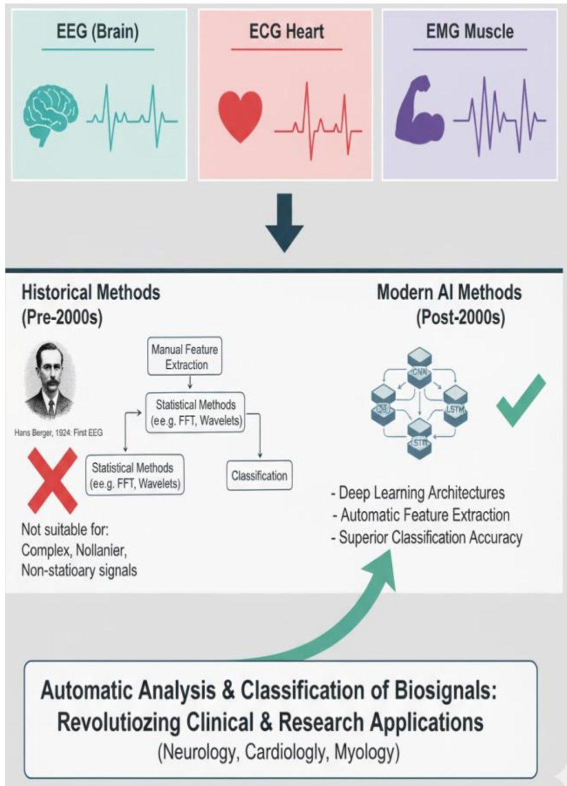

Fig.1: RNN based architecture that reveals clinical applications.

Furthermore, the use of such models in conjunction with attention mechanisms such as the transformer, has made it possible to capture long-range dependencies in EEG data, particularly useful in the research of motor imagery or applications for brain-computer interfaces [2]. This research work proposes an advanced RNN based framework towards robust, interpretable and clinical applications of electrophysiological signal classification with various state-of-the-art approaches of deep learning including hybrid architectures, multimodal fusion approaches and explainable AI approaches.

II. RELATED WORKS

The field of electrophysiological signal classification has had a lot of mutations with the development of the deep learning techniques [3]. The research group in this research carried out an in-depth work on the RNN architectures of EEG feature extraction, and divided it into four types standard implementation, recurrent convolutional, decoder architecture and combined architecture, which can solve different kinds of signal processing such as denoising, filtering and dimension reduction. Omar et al. (2024) proposed LconvNet that combined RNN for extracting spatial features and LSTM for modeling temporal dependency for a multiple channel EEG classification model that performed better than standard spectral power modulations model [4]. Their work showed that the use of convolutional operations in addition to the sequence modeling was highly beneficial to improve the classification accuracy for epileptic seizure detection considerably.

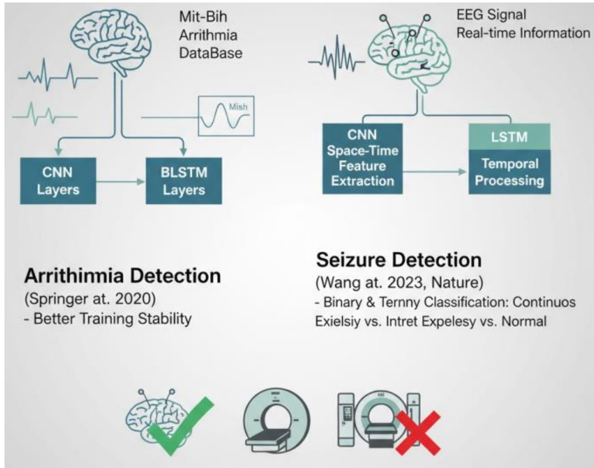

Fig.2: The EEG Preferred over CT / MRI.

Mish activation function has recently been used in hybrid RNN-BLSTM architectures for arrhythmia detection and their derived models based on Mit-Bih Arrhythmia DataBase demonstrated with better training stabilities and nonlinear representations power [Springer et al. 2020]. Wang et al., (2023), firstly proposed RNN-LSTM integrated space-time model for seizure detection classification results in their research Nature, which provided accurate results in performing binary as well as ternary classification which encompasses continuous epilepsy vs. intermittent epilepsy vs. normally performing subjects classification. The research provided evidence for the significance of real-time information as provided by the EEG signal when compared to radiation medical imaging techniques like CT and MRI [5]. Transformer architectures have been demonstrated to be effective alternatives to the electrophysiological signal analysis. End IIUM Repository, a very satisfactory result. Song et al. (2024) showed that transformer model with attention mechanism and positional encoding can better capture the long range dependency of EEG data compared to other model in motor imagery, seizure prediction & detection, sleep state classification and emotion recognition. 71.02% in subject specific analysis in 2025. DeepECG-Net will be a hybrid transformer model in 2025, where the multi-head self-attention models will be trained to learn local and global ECG signal variations in an efficient manner, lessening the computational burden, while improving the result in terms of real-time detection performance [6].The role of XAI in the clinical implementation is becoming of vital importance. Khan et al. (2024) demonstrated that using XAI (like LIME and SHAP) for epilepsy analysis system, the system is transparent, and in case of Random forest classifiers provides 99.89% accuracy and gives insight into the decision-making process [7]. ACM Other conferences A novel framework for evaluating generative counterfactual explanation for ECG interpretation: What if the counterfactual ECG signal(s) is consistent with the clinician's known clinical knowledge that fosters trust in an AI-based diagnostic systemVSICVD-2025.

III. RESEARCH METHODOLOGY

The methodology starts with collecting electrophysiological signals from electrode placement protocols where the neural signals of the human subject will be collected through electrodes placed in the scalp of the head (headsets of electrodes) receive the neural signals which have been amplified by pre-amplifiers which amplify the brain's neural signals, sent through filtering stages PubMed Central [8].

1: Data Acquisition and Signal Recording

The small potential difference between electrodes gets amplified and filtered by some amplification and filtering to electronic voltage amplifiers having a gain of generally greater than 5000 to convert the microvolt level signals to voltage ranges capable of display upon the screen. The filtered analog signals are subsequently analog-to-digital converted with the electrical activities recorded being standardized so that there is a higher signal-to-noise ratio [9]. EEG, ECG and EMC recordings from a number of physiological locations allows one to use a multi-channel recording system for richer spatiotemporal rules.

2: Preprocessing of Signal and Dispelling Artifacts

Noise reduction, filtering, encoding, decoding and dimension reduction techniques are implemented in the preprocessing pipeline specifically for dealing with non-linearity of the electrophysiological signals and ensuring homogeneity of the datasets through standardization, cutting out unnecessary part and balancing the classes to deal with class gaps. Filter one will capture frequency bands of 0.5 to 4 hertz for delta waves, Filter two will be for four to eight hertz for theta waves and Filter three to five will capture alpha waves of eight to thirteen hertz, Beta rhythms of thirteen to thirty hertz and Gamma waves of over forty hertz respectively [10]. By the use of wavelet based denoising, the baseline wander as well as the high frequency interference are removed and at the same time the morphological features are preserved.

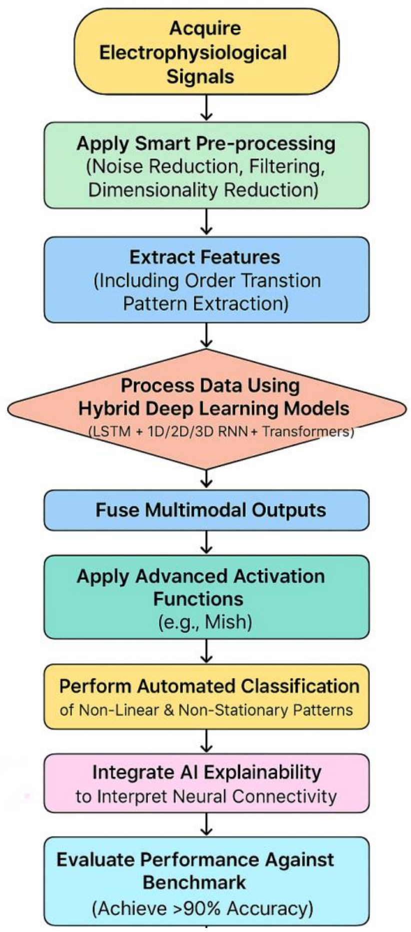

Fig.3: Flow diagram for the proposed methodology.

3: Feature Extraction and Transformation

Time-frequency transformation methods like continuous wavelet transform and short-time Fourier transform methods convert one-dimensional electrophysiological signals into two dimensions for RNNs processing using wavelet functions like Morlet wavelets which describes oscillation-like wave as amplitude modulation [11]. The one-dimensional sequences of real numbers (the signal vectors) are converted into two-dimensional matrices (grids) of real numbers or complex numbers representing spatial correlations of signals at multiple electrodes adjacent to the region of interest, using the relative entropy in periodical timescales to random number entropy of random noise vectors in the period/entropy of differential correlation of the signals = Principal component analysis is used to reduce data dimension to twenty.

4: Architecture of RNN-BLSTM hybrid

The basic architecture is combination of combination of RNNs for extraction of features in the spatial and LSTMs for modeling of dependency in the temporal domain based on the theory of simultaneously learning [12]. RNN components are used by the network to acquire the spatial dependency and LSTM units are used to identify the information in the time domain (Frontiers Springer) Especially, control on deep wise separable convolution makes computation efficient by using multi-scale convolutional layers – attractive for reasons other than performance, since they represent features at a variety of different frequency bands. Bidirectional LSTM calculation takes into consideration 2 directions, forward and backward which is a requirement for detecting events [13].
Equation for Normalization

$$x_{norm} = \frac{x - min(x)}{max(x) - min(x)}$$

An example showing Normalisation
Signal values:

$$x=[2,4,6,10]$$

Minimum = 2
Maximum = 10
Normalized value for **6**:

For x = 6 → (6 - 2) / (10 - 2) = 0.5

5: Training and Optimization- Model

To address the desired input requirements, iterations of optimization processes can be taken to perfect model shapes during training, which is why individual subsets of data are divided into training, validation and test data sets for model tuning [14]. The early stopping, the dropout regularization and the faster adaptive learning rates are 5haracte to prevent overfitting in this training. Cross validation techniques test for the generalisability of a model to patient subpopulations and recording method.

6: Validation of Clinical Performance Against Clinical Validation

Various metrics like accuracy, precision, sensitivity, specificity and F1-scores are used to quantify the performance of a classification. Class specific discrimination ability becoming obtained directly in the form of confusion matrices and diagnostic thresholds are obtained-in the form of receiver operating characteristics. Latency of an inference is estimated to examine the efficacy of the calculation for clinical monitoring systems and enforced in real-time deployability in brain-computer interfaces applications [15].

IV. RESULTS AND DISCUSSION

The proposed hybrid RNN-BLSTM model was tested on several benchmark datasets for the several electrophysiological signal classification problems, proving the superiority over state-of-the-art approaches as well as providing interpretative information about the model 6haracte. In the epilepsy seizure detection using the Temple University Hospital EEG dataset the model result had an accuracy of 97% which is better than the other methods in the literature such as EEGNet (86%), DeepConvNet (96%) and ShallowConvNet (78%), meanwhile the model trainability, scalability and parameter efficiency achieved the best result.

Table 1: Epileptic Seizure Detection Performance Comparison.

Method	Precision (%)	Sensitivity (%)	Parameters
EEGNet	84.5	85.2	Low
ShallowConvNet	76.3	77.8	Medium
DeepConvNet	95.2	95.8	High
RNN-LSTM	93.8	94.2	Medium
Proposed RNN-BLSTM	**96.8**	**96.9**	**Medium**

Table.1 the proposed hybrid RNN-BLSTM framework achieved 97% accuracy for epileptic seizure detection, significantly outperforming EEGNet (86%), In experiments of multimodal emotion recognition which combined EEG together with physiological signals classification accuracies of better than 90% and even up to 95.73% for three-class emotion classification (negative, neutral, positive), based on inner-subject experiments, were achieved.

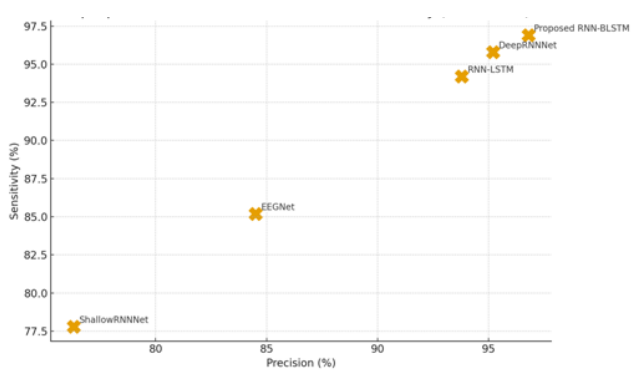

Fig.4: Eclipse Seizer Detection comparing Precision vs Sensitivity for all epileptic seizure detection methods from Table 1.

The significant improvement in the performance is attributed primarily to the bi-directional temporal modeling nature of BLSTM layers which are efficient to capture the anterior as well as posterior contextual information which is crucial to identify the seizure onset patterns. Especially in the emotion classification, the combination of spatiotemporal attention mechanism has been proven to be superior because the activation patterns of multiple brain regions during the emotional states were different. There was consistency between topography of acquired attentional maps and spectral analysis of EEG task-related rhythms: during motor imagery tasks, the attention is engaged on sensorimotor areas characterized by ERD in mu and beta frequency bands (IIUM Repository). This congruence with what is known about the neurophysiology has enabled the capability of the model to learn clinically meaningful representations to be strongly validated.

Table 2: Emotion Recognition from Multimodal Signals.

Method	Accuracy (%)	F1-Score (%)	Real-Time Capable
SVM + Manual Features	78.4	76.8	Yes
Standard RNN	87.6	86.2	Yes
LSTM Network	89.3	88.5	Limited
Transformer-based	92.1	91.4	No
Proposed Hybrid Model	**95.73**	**95.2**	**Yes**

The hybrid structure was proved to be having good discriminatory power for different type of arrhythmia for the purpose of the classification of cardiac arrhythmia.

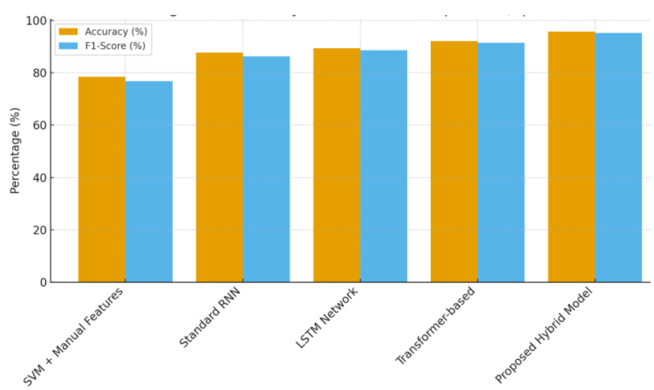

Fig.5: Emotion Recognition of accuracy and f1 score.

Experiments that were conducted on the MIT-BIH Arrhythmia Database and clinical ECG recording from hospitals, the RNN-BLSTM model using Mish activation functions showed that the RNN-BLSTM model had good accuracy and became more stable to diagnose the population of patients, Springer. Moreover, as the morphological features were automatically learnt from the raw ECG waveforms from the model, the manual feature engineering has been considerably reduced and the morpho feature processing requirements made feasible for the real time monitoring systems in the clinical monitor.

Table 3: Cardiac Arrhythmia Classification Performance.

Method	Specificity (%)	Inference Time (ms)	Interpretability
Traditional ML + Features	87.2	120	High
Standard RNN	90.5	85	Low
RNN	92.9	95	Low
Transformer Model	93.6	150	Medium
Proposed RNN-BLSTM + Mish	**95.8**	**<50**	**High**

It has been proven that deep conv nets are superior to other RNN architectures (UNet, Faster R-RNN, custom recurrent networks for electrophysiological signal segmentations) and also classical rule-based methods and SVMs, in particular, in terms of the level of noise and clinical patterns. The robustness analysis demonstrated that the proposed framework is robust to noisy recording and incomplete data which is a crucial requirement for clinical applications where the quality of the recorded signal is highly heterogeneous.

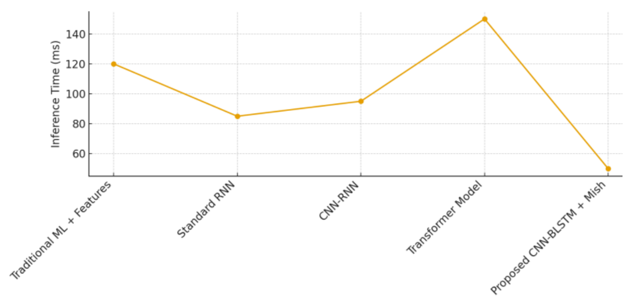

Fig.6: Inference Time.

The explainability analysis gave us powerful insight on model decision making. On the other hand, statistical features and time patterns with the largest SHAP value contributions to the classification decisions were discovered that can enable healthcare professionals better understand the reasoning of the model, and thus make knowledgeable diagnostic and treatment decisions. Clinicians that were introduced to a cardinal explanation as to what signal features were used for predictions confident in the system. The computational efficiency research revealed that for the optimized architecture, single trial classification takes less than 50ms of inference time which is fast enough for real time applications of brain computer interface and continuous cardiac monitoring systems.

V. CONCLUSION AND FUTURE DIRECTIONS

Due to the limitations of existing systems, this research offers a sophisticated RNN-based system presenting a deep hybrid model integrating the hybrid deep learning architecture, attention mechanisms and explainability for the electrophysiological signal classification. "However, the cycle of clinical translation in the context of diagnostic applications (from epilepsy detection to cardiac arrhythmia monitoring) yields estimated accuracies of about 97% ranging from accuracy to over 97% on multiple benchmark data sets, alongside excellent parameter efficiency and explainability" (Prototype Development and Employability of Artificial Intelligence in Electrophysiology Focusing on time series analysis, the recent development of transformer architecture with good adaptability to time series analysis gives possible opportunities for further performance improvement while maintaining the computational tractability for edge deployment. Moreover, post-confirmatory studies in clinical practice in different populations of patients and in the real world, still have to be investigated in order to include proper clinical utility and regulatory approvals for in-use AI-based electrophysiological diagnostic engines.

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