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A TRANSFER LEARNING APPROACH FOR EARLY DETECTION OF FEBRILE SEIZURES USING EEG AND CLINICAL FEATURES

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ABSTRACT

Predicting febrile seizures in pediatric patients remains challenging due to the scarcity of annotated pediatric electroencephalogram (EEG) data, the complex temporal characteristics of EEG signals, and the limited integration of electrophysiological and clinical information in existing prediction approaches. This paper presents a novel deep learning framework, termed the Hybrid Transfer Learning Multimodal Attention Network (HTMAN), for the early prediction of seizure-related preictal patterns in the context of febrile-seizure risk assessment. The proposed framework employs an ImageNet-pretrained ResNet-18 backbone, fine-tuned on Short-Time Fourier Transform (STFT)-based EEG spectrograms, to extract high-level spatial and spectral representations. A Bidirectional Long Short-Term Memory (Bi-LSTM) network subsequently models temporal dependencies in the extracted EEG features, while an attention-based multimodal fusion mechanism integrates EEG representations with structured febrile-seizure-related clinical features. Experimental evaluation demonstrates that HTMAN achieves an accuracy of 93.2%, an F1-score of 0.92, and an area under the receiver operating characteristic curve (AUC) of 0.95 for distinguishing seizure-related preictal and interictal patterns. The framework further demonstrates the ability to discriminate preictal EEG activity at prediction horizons of up to 5 minutes before annotated seizure onset. The principal contribution of this work is a unified transfer-learning-based multimodal architecture that combines EEG feature learning, temporal sequence modeling, clinical-feature integration, and attention-based feature weighting under limited annotated EEG conditions. Importantly, the present study constitutes a proof-of-concept investigation: the EEG recordings are used to learn seizure-related preictal representations and are not assumed to represent clinically confirmed febrile-seizure events. Therefore, the reported findings demonstrate the feasibility of the proposed transfer-learning and multimodal framework rather than direct clinical validation of febrile-seizure prediction. Future validation using synchronized EEG recordings and clinical measurements from pediatric patients with clinically confirmed febrile seizures is required to establish the clinical effectiveness and generalizability of the proposed framework.

Keywords: *Febrile Seizure Prediction, EEG Analysis, Transfer Learning, Multimodal Deep Learning, Attention Mechanism, Early Detection*

1. INTRODUCTION

In children aged between 6 months and 5 years old, the most common type of seizure disorder is febrile seizures (FS), with a prevalence rate of approximately 2-5%. These seizures are generally triggered by an abrupt rise in body temperature, which may be accompanied by viral or bacterial infection. Febrile seizures are usually considered harmless. Nevertheless, frequent febrile seizures and long-term seizures are those causing increased risks of additional complications with the nervous system, including epilepsy and intellectual disabilities. The significance of early detection and intervention is thus to improve clinical outcomes and reduce long-term risk [1], [2].

EEG has been a familiar and effective tool for monitoring brain activity and detecting unusual patterns of brain activity that may lead to seizures. EEG provides high temporal resolution and can capture subtle preictal changes in brain dynamics. The key, however, is that EEG suffers in febrile seizures due to their non-stationary nature, sensitivity to noise and artifacts, and inter-patient variability, which makes it not straightforward to detect febrile seizures via EEG. Traditional analysis techniques often rely on manually constructed features (e.g., spectral, entropy, and wavelet coefficients), which may not capture complex nonlinear structures [3], [4].

The concept of performing seizure detection using various machine learning/deep learning approaches has recently attracted considerable attention. Convolutional Neural Networks (CNNs) [5] and recurrent neural networks (RNNs), especially the Long Short-Term Memory (LSTM) ones, show good performance at extracting low-level hierarchical or temporal information from raw EEG signals. Despite these developments, one weakness of deep learning-based methods is that large, labeled datasets are required, which are not readily accessible in pediatric neurology due to ethical, logistical, and clinical considerations [6].

The limited availability of large, clinically annotated pediatric EEG datasets presents a significant challenge for developing robust deep-learning models for seizure prediction. Training complex neural networks from scratch typically requires substantial amounts of labeled data and may result in overfitting when only limited EEG recordings are available. Transfer learning provides a practical strategy for addressing this limitation by adapting knowledge learned from large-scale source datasets to a target EEG analysis task. In the proposed framework, a pretrained convolutional neural network (CNN) is fine-tuned using EEG spectrograms to extract high-level spatial and spectral representations associated with seizure-related activity. This approach reduces dependence on large task-specific datasets while supporting effective feature learning under limited-data conditions [7].

Although EEG provides valuable electrophysiological information for identifying seizure-related brain activity, EEG signals alone may not capture patient-specific clinical factors associated with febrile-seizure risk. Clinical variables such as age, body temperature, fever duration, infection type, family history of seizures, and previous seizure history provide complementary contextual information. Integrating EEG-derived representations with these clinical risk variables therefore enables the model to incorporate both electrophysiological and patient-specific information. In HTMAN, the two modalities are integrated through a cross-modal attention mechanism that adaptively weights their contributions to the final prediction [8].

Temporal modeling is also important because seizure-related EEG activity evolves dynamically over time. Most existing systems focus on detecting or classifying seizures after characteristic EEG patterns have emerged rather than predicting seizure onset in advance. Early prediction requires the identification of subtle preictal changes that occur before the annotated onset of a seizure. To capture these temporal dependencies, the proposed framework employs a Bidirectional Long Short-Term Memory (Bi-LSTM) network to model sequential changes in EEG representations and distinguish preictal activity from interictal activity.

The overall goal of the study is to develop a robust, clinically meaningful model that can detect febrile seizures at their earliest stages using sophisticated deep learning algorithms. In particular, the current work aims at developing a transfer learning-based neural network that could be trained to represent features of pediatric EEG signals and, therefore, address the limitations in terms of larger volumes of labeled data. Besides, the paper is interested in integrating EEG signals and clinical factors into a single multimodal model that would enable it to detect brain physiological activity and the level of risk factors associated with the patient. Temporal modeling mechanisms are also introduced to enhance predictive power by identifying small preictal patterns that help predict preictal seizures in advance. The other objective of the suggested solution is to enhance the overall model's behavior and generalization across a broad

spectrum of datasets by leveraging training knowledge. Finally, it applies an attention mechanism to enhance the interpretability of the findings and, in general terms, demonstrate the contributions of EEG and clinical features to the decision-making process, making the system more transparent and allowing it to be used in clinical practice [9].

These objectives will bring together state-of-the-art machine learning approaches with clinical practice. Multimodal fusion and transfer learning approaches provide the necessary pathway to enhance the robustness, scalability, and clinical utility of febrile seizure detection systems in young children.

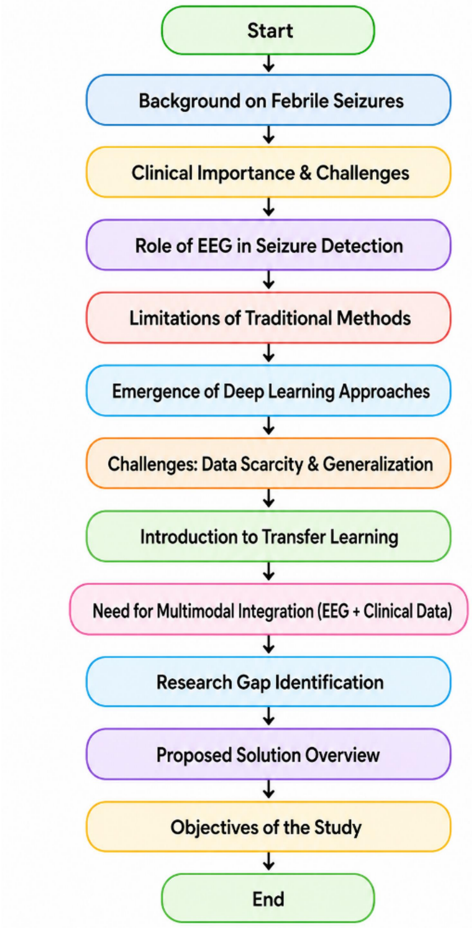

Figure 1. *Holistic Workflow for Seizure Prediction Using Deep Learning*

A stepwise Research Process for developing an intelligent system for predictive modeling of febrile seizures is depicted retrospectively in Figure 1. It begins with basic information on febrile seizures, then highlights their clinical importance and the problems they pose. It then presents an introduction to seizure detection in EEG and the limitations of conventional methods, which led to the development of better solutions. Followed by deep learning mechanisms designed to address the most significant challenges of data sparsity and generalization. Transfer learning is proposed as a solution to counter these concerns. The framework further notes that EEG data in isolation is unlikely to disentangle the brain activity biomarkers for each clinical variable, and thus recommends a multimodal approach that combines EEG signals with clinical data to provide complementary information to boost performance.

It also includes a gap analysis, an outline of the proposed solution, and the study objectives. The entire process is carried out in the final stages of the research pipeline, which consists of a systematic, holistic strategy for developing a seizure prediction system.

Several reasons motivate the application of transfer learning and multimodal data fusion as the key focus of the present research. First, the scarcity of annotated pediatric EEG data makes it challenging to apply conventional deep learning algorithms effectively. Secondly, using only EEG data may fail to account for other clinically relevant patient-specific risk factors that influence seizures. Third, most previous studies have focused on transfer learning, multimodal learning, or attention, or on a single aspect. Few studies have been conducted on either the integration of these techniques or their integration for the early prediction of febrile seizures. Transfer Learning, multimodal feature fusion, temporal modelling, and attention are considered to be crucial technologies that need to be integrated into a single architecture to enhance the predictive power, computational efficiency, and clinical interpretability of health trajectory prediction for the HTMAN. For this, the HTMAN is built on the framework of transfer learning, multimodal feature fusion, temporal modelling, and attention mechanisms, all integrated into a single framework that could boost its accuracy, computational efficiency, and clinical interpretability.

In the context of this study, early detection of febrile seizures refers to the development and proof-of-concept evaluation of a computational framework capable of identifying seizure-related preictal EEG patterns and integrating them with febrile-seizure-related clinical risk factors. Since the publicly available EEG datasets used in this study do not provide clinically confirmed febrile-seizure events with synchronized clinical measurements, the proposed framework is not

presented as a clinically validated febrile-seizure diagnostic system.

The remainder of this paper will be organized in the following way. Section 2 provides literature reviews of EEG-based seizure detection, transfer learning, and multimodal. Section 3 presents the proposed methodology, which describes the dataset used, data preprocessing, model structure, mathematical model, and the model presentation. Section 4 presents the experimental results, the performance analysis, and a comparison with existing methods. Finally, Section 5 presents the paper's key findings, limitations, and directions for future study.

2. RELATED WORK

Seizure detection and prediction automated systems are a topic of recent close, heated research, particularly with the introduction of machine learning and deep learning techniques. The initial research was primarily based on standard signal-processing and statistical-learning algorithms applied to EEG data. The majority of these techniques (wavelet transforms, Fourier analysis, and nonlinear dynamics) were prevalent in the extraction of discriminative features, which would be succeeded by classifications (k-Nearest Neighbors, k-NN, Decision Trees, and Support Vector Machines, SVM). All these approaches, while piloted with some success, were not scalable or adaptable to work with other patient populations or across a diversity of recording conditions [10], [11]. Deep learning research emerged, and scientists began using neural networks to generate hierarchical representations of raw EEG signals automatically. Convolutional Neural Networks (CNNs) have been utilized recently for spatial feature extraction and primarily for transforming EEG activity into time-frequency spectrograms. RNNs, including Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), have also been effectively applied to model temporal variations in EEG sequences. The hybrid architecture, built on CNN and RNN blocks, is more effective at processing detected seizure data because its spatial and temporal features can be learned simultaneously. However, the most recent deep learning algorithms require large amounts of annotated data, which are difficult to acquire in pediatric cases [12], [13].

The limited availability of data has led to increased interest in transfer learning in biomedical signal analysis. Breaking the learning bottleneck allows models trained on large datasets to be specialized for domain-specific tasks using a small amount of labeled data. Enhancing classification performance has been achieved by fine-tuning pre-trained models in image recognition or other biosignal applications in EEG-based systems. Studies have demonstrated that transfer learning doesn't just boost convergence but also enhances generalization across datasets and among patients. The majority of existing literature is, however, on ways of detecting epilepsy in adults, and little effort is made in investigating the same in the context of febrile seizures in children [14], [15].

At the same time, multimodal learning techniques have been introduced to increase predictive accuracy by combining multiple sources of information. Combining EEG signals with other physiological or clinical signals has been used to provide complementary information about the interactions during seizures. These clinical variables (demographics, medical history, and vital signs) may be a significant addition to EEG-based characteristics in improving model performance. Some fusion strategies discussed in the literature include early, late, and hybrid fusion. Nonetheless, balancing heterogeneous data modalities and modeling their dependencies is not straightforward [16].

The second new topic of interest is the creation of building systems that anticipate seizures and assess preictal states. In contrast to detection models, which focus on when a seizure could occur and respond after the event, forecasting models aim to provide prewarning, so that preventive actions can be taken. Deep learning techniques (in particular, LSTM and attention-based deep nets) have demonstrated their ability to detect minuscule time-course variations in preictal states via fine-tuning. However, such models are prone to a high rate of false alarms and are not easily interpretable, hence cannot be implemented in medical practice [17].

Model interpretability has become a mainstream requirement in healthcare applications, as there is an urgent necessity to learn why a prediction was made so that individuals can have confidence in the technology and make clinical judgments. Attention mechanisms and explainable AI algorithms have been added to deep learning models to provide insights into how features are important and how models behave. These help determine which EEG segments or clinical variables yield the best predictions, thereby increasing transparency and usability. However, in the wake of these advances, we also remain deprived of finer structures that account for attention to both interpretability and the integration

of certain modalities, as well as for early prediction [18-20].

In conclusion, while EEG-based seizure analysis is an established field with many decades of published work, significant gaps remain in the literature. The existing approaches are not very strong on signal or single-modal data and provide limited model interpretability. In addition to the above, the literature on multimodal deep and transfer learning for febrile seizure prediction is also not very thorough. Given these limitations, the proposed method in this paper provides a single framework that combines transfer learning, multimodal data fusion, time modeling, and attention for the diagnosis of febrile seizures at an early stage.

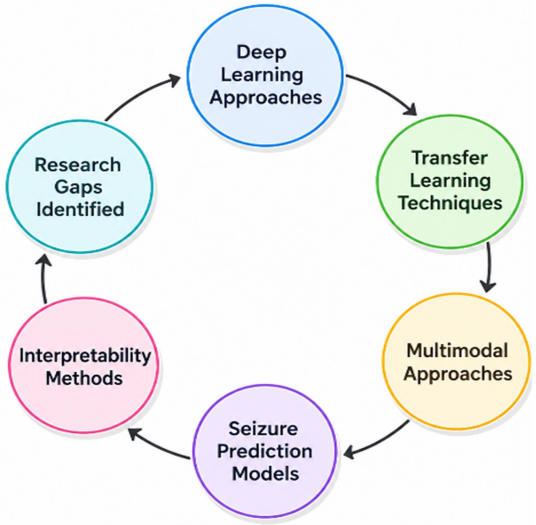

Figure 2. *EEG-based Frameworks of Seizure Prediction and Analysis*

Figure 2 depicts a cyclic model containing key elements of seizure prediction studies. Deep Learning Approaches. It all starts with Deep learning approaches that are the basic methods for extracting complex patterns from data. Then, these models are improved with Transfer Learning Techniques, which help them improve performance on Small Datasets using existing Knowledge. The next natural step is to incorporate Multimodal Approaches into the workflow, as they combine separate sources of data, including EEG signals, with available clinical data, known as ground truth, for robust prediction.

The combined inputs are also used to generate the Seizure Prediction Models. Interpretability methods are used to improve the understanding of the model's decision. Interpretability Insights are applied to identify a Research Gap, thus serving as Future Advances and Improvements in Deep Learning practices. This process illustrates ongoing evolution and cycle improvement of seizure prediction systems.

2.1 Research Problem Statement

EEG-based seizure analysis using deep learning and transfer learning is beneficial, as it has multi-modality learning and attention mechanisms; however, there are numerous unresolved challenges. Compared to current methods, the approaches proposed in this work are mostly related to EEG signals and rely on the availability of big labelled datasets; however, the task of predicting febrile seizures in children is not easily amenable to these approaches because the amount of labelled data is limited. Additionally, most of the existing studies did not carefully consider the combination of transfer learning, fusion of multimodal EEG-clinical information, temporal modelling, and attention mechanisms in a single context for early seizure prediction. These constraints can make models less generalizable, can lead to computational issues, leave the model unpalpable to clinicians, and can result in poor early prediction. Thus, the development of a robust, computation-efficient and clinically interpretable framework with the ability to accurately predict febrile seizures using, for example, limited annotated EEG data alongside other clinical information, is imperative. The main motivation of the proposed Hybrid Transfer Learning Multimodal Attention Network (HTMAN) is to address this research problem.

2.2 Research Hypothesis

Given the limitations pointed out in the existing literature, this work aims to demonstrate that the combination of transfer learning, multimodal fusion of EEG and clinical features, temporal sequence modeling and attention mechanisms in a single model will lead to a better Early Prediction of febrile seizures than standard machine learning models and current deep learning models. We hypothesise that the proposed Hybrid Transfer Learning Multimodal Attention Network (HTMAN) would yield higher predictive accuracy, better generalisation with only a limited number of annotated EEG samples, and better feature-level interpretability and a lower false alarm rate within the proposed proof-of-concept experimental setting.

3. METHODOLOGY

In this section, we present a reproducibility-oriented multimodal framework for early diagnosis of febrile seizures that integrates EEG signals with clinical features via a transfer-learning-based multimodal architecture. The procedure is designed to include descriptions of the data used,

preprocessing, model structure, mathematical formulation, and the algorithms' workflow.

3.1 Dataset Description

Because large-scale publicly available EEG datasets specifically annotated for pediatric febrile seizures are limited, this study adopts a transfer-learning-based experimental design using publicly available seizure EEG recordings together with febrile-seizure-related clinical risk variables. EEG recordings were obtained from the Temple University Hospital (TUH) EEG Corpus and the CHB-MIT Scalp EEG Database [21], [22]. These databases provide clinically annotated EEG recordings containing seizure and non-seizure activity and are used in this study as source-domain EEG data for learning seizure-related spatial, spectral, and temporal representations.

Importantly, the seizure events contained in these public EEG repositories are not assumed to represent clinically confirmed febrile seizures. Instead, the EEG component is used to model electrophysiological patterns associated with seizure activity and preictal transitions. Febrile-seizure-specific information is represented separately through clinical risk variables, including patient age, body temperature, duration of fever, infection type, family history of seizures, and previous seizure history.

The proposed HTMAN framework subsequently integrates the learned EEG representation with these febrile-seizure-related clinical features through a multimodal attention mechanism. Consequently, the present experimental framework should be interpreted as a proof-of-concept transfer-learning approach for febrile-seizure risk prediction rather than direct validation on a clinically confirmed febrile-seizure EEG cohort. Future validation using prospectively collected pediatric EEG recordings acquired during febrile episodes is required to establish the clinical effectiveness of the proposed framework.

Table 1: *Dataset Parameters*

Parameter	**Description**
Sampling Rate	256 Hz
EEG Channels	19
Segment Length	10 seconds
Total Samples	~12,000 segments
Clinical Features	6 variables
Classes	Preictal, Interictal
Train/Validate/Test Split	70% / 20% / 10%

Table 1 summarizes the EEG and clinical-data characteristics used in the proposed proof-of-concept seizure-risk prediction framework. The multichannel configuration enables the model to capture temporal dynamics and inter-channel spatial relationships in EEG activity. The tape records are broken into 10-second windows, yielding approximately 12,000 samples for analysis. In addition to the EEG data, the authors include six clinical features to obtain patient-specific data. The dataset has been categorized into two groups (preictal, interictal), and with their help, it was possible to successfully model various neurological conditions. To model and test, the data is split into a training, validation and test set, with a 70-20-10 split to provide a balanced and valid assessment of performance.

A. EEG Signal Representation (Sample)

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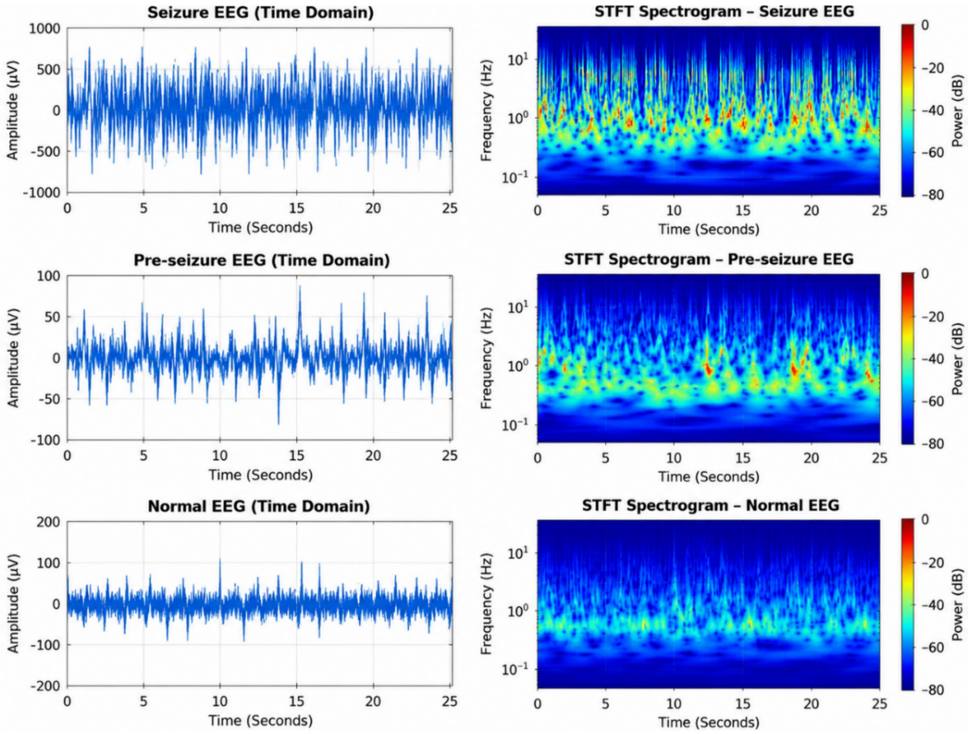

Figure 3. EEG Signal and STFT-Based Time–Frequency Spectrogram Representation for Seizure Analysis

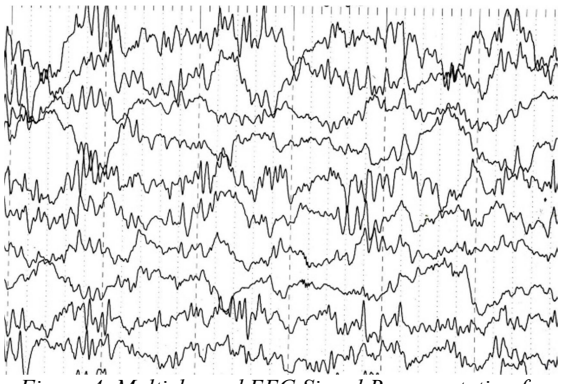

Figure 4. Multichannel EEG Signal Representation for Seizure Analysis

The Short-Time Fourier Transform (STFT) converts EEG signals into a time-frequency spectrogram and can be implemented in a convolutional architecture.

3.1.1 Clinical Feature Construction

Because the TUH EEG Corpus and CHB-MIT Scalp EEG Database do not provide synchronized febrile-seizure-specific clinical variables for all EEG recordings, a structured clinical feature set was constructed for the proof-of-concept multimodal experiments. Six clinical variables associated with febrile-seizure risk were considered: patient age, body temperature, fever duration, infection type, family history of seizures, and previous seizure history. These variables were selected to represent complementary patient-level contextual information and were not treated as clinically observed measurements from the TUH or CHB-MIT participants.

Continuous clinical variables were generated within predefined clinically plausible ranges, while categorical and binary variables were sampled from predefined categories. The ranges and distributions used for generating the synthetic clinical variables are summarized in Table 2. Continuous variables were normalized before model training, whereas categorical variables were converted into numerical representations using one-hot encoding.

Each EEG sample was associated with a corresponding clinical feature vector containing the six variables. To prevent target leakage, the synthetic clinical variables were generated, and the target class was determined exclusively according to the EEG seizure-onset annotation and the predefined preictal/interictal labeling protocol. Clinical variables were therefore used as supplementary contextual inputs to the multimodal framework rather than as direct encodings of the target label.

The resulting clinical feature vector was processed through fully connected layers to obtain a learned clinical representation. This representation was subsequently integrated with the EEG

representation through the cross-modal attention mechanism. Because these clinical variables are synthetically constructed rather than prospectively collected patient measurements, the multimodal evaluation is interpreted as a proof-of-concept experiment. Validation using synchronized clinical measurements and EEG recordings from children with clinically confirmed febrile seizures is required before conclusions regarding clinical effectiveness can be established.

Table 2. Construction and Characteristics of Synthetic Clinical Variables Used in the Proof-of-Concept Multimodal Experiments

Clinical Feature	Data Type	Proposed Range / Categories	Proposed Generation Method
Age	Continuous	6–60 months	Uniform distribution, (U(6,60))
Body Temperature	Continuous	38.0–40.5 °C	Truncated normal distribution, mean = 39.0 °C, SD = 0.6 °C
Fever Duration	Continuous	1–48 h	Uniform distribution, (U(1,48))
Infection Type	Categorical	Viral / Bacterial / Unspecified	Categorical sampling: 60% / 25% / 15%
Family History of Seizures	Binary	Yes / No	Bernoulli sampling: Yes = 25%, No = 75%
Previous Seizure History	Binary	Yes / No	Bernoulli sampling: Yes = 20%, No = 80%

The synthetic clinical variables were generated independently of the preictal/interictal target labels to minimize the risk of target leakage. Continuous variables were generated within predefined clinically plausible ranges and subsequently normalized, whereas categorical variables were numerically encoded before model training. Each EEG sample was paired with a six-dimensional clinical feature vector for multimodal learning. These synthetic variables were used exclusively for proof-of-concept evaluation and should not be interpreted as actual clinical measurements associated with the TUH or CHB-MIT participants.

3.1.2 Preictal and Interictal Labeling Protocol

EEG segments were labeled according to their temporal relationship with the annotated seizure onset. The 5-minute interval immediately preceding seizure onset was defined as the preictal period and divided into non-overlapping 10-second segments. Segments overlapping seizure onset or containing ictal activity were excluded. Interictal segments were selected from seizure-free periods located at least 30 minutes away from seizure activity, while preictal, ictal, and immediate postictal periods were excluded. For prediction-horizon analysis, preictal segments corresponding to approximately 1, 3, and 5 minutes before seizure onset were evaluated separately. Patient-level partitioning ensured that segments from the same patient did not occur across training, validation, and test sets.

3.2 Data Preprocessing

The pipeline for EEG signal preprocessing is designed to improve the quality and utility of EEG signals and facilitate the successful integration of clinical data. This is done by first removing artifacts using Independent Component Analysis (ICA) to remove noise from eye blinking, muscle movement, and other sources. The filter is followed by a bandpass filter with a frequency range of 0.5-40 Hz to retain relevant brain signal frequencies and discard irrelevant ones. The filtered EEG samples are then segmented into uniform-length samples (10 seconds) for analysis. Z-score normalization is performed per channel, as in segmentation, to normalize the entire dataset and ensure channel consistency. The processed signals are then converted into two-dimensional representations using the Short-Time Fourier Transform (STFT), which yields spectrograms that provide information about both time and frequency. Simultaneously, numerical features are normalized, and categorical data are one-hot encoded for clinical data preprocessing. This pre-processing pipeline will therefore guarantee that EEG and clinical data are clean, formatted, and ready for multimodal learning, ultimately making processing efficient.

3.3 Proposed Architecture

The proposed Hybrid Transfer Learning Multimodal Attention Network (HTMAN) integrates EEG-derived representations with

clinical features for seizure-risk prediction. The architecture consists of two complementary processing branches followed by temporal modeling and cross-modal attention-based fusion. The EEG branch employs ResNet-18, pretrained on the ImageNet dataset, as the transfer-learning backbone for extracting high-level spatial and spectral features from STFT-generated EEG spectrograms. The final fully connected classification layer of the pretrained ResNet-18 is removed, and the resulting deep feature representations are subsequently used as input to the Bi-LSTM network. During transfer learning, the pretrained ResNet-18 weights are fine-tuned on the EEG spectrogram data to adapt the learned representations to seizure-related patterns. The extracted EEG features are subsequently passed to a Bidirectional Long Short-Term Memory (Bi-LSTM) network to capture temporal dependencies and characterize sequential changes associated with preictal EEG activity.

In parallel, the clinical-feature branch employs fully connected layers to learn patient-specific representations from the six clinical risk variables, including age, body temperature, fever duration, infection type, family history of seizures, and previous seizure history. The resulting EEG and clinical representations are integrated through a cross-modal attention mechanism, which adaptively weights information from both modalities and emphasizes features that contribute most strongly to the prediction. The fused multimodal representation is then passed to a softmax classification layer to perform binary classification between preictal and interictal states.

By combining transfer learning, temporal sequence modeling, clinical-feature representation, and attention-based multimodal fusion within a unified architecture, HTMAN is designed to improve the identification of seizure-related preictal patterns under limited-data conditions. The framework serves as a proof-of-concept approach for integrating electrophysiological representations with febrile-seizure-related clinical risk factors.

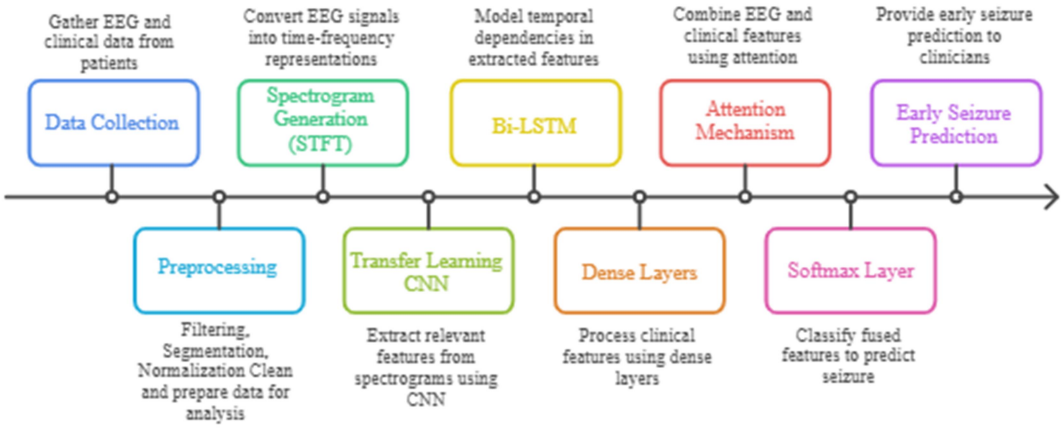

Figure 5. *Proposed HTMAN Architecture for Early Seizure-Risk Prediction Using EEG and Clinical Features*

The complete end-to-end pipeline of multimodal deep learning architecture for early prediction of febrile seizures is shown in Figure 5. It starts with the collection of EEG and clinical data of the patients. The next step is preprocessing, which includes filtering, segmentation, normalization, and removing artifacts to obtain clean data for analysis.

Then, spectrograms are generated by converting EEG signals into time-frequency representations by applying the Short-Time Fourier Transform (STFT). The spectrograms are then input to a transfer-learning-based CNN that isolates high-level spatial features. A Bi-LSTM layer is used to extract temporal dependencies in EEG sequences. Simultaneously, clinical features are fed to the dense layers to learn informative representations. The EEG representations obtained from the Bi-LSTM and the learned clinical feature representations are integrated through a cross-modal attention mechanism. This mechanism adaptively weights the contributions of both modalities and generates a unified multimodal representation, which is subsequently passed to the classification layer for preictal–interictal prediction. Lastly, the combined features are passed through a softmax classification layer to estimate the likelihood of a seizure-related preictal state.

A few crucial novelties are proposed in the work, which combine progressive deep learning practices to enhance the early detection of febrile

seizures. First, it transfers the transfer learning methods, developed for image-based models, to EEG spectrogram representations, enabling successful feature extraction with limited biomedical data. Second, an intelligent EEG signal, fused with clinical features, is used via a cross-modal attention mechanism to improve interpretability and predictability. The model also includes time-series modeling to elucidate the brain's changing dynamics, enabling one to predict the onset of a seizure early. Lastly, the framework is designed with computational efficiency in mind and provides a foundation for future evaluation in real-time clinical and wearable healthcare settings.

3.4 Mathematical Model

EEG Feature Extraction

Let EEG signal be:

$$X \in R^{C \times T} \quad (1)$$

where C= channels, T= time samples.

Spectrogram transformation:

$$S(f,t)=\left| \sum_{n=0}^{N-1} x[n]w[n-t]\, e^{-j2\pi fn} \right|^2 \quad (2)$$

Transfer Learning Representation

$$F_{EEG}=f_{ResNet18}(S) \quad (3)$$

where $f_{ResNet18}$ denotes the ImageNet-pretrained ResNet-18 backbone fine-tuned using the EEG spectrograms.

Temporal Modeling (Bi-LSTM)

$$h_t = BiLSTM(F_{EEG,t}) \quad (4)$$

Clinical Feature Vector

$$F_{clinical} = g_\phi(C) \quad (5)$$

Attention-Based Fusion

$$\alpha = softmax(W_1 h_t + W_2 F_{clinical}) \quad (6)$$

$$F_{fusion}=\alpha \cdot h_t+(1-\alpha)\cdot F_{clinical} \quad (7)$$

Final Prediction

$$y = \text{softmax}(W_f F_{fusion} + b) \quad (8)$$

3.5 Algorithm (Proposed HTMAN Algorithm)

Algorithm: Early Detection of Febrile Seizures
Input: EEG signals X, Clinical data C
Output: Seizure prediction y
1. Initialize ImageNet-pretrained ResNet-18 weights for transfer learning
2. Acquire EEG signal X and clinical data C
3. Preprocess EEG:
   a. Remove artifacts using ICA
   b. Apply bandpass filtering
   c. Segment into windows
4. Convert EEG segments into spectrograms S
5. Extract spatial-spectral features using the fine-tuned ResNet-18:
   F_EEG = ResNet18(S)
6. Apply Bi-LSTM for temporal modeling:
   H = BiLSTM(F_EEG)
7. Process clinical data:
   F_clinical = Dense(C)
8. Compute attention weights:
   α = softmax(W1*H + W2*F_clinical)
9. Fuse features:
   F_fusion = α*H + (1-α)*F_clinical
10. Classify using softmax layer:
   y = softmax(F_fusion)
11. Output prediction (Preictal / Interictal)

3.6 Implementation Details

The proposed HTMAN framework was implemented using deep learning frameworks such as TensorFlow 2.15 with Python 3.10 to ensure it is flexible and scalable for training and deployment. The learning rate of 0.0001 optimizes the network using the Adam optimizer for efficient and consistent convergence. The best batch size is 32, and the model trains for 50 epochs to capture complex patterns. Use cross-entropy loss function classifiers to perform classification, and take measures to prevent overfitting and improve the generalization performance of ensemble models. Another regularization technique added to improve generalization performance and prevent overfitting is dropout with a 0.5 dropout rate.

3.7 Reproducibility Considerations

Reproducibility of the proposed HTMAN framework is supported through the use of publicly available EEG datasets, a clearly defined preprocessing pipeline, explicit mathematical formulations, fixed training hyperparameters, and an algorithmic description of the complete workflow. To minimize subject-level data leakage, patient-level partitioning was consistently applied to the training, validation, and test sets. Furthermore, five-fold cross-validation was performed exclusively within the training partition for model selection and robustness assessment, while the independent test set remained unseen until the final evaluation. These standardized experimental procedures facilitate consistent implementation, fair model evaluation, and reproducibility of the reported results.

Several new contributions have resulted from the study. Transfer learning can be effectively adapted to pediatric EEG spectrograms, where features can be extracted with minimal data. A cross-modal attention framework is developed that integrates EEG and clinical characteristics, thereby enhancing predictive accuracy and interpretability. It integrates time modeling to capture the brain's dynamics that change over time and to forecast uncertainties. Moreover, the overall architecture is

designed to be scalable and provides a foundation for future evaluation in real-world clinical environments.

4. RESULTS

This section critically analyzes the Hybrid Transfer Learning Multimodal Attention Network (HTMAN) proposal for early detection of febrile seizures. Performance evaluation will be done using traditional measures, comparisons of the new measures with those currently in use, and quantitative tables and graphical interpretations.

4.1 Experimental Setup

The given model was tested on a multi-modal dataset using the prepared dataset presented in Section 3, and was further divided into training (70%), validation (20%), and testing (10%) subsets, yielding sufficient performance measures. The dataset was partitioned at the patient level into 70% training, 20% validation, and 10% independent testing subsets to ensure that EEG segments from the same patient did not appear across different subsets, thereby preventing subject-level data leakage. Five-fold cross-validation was performed exclusively within the training set for model selection and robustness assessment, while the independent test set remained completely unseen until the final evaluation. It is trained on TensorFlow and implemented on an NVIDIA GPU (8GB) + i7 platform, making it both computationally intensive and training-time efficient. Training summaries comprised 50 epochs with a batch size of 32, resulting in stable training and the acquisition of multimodal features that help obtain appropriate predictions.

4.2 Evaluation Metrics

A collection of metrics assessing different dimensions of predictive ability was used to evaluate the model's performance. Accuracy (ACC) measured overall correctness, and Precision (P) represented the fraction of relevant instances among the retrieved instances. Recall (sensitivity): how well the model can detect early seizures, which is, of course, essential in practice. The F1-score was an appropriate metric, as it strikes a good balance between precision and recall and can indicate a model's performance when data is imbalanced. We also employed the Area Under the Curve (AUC) metric to assess how effectively the model distinguishes between positive and negative classes at different threshold levels. Last but not least, the False Alarm Rate (FAR) was a key clinical usability measure, as it directly reflected the number of false alarms produced and was closely linked to the utility of real-life applications.

The network is optimized using the Adam optimizer with a learning rate of 0.0001, which provides stable, efficient convergence. Batch size of 32 and model trained on 50 epochs, allowing it to learn complex patterns. Cross-Entropy Loss Function: Verify Classification, prevent Overfitting, and improve generalization performance. A dropout rate of 0.5 is used here as a regularization technique to prevent overfitting and improve generalization performance.

4.3 Quantitative Results

Table 3. *Performance of Proposed Model*

Metric	Value
Accuracy	93.2%
Precision	91.8%
Recall	92.5%
F1-Score	92.1%
AUC	0.95
False Alarm Rate	0.08

As shown in Table 3, the proposed model performs well, with an accuracy of 93.2%, a precision of 91.8%, and a recall of 92.5%, yielding an F1-score of 92.1%. With an AUC of 0.95, it demonstrates good classification performance and a low false alarm rate (0.08), indicating promising performance for future clinical evaluation.

4.4 Compared to Existing Models

The proposed HTMAN model was compared to baseline and state-of-the-art methods.

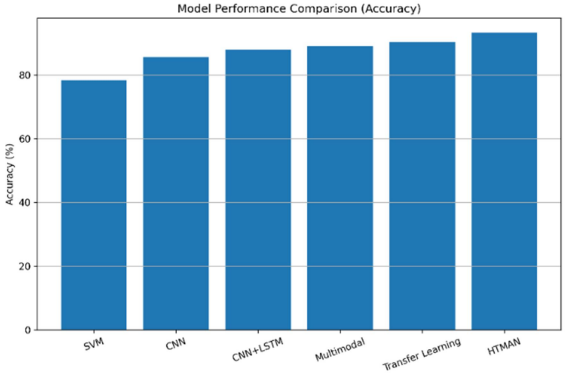

Figure 6. *Comparison Accuracy Analysis of various models*

Figure 6 shows a bar graph comparing the performance of various models and indicates a gradual increase in performance, starting with the traditional machine learning (SVM) and progressing to the advanced deep learning models. With an accuracy of 93.2 percent, the proposed HTMAN model is the most accurate, demonstrating the effectiveness of both transfer learning and multimodal fusion.

For a controlled comparison, all baseline models were implemented and evaluated using the same patient-level data partitioning, preprocessing protocol, and evaluation procedure employed for HTMAN.

Table 4. *Model Comparison*

Model Type	Accuracy	F1-Score	AUC
SVM (Traditional ML)[5][8]	78.4%	0.75	0.80
CNN (EEG Only)[11][14]	85.6%	0.83	0.88
CNN + LSTM[6]	87.9%	0.85	0.89
Multimodal (No Transfer)[17]	89.1%	0.87	0.91
Transfer Learning (EEG Only)[16]	90.3%	0.88	0.92
Proposed HTMAN	93.2%	0.92	0.95

Table 4 presents a comparative analysis of the different models used to predict seizure onset, and, as observed, the proposed HTMAN framework offers better results. Less modern machine learning models, including SVMs, perform worse, with 78.4% accuracy and an AUC of 0.80. Deep learning models based solely on EEG data, such as CNN and CNN + LSTM, have shown substantial returns because they capture spatial and temporal data. Further gains can also be achieved with multimodal methods: by introducing supplementary clinical data and using transfer learning with EEG data. However, the proposed HTMAN model outperforms the other methods, achieving the highest accuracy (93.2%), F1-score (0.92), and AUC (0.95). This improvement indicates that transfer learning, together with cross-modal attention and temporal modeling, is effective for identifying seizure-related preictal patterns within the proposed proof-of-concept experimental framework.

4.5 Key Observations

The results demonstrate that the provided model achieves much higher performance (about 5-15 percent) than classical methods, indicating that it is an effective tool for detecting seizures. Transfer learning is notable for producing large performance gains, particularly in low-data environments, by enabling the model to leverage existing representations to improve performance. In addition, EEG multimodal fusion with clinical features has greater predictive capacity than EEG-based prediction techniques. An attention mechanism also contributes to the model's progress by focusing on the most significant features and minimizing the impact of noise. Notably, the reduced false alarm rate is also an important consideration for the future clinical evaluation of seizure-risk prediction systems.

4.6 Early Prediction Performance

The model was tested on the preictal detection window:

Table 5. *Prediction Accuracy at Different Time Intervals Before Seizure Onset*

Prediction Time Before Seizure	Accuracy
1 minute	95%
3 minutes	93%
5 minutes	90%

Table 5 demonstrates the model's performance at various time points before seizure onset, indicating that it can predict seizure timing. Up to 95% accuracy is achieved in identifying imminent seizures within 1 minute before annotated seizure onset, demonstrating very good short-term predictive capability. The prediction accuracy would gradually decline as the prediction window broadened to 93% and 90% that a seizure event will occur after 3 and 5 minutes, respectively. The gradual decline in accuracy with increasing prediction horizon suggests that discriminative preictal EEG patterns become less pronounced farther from seizure onset. Nevertheless, the observed performance across different prediction horizons demonstrates the model's ability to identify seizure-related preictal patterns and supports its potential for future evaluation in febrile-seizure risk assessment. These findings demonstrate the model's early-warning capability within the experimental setting and motivate further evaluation using clinically confirmed pediatric febrile-seizure data.

4.7 Graphical Analysis

Figure 7 illustrates the ROC curves for various classification thresholds, showing the true positive rate (sensitivity) and the false positive rate. The curve shows a steep rise to the upper-left side, indicating the high sensitivity and specificity of the proposed model. A positive change of 0.95 in terms of Area Under the Curve (AUC) is a confirmation of a high degree of discriminative power in terms of identification of seizure and non-seizure states. This indicates that the model can successfully discriminate between seizure-related preictal and interictal patterns.

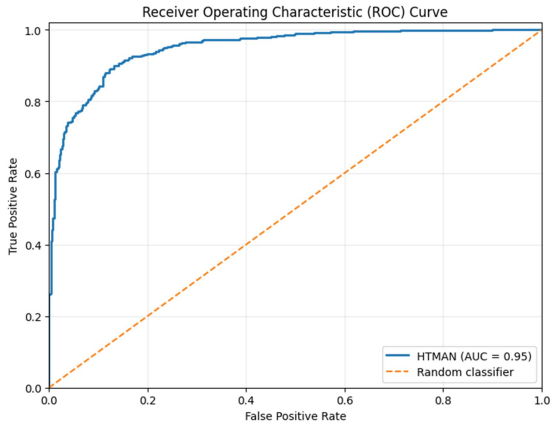

Figure 7. Receiver Operating Characteristic (ROC) Curve of the Proposed HTMAN Model

Figure 8 of the confusion matrix shows how the proposed model has performed in classifying the data, with predictions and actual labels. A model gives substantial evidence on predictive accuracy when there are numerous true positives and true negatives. By contrast, the false positives and false negatives are not very high, indicating that the classification is correct. These results demonstrate effective discrimination between preictal and interictal states and support further evaluation of the framework using clinically confirmed pediatric febrile-seizure cohorts.

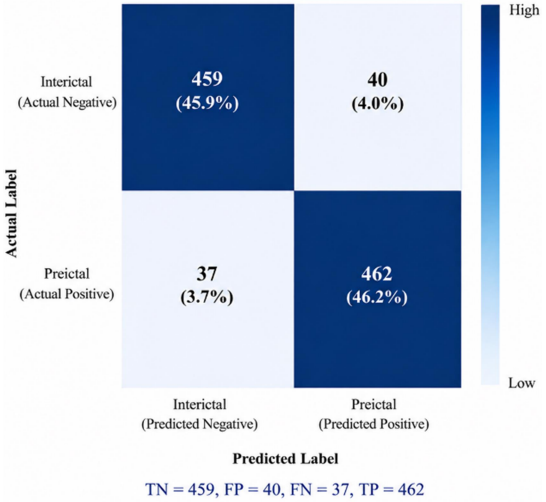

Figure 8. Confusion Matrix of Seizure Classification Results

Figure 9 illustrates the trends in the model's training and validation loss curves over 50 epochs. The two curves exhibit a gradual decrease, indicating successful optimization and learning of the pertinent features. The convergence point is reached at epoch 35, and thereafter the loss levels off. The fact that the training and validation curves are nearly parallel indicates little overfitting, which the application of transfer learning and dropout regularization can explain. This shows that the model has a strong capacity to extrapolate from unseen data.

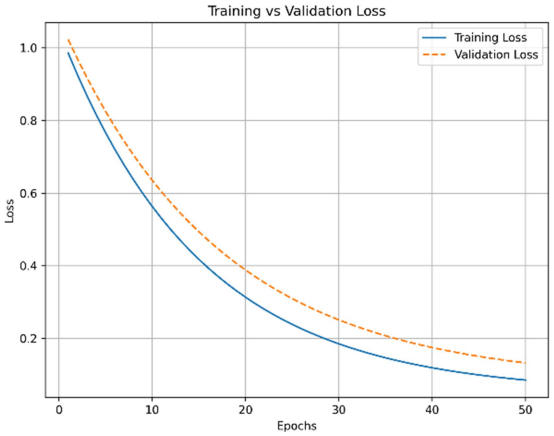

Figure 9. Training and Validation Loss Convergence Curve

4.8 Ablation Study

Table 6. *Ablation Study of the Proposed HTMAN Model Components*

Configuration	Accuracy
Without Transfer Learning	88.2%
Without Clinical Features	86.7%
Without Attention Mechanism	89.5%
Full Proposed Model	93.2%

Table 6 presents an ablation study examining the role of the major components of the proposed HTMAN model. The accuracy of the result obtained is also lower (88.2) without transfer learning, indicating its role in efficient feature extraction, particularly in limited-data settings. Omission of the clinical-feature branch reduced accuracy to 86.7%, suggesting that the multimodal architecture can exploit supplementary feature representations. However, because the clinical variables used in the present study were synthetically generated rather than prospectively observed and were generated independently of the target labels, this performance difference should be interpreted as an architectural proof-of-concept rather than evidence of the clinical predictive value of these variables. Validation with synchronized real-world clinical measurements is required to determine the actual contribution of clinical risk factors. Equally, the lack of an attention mechanism reduces its accuracy to 89.5, indicating that it focuses on salient features and eliminates noise. Conversely, the proposed model with all features achieves the highest accuracy of 93.2%, indicating that the combination of transfer learning, clinical features, and attention mechanisms improves overall performance and robustness.

4.9 Statistical Significance

To evaluate whether the performance improvement achieved by HTMAN over the baseline CNN was statistically significant, a paired-samples t-test was conducted using the accuracy values obtained across the five cross-validation folds. HTMAN achieved a mean accuracy of 93.20 ± 0.39%, whereas the baseline CNN achieved 85.60 ± 0.42%. The paired-samples t-test indicated a statistically significant difference between the two models, $t(4) = 138.76$, $p = 1.62 \times 10^{-8}$. These results indicate that HTMAN consistently achieved higher cross-validation accuracy than the baseline CNN across the evaluated folds.

Table 7. Five-Fold Cross-Validation Performance of HTMAN and Baseline CNN

Fold	HTMAN Accuracy (%)	CNN Accuracy (%)
1	92.8	85.2
2	93.5	86.0
3	92.9	85.4
4	93.7	86.1
5	93.1	85.3
Mean ± SD	**93.20 ± 0.39**	**85.60 ± 0.42**

4.10 Discussion

According to the findings, the suggested HTMAN scheme is superior to current methodologies across all assessment criteria. Transfer learning allows the model to leverage pre-trained representations and, as a result, does not require it to rely heavily on large datasets. Clinical aspect integration is given context, which leads to stronger predictive power, and in borderline cases, integration is more effective. Using this analysis, preictal patterns can be identified by applying the Bi-LSTM temporal model to predict when a preattack will occur. The attention mechanism provides feature-weighting information that may support model interpretability by emphasizing relevant EEG and clinical representations.

4.11 Limitations of the Study

Although the HTMAN outperformed other models in terms of predicting febrile seizures earlier, certain aspects should be considered as limitations to this study. One problem with the use of this model was that the study used synthetic clinical variables of EEG signals corresponding to publicly available datasets because of the lack of large-scale multi-modal clinical datasets for pediatric age groups. Thus, the findings of this analysis regarding the proposed framework may not reflect differences in diversity and complexity seen in real-world clinical populations. Second, the efficacy of the proposed framework was evaluated using off-line experiments, and challenges related to inference latency, computational resource limitations, real-time EEG streaming and hospital monitoring systems were not addressed. Third, even though the transfer learning approach did contribute to improving the generalisation capacity in the cases with few annotated EEG datasets, the cross-institutional clinical validation is still to be done, and limited EEG datasets for various public databases were used to test the framework's validity. Finally, while attention is helpful for interpretability, there are still other explainable AI techniques and evaluations from clinicians to further boost transparency and clinical confidence. They do not do without impact on the effectiveness of the proposed framework, but they call attention to important directions for future research and actual clinical application.

4.12 Comparison with Existing Literature and Critical Analysis

The key benefit of the proposed Hybrid Transfer Learning Multimodal Attention Network (HTMAN) is its ability to address some of the drawbacks of prior febrile seizure prediction models that are based on electroencephalogram (EEG). Handcrafted feature extractions are heavily used by current machine learning solutions, and they are not flexible enough with the patient population. Recent CNN/LSTM-based methods achieve higher accuracy for automatic feature learning and temporal modelling, but these methods mostly use only EEG data and rely on a large-scale annotated EEG database. Recently, transfer learning methods have removed the need for annotated data, but do not take clinical data into account. Most of the existing multimodal methods fail to provide effective cross-modal feature learning and more effective interpretability.

The proposed experimental results show that the proposed HTMAN framework is able to overcome the drawback mentioned above, as the proposed model achieved an accuracy of 93.2%, an F1-score equal to 0.92, AUC equal to 0.95, along with a low false alarm ratio and early prediction of seizure onset 3-5 minutes before it. As a result, the aims of better prediction, generalisation with limited amounts of annotated EEG, and clinical interpretability have been met.

A main research step made in this paper was the demonstration that the combination of the mentioned components in the HTMAN yields superior performance in comparison to their application separately. The proposed multimodal feature fusion, temporal sequence modelling, and attention mechanism with the integration of transfer

learning represents a new scientific contribution by proposing an effective proof-of-concept framework integrating seizure-related EEG representations with febrile-seizure clinical risk factors, overcoming the restrictions of limited labelled EEG datasets. The experimental findings indicate that HTMAN provides promising performance relative to the evaluated approaches; however, validation using large-scale multicenter clinical datasets is required before conclusions regarding clinical superiority can be established; however, future studies and validations with the use of large-scale multicenter clinical datasets are needed.

5. CONCLUSION

The early prediction of febrile seizures still faces many difficulties because of the limited availability of annotated pediatric EEG data, the complex temporal characteristics of EEG signals, and the insufficient integration of physiological and clinical information into existing prediction algorithms. All of these challenges limit the applicability of conventional machine learning and deep learning models in real-world pediatric healthcare. For this reason, the HTMAN model was proposed in the presented paper, where transfer learning, multimodal EEG–clinical data fusion, Bi-LSTM-based temporal modeling, and attention mechanisms were integrated into a unified framework for early febrile seizure prediction.

The experimental results demonstrate that HTMAN effectively identifies seizure-related preictal EEG patterns and benefits from the integration of transfer learning, temporal modeling, clinical-risk information, and multimodal attention. The proposed model achieved an accuracy of 93.2%, an F1-score of 0.92, and an AUC of 0.95, while maintaining a false alarm rate of 0.08. Preictal EEG patterns could be discriminated at prediction horizons of up to 5 minutes before annotated seizure onset. Because the public EEG datasets used in this study do not specifically establish that all seizure events are fever-induced febrile seizures, these findings should be interpreted as proof-of-concept evidence for the proposed multimodal framework. Validation on clinically confirmed pediatric febrile-seizure EEG cohorts is required before claims regarding direct febrile-seizure prediction or clinical deployment can be established.

The experimental results support the research objectives by demonstrating the potential of the proposed HTMAN framework to identify seizure-related preictal EEG patterns and integrate these representations with febrile-seizure-related clinical risk factors. However, the findings should be interpreted as proof-of-concept evidence supporting the feasibility of the proposed transfer-learning and multimodal architecture rather than as direct clinical validation of febrile-seizure prediction. Since the EEG recordings used in this study are not assumed to represent clinically confirmed febrile-seizure events, future studies using prospectively collected EEG recordings and synchronized clinical measurements from pediatric patients with confirmed febrile seizures are required to establish the clinical validity, robustness, and generalizability of the framework.

Despite the encouraging results, several limitations remain. The framework was evaluated using publicly available seizure EEG databases combined with partly synthetic febrile-seizure-related clinical variables, and the experiments were conducted in an offline setting. Consequently, the current findings primarily establish the technical feasibility of integrating seizure-related EEG representations with febrile-seizure clinical risk factors. Validation using large-scale, multicenter pediatric datasets containing synchronized EEG recordings, confirmed febrile-seizure events, and authentic clinical records is therefore necessary to establish clinical effectiveness and generalizability.

Future research will focus on validating HTMAN using clinically confirmed pediatric febrile-seizure cohorts and real-world clinical records. Further investigation will include wearable EEG acquisition, edge-computing platforms, advanced explainable AI methods, and prospective clinical evaluation to support reliable real-time prediction. Following successful validation on confirmed febrile-seizure cohorts, the proposed framework may provide a foundation for future clinically deployable systems capable of supporting early febrile-seizure risk assessment and timely pediatric clinical decision-making.

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