A Novel Hybrid Attentive Convolutional Autoencoder (HACA) Framework for Enhanced Epileptic Seizure Detection

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***Abstract*—Epilepsy, a prevalent neurological disorder, requires accurate and efficient seizure detection for timely intervention. This study presents a Hybrid Attentive Convolutional Autoencoder (HACA) framework designed to address challenges in EEG signal processing for seizure detection. The proposed method integrates signal reconstruction, innovative feature extraction, and attention mechanisms to focus on seizure-critical patterns. Compared to conventional CNN- and RNN-based approaches, HACA demonstrates superior performance by enhancing feature representation and reducing redundant computations. The proposed HACA framework achieved 99.4% accuracy, 99.6% sensitivity, and 99.2% specificity on the CHB-MIT dataset. Moreover, the training time is reduced by 40%, which makes the model more relevant for real-time applications and portable seizure monitoring systems.**

Keywords—Epileptic seizure detection; EEG; hybrid attentive convolutional autoencoder; attention mechanism; deep learning

I. Introduction

Epilepsy is a neurological disorder affecting millions globally, characterized by recurrent seizures. Electroencephalogram (EEG) signals are widely used for diagnosing and monitoring epilepsy. Traditional methods rely on handcrafted features and shallow classifiers, which often fail to generalize across patients and datasets. Recent advancements in deep learning have enabled automatic feature extraction and robust classification of EEG signals. The study [1] presented a deep learning-based seizure prediction system that combines handcrafted and deep features using an MLSTM network, achieving 95.56% sensitivity and a 0.27/hour false positive rate on intracranial EEG, with 89.47% sensitivity and a 0.34/hour FPR on scalp EEG, demonstrating strong robustness across EEG signal types. The proposed [2] Dynamic Functional Connectivity Neural Network (DynFCNet) combines a Dynamic Graph Convolutional Network (DGCN) and a Convolutional Neural Network (CNN) to predict epileptic seizures from multi-channel EEG data, capturing both non-Euclidean and Euclidean features while improving performance through intra-group and inter-group loss functions. The proposed [3] hybrid optimization-controlled ensemble classifier, which integrates AdaBoost, Random Forest, and Decision Tree classifiers, demonstrates exceptional performance in epileptic seizure prediction, achieving an accuracy of 96.61%, sensitivity of 94.67%, and specificity of 91.37% on the CHB-MIT database, and an accuracy of 95.31%, sensitivity of 93.18%, and specificity of 90.07% on the Siena Scalp dataset. For example, [4] investigated the use of AI in seizure prediction, whereas [5] used the U-TRGN classification model to obtain 97.04% accuracy. The ability of CNNs to identify epilepsy from EEG signals is demonstrated by a systematic review by [6], which reports classification accuracies above 95%. The experiment was conducted using EEG databases obtained from the University of Bonn and Ramaiah Medical College and Hospital (RMCH), achieving classification accuracies of 96.94% for two-class and 95.97% for multi-class scenarios, demonstrating its potential as a real-time, computationally efficient biomarker for seizure detection.

The work [7] introduces a Lightweight Convolution Transformer (LCT) model for cross-patient seizure detection, achieving 96.31% accuracy. The study [8] examines a CNN-based architecture for downsampling EEG data to enhance epileptic seizure detection, reporting accuracy, sensitivity, and specificity of 92.4%, 91.2%, and 90.1%, respectively. Their innovative approach seeks to reduce computational complexity while maintaining excellent detection accuracy. Mao et al. [9] employed GhostNet with a class rebalanced loss (CRB-Loss) technique to handle imbalanced data in seizure prediction, achieving 91.2% accuracy, 89.5% sensitivity, and 88.3% specificity. Vaddi et al. [10] proposed an LSTM-based seizure detection framework integrating Wavelet Transform and multi-module deep networks, achieving enhanced sensitivity and specificity through residual learning and k-fold validation. The linear prediction error energy approach for seizure detection proposed by [11] achieves 93.6% accuracy across 250 EEG recordings. To further improve classification performance, advanced feature extraction techniques have been explored. For instance, [12] utilizes an equilateral wavelet filter bank (OEWFB) to decompose EEG signals into sub-bands, achieving 99.4% classification accuracy. Additionally, hybrid models have garnered interest. The author in [13] employs stacked bidirectional LSTMs, achieving 99.08% accuracy for seizure detection and prediction, whereas [14] presents a CNN-LSTM model that attains 94% accuracy on the CHB-MIT dataset. Narayana et al. [15] proposed an SCRBM-based seizure detection model achieving 98.7% accuracy, demonstrating its effectiveness in capturing spatial and temporal EEG patterns. Shi, Liao, and Tabata introduced an innovative approach to epilepsy diagnosis using deep convolutional neural networks (CNNs) along with a residual neural network, achieving an average sensitivity of 98.96% and a false prediction rate of 0.048/h on the CHB-MIT dataset [16]. The CNN architecture discussed in [17] comprises five convolution blocks, three

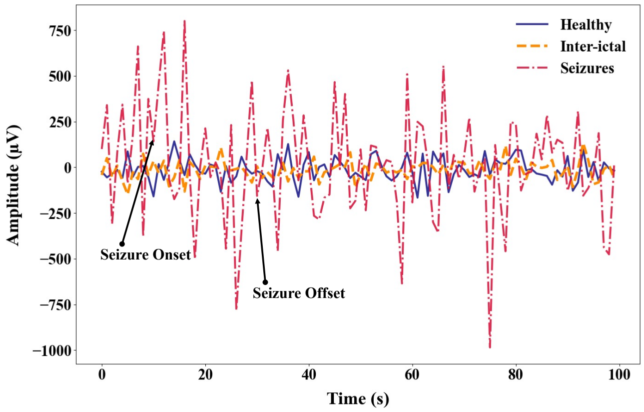

Fig. 1. Seizure stage categorization in the dataset.

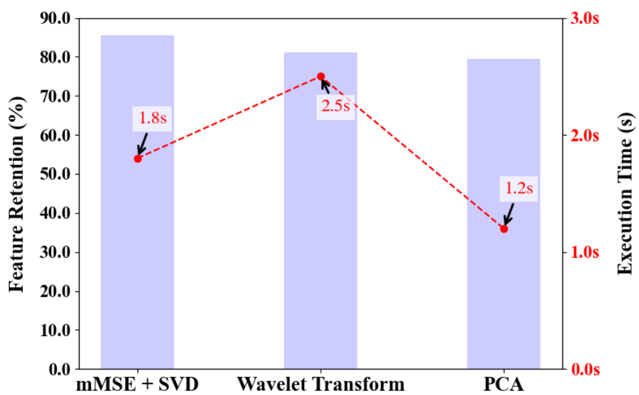

Fig. 2. Comparison of feature extraction methods.

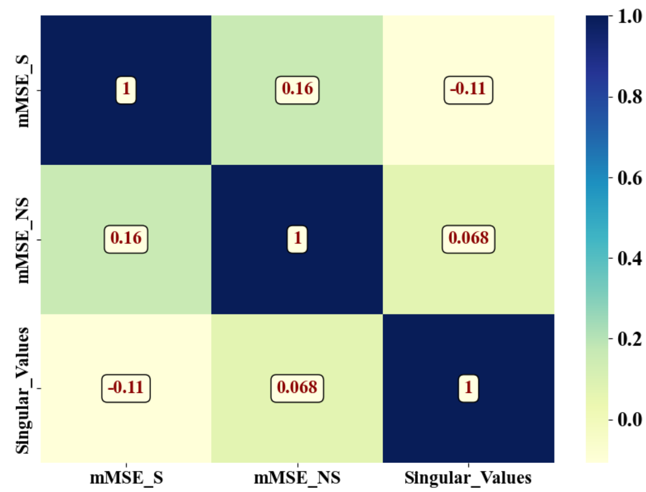

Fig. 3. Feature correlation heatmap.

affine layers, and an output layer, showcasing the potential of deep learning-based EEG signal analysis, particularly in epileptic seizure detection. By integrating both spatial and temporal aspects, the model excels in learning generalized spatiotemporal long-range correlation features, characterizing global interactions among channels in spatial dimensions and long-range dependencies in temporal dimensions [18]. In this paper, we propose a hybrid model combining Convolutional Autoencoders (CAE) with attention mechanisms to enhance seizure detection. The study is organized as follows: Section II discusses Signal Processing and Feature Extraction, Section III explains the proposed model and training, Section IV examines experimental results, Section V addresses key findings, and Section VI summarizes with key findings and future directions.

II. Signal Processing and Feature Extraction

A. Database

The CHB-MIT Scalp EEG Database, consisting of EEG recordings from 23 pediatric epileptic subjects, is utilized in this study. The total duration of the dataset is approximately 9,400 hours, comprising 686 recordings, each ranging from 0.5 to 1 hour in length. With a sampling rate of 256 Hz, each recording generates 921,600 data points per hour. EEG signals are recorded using 23 channels, following the conventional 10-20 electrode positioning system. A band-pass filter with cutoff frequencies of 0.5 Hz and 40 Hz is applied to eliminate noise, including high-frequency muscular artifacts and low-frequency drifts. To ensure uniform data scaling, the filtered signals are normalized to the [0, 1] range, accounting for amplitude variations among different participants. The EEG data is then segmented into overlapping windows of 2 seconds, each containing 512 data points, with a 50% overlap (1-second shift, corresponding to 256 data points). Fig. 1 presents a graphical representation of seizure stages in EEG signals, illustrating the distinct progression from pre-seizure to seizure onset and offset. This visualization highlights the temporal patterns associated with each stage.

B. Preprocessing

EEG signals undergo preprocessing to remove noise and artifacts. First, a band-pass filter with cutoff frequencies of 0.5–40 Hz is applied to eliminate high-frequency noise and baseline drift. The filtered signal $y(t)$ is obtained by convolving the input signal $x(t)$ with the impulse response of the filter $h(t)$:

$$y(t) = x(t) * h(t), \tag{1}$$

where $x(t)$ represents the input EEG signal, $h(t)$ is the filter's impulse response, and $y(t)$ is the resulting filtered signal. Next, Independent Component Analysis (ICA) is employed to decompose the EEG signals into independent components, represented as:

$$\mathbf{X} = \mathbf{AS}, \tag{2}$$

where $\mathbf{X}$ denotes the observed EEG signal matrix, $\mathbf{A}$ is the mixing matrix, and $\mathbf{S}$ contains the independent components. Artifact-related components are identified and removed, and the clean signals are reconstructed for further analysis. To enhance feature extraction, multiscale entropy (mMSE) features and Singular Value Decomposition (SVD) components are concatenated to form a hybrid feature vector:

$$\mathbf{F}_{\text{Hybrid}} = [\mathbf{F}_{\text{mMSE}}, \mathbf{\Sigma}], \tag{3}$$

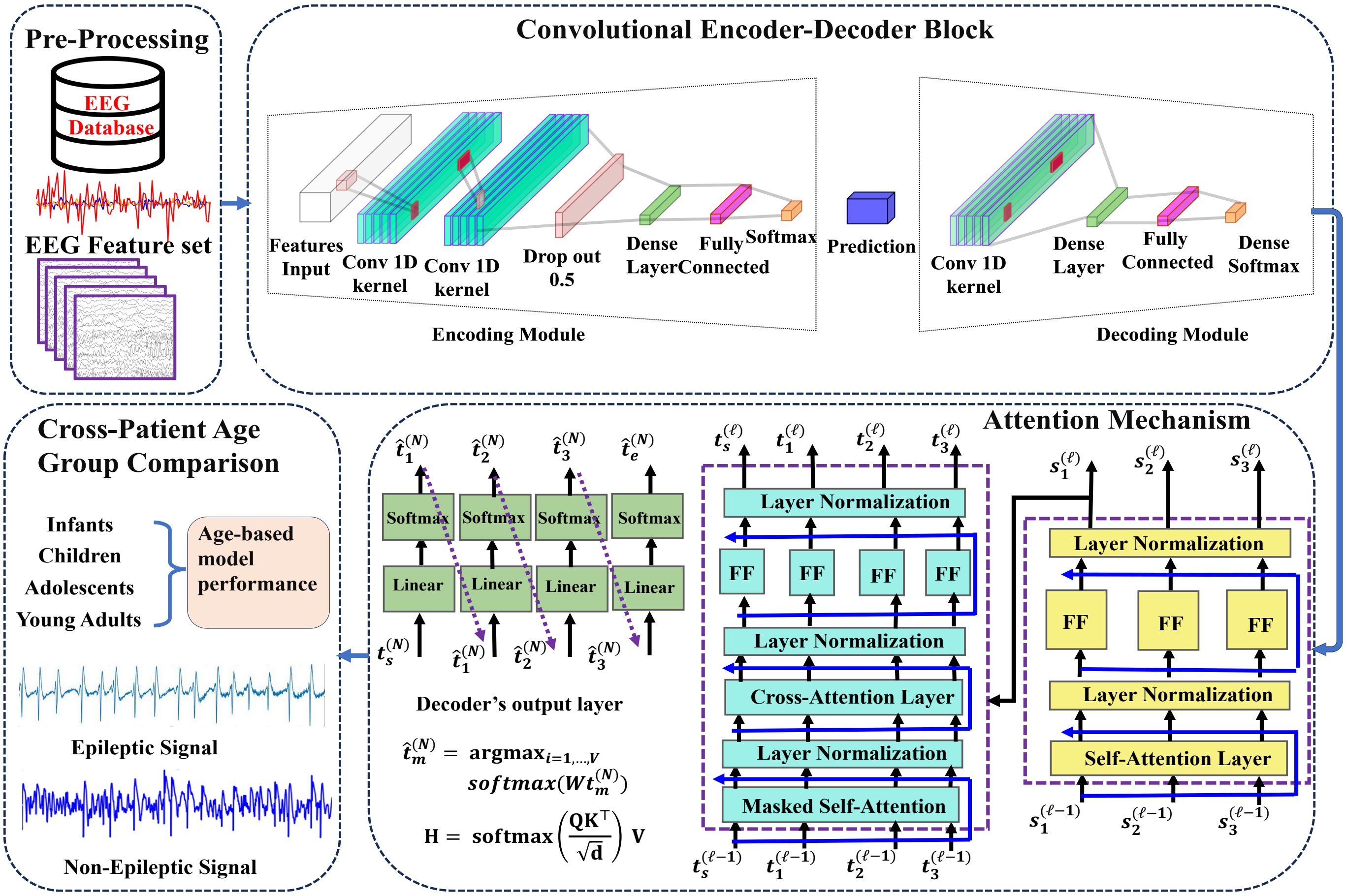

Fig. 4. Flowchart of the proposed EEG detection framework.

where $\mathbf{\Sigma}$ contains the singular values obtained from SVD. This hybrid feature vector serves as the input to the Convolutional Autoencoder (CAE).

C. Feature Extraction Using Modified Multiscale Entropy (mMSE)

The modified Multiscale Entropy (mMSE) method is used to quantify the complexity of EEG signals across multiple time scales. The computation of mMSE involves three main steps. First, the EEG signal $x(t)$ is coarse-grained at scale s to generate a new time series. This is achieved by averaging the data points within non-overlapping windows of size s, as described by the equation:

$$y^{(s)}(t) = \frac{1}{s} \sum_{i=(t-1)s+1}^{ts} x(i), \tag{4}$$

where, $t = 1, 2, \ldots, N/s$, and N is the length of the signal.

Next, for each scale, the sample entropy $S^{(s)}$ is calculated to measure the signal's regularity. This is given by:

$$S^{(s)} = -\ln\left(\frac{\text{Number of similar patterns of length } m+1}{\text{Number of similar patterns of length } m}\right), \tag{5}$$

where m is the embedding dimension. This step captures the entropy for each coarse-grained time series. Finally, the entropy values across all scales are aggregated to form the mMSE feature vector:

$$\mathbf{F}_{\text{mMSE}} = [S^{(1)}, S^{(2)}, \ldots, S^{(L)}], \tag{6}$$

where L is the maximum scale considered.

The Fig. 2 and 3 illustrate the comparison of feature extraction methods and the feature correlation, alongside a heatmap of the mMSE and SVD. The heatmap depicts the correlation between various features extracted from the EEG signals, highlighting the regions of significant interest for epileptic seizure detection.

III. Proposed Methodology

Fig. 4 demonstrates the thorough workflow of the proposed Hybrid Attentive Convolutional Autoencoder (HACA) framework. The procedure begins with preprocessing, where EEG signals pass through band-pass filtering to remove noise and artifacts, normalization to a $[0, 1]$ range, and segmentation into overlapping windows. Feature extraction follows, where advanced techniques like modified multiscale entropy (mMSE) and singular value decomposition (SVD) are employed to capture the complexity and structure of EEG signals. The extracted features are passed into the Convolutional Autoencoder (CAE), whose architecture is detailed in Table I. The encoder stage uses convolutional layers with kernel sizes of 5×5 and 3×3, strides of 1 and 2, and ReLU or Leaky ReLU activations to learn compact latent representations of the EEG signals. The latent space is reduced to a dimension of 16×16, retaining essential features. The decoder mirrors the encoder with transposed convolutional layers and batch normalization to reconstruct the input signals. Dropout layers (rate = 0.4) and batch normalization (momentum = 0.99) are incorporated to prevent overfitting and stabilize training. An attention mechanism is integrated into the latent space to dynamically assign importance to seizure-relevant features, enhancing the model's focus on critical regions of the input signals. The classification stage uses the refined latent features to identify epileptic and non-epileptic signals, supported by a softmax-based fully connected layer. Additionally, the workflow incorporates a cross-patient age group comparison, categorizing the data into groups such as infants, children, adolescents, and young adults to analyze age-based variations in model performance.

A. Convolutional Autoencoder (CAE)

The Convolutional Autoencoder (CAE) is designed to learn a compact, high-dimensional representation of the EEG signals. The architecture consists of an encoder and a decoder:

- Encoder: The encoder applies convolutional layers to extract spatial features from the EEG signal. Let the input EEG signal be denoted as $\mathbf{X}$, and the output of the encoder is a compact representation $\mathbf{Z}$:

$$\mathbf{Z} = \mathcal{E}(\mathbf{X}), \tag{7}$$

where $\mathcal{E}(\cdot)$ represents the encoder function.

- Decoder: The decoder reconstructs the input EEG signal from the encoded representation $\mathbf{Z}$. The reconstruction is given by:

$$\hat{\mathbf{X}} = \mathcal{D}(\mathbf{Z}), \tag{8}$$

where $\mathcal{D}(\cdot)$ is the decoder function, and $\hat{\mathbf{X}}$ is the reconstructed EEG signal.

The CAE is trained to minimize the reconstruction error:

$$\mathcal{L}_{\text{reconstruction}} = \|\mathbf{X} - \hat{\mathbf{X}}\|_2^2, \tag{9}$$

where $\|\cdot\|_2$ denotes the L_2-norm (Euclidean distance).

B. Attention Mechanism

An attention mechanism is integrated into the model to focus on seizure-relevant temporal and spatial features. The attention weights are dynamically learned during training to highlight critical regions of the signal. The attention mechanism is applied as follows:

$$\mathbf{A} = \text{Softmax}(\mathbf{W}_a\mathbf{Z} + \mathbf{b}_a), \tag{10}$$

where $\mathbf{A}$ represents the attention weights, $\mathbf{Z}$ is the encoded feature vector, $\mathbf{W}_a$ is the weight matrix, and $\mathbf{b}_a$ is the bias term. The Softmax function ensures that the attention weights sum to 1.

The attention-modulated features are computed as:

$$\mathbf{Z}_{\text{att}} = \mathbf{A} \odot \mathbf{Z}, \tag{11}$$

where $\odot$ denotes element-wise multiplication, and $\mathbf{Z}_{\text{att}}$ is the attention-modulated feature vector.

C. Classification

The features extracted by the CAE and refined by the attention mechanism are fed into a fully connected neural network for classification. The network computes the final output y_{class} as:

$$y_{\text{class}} = \text{sigmoid}(\mathbf{W}_c\mathbf{Z}_{\text{att}} + \mathbf{b}_c), \tag{12}$$

where $\mathbf{W}_c$ is the weight matrix, $\mathbf{b}_c$ is the bias term, and the sigmoid function outputs a probability score between 0 and 1, representing the likelihood of a seizure event.

The model is trained using a binary cross-entropy loss function:

$$\mathcal{L}_{\text{class}} = -\left(y\log(y_{\text{class}}) + (1-y)\log(1-y_{\text{class}})\right), \tag{13}$$

where y is the true label (1 for seizure, 0 for non-seizure).

The Algorithm 1 outlines the training process of the proposed Hybrid Attentive Convolutional Autoencoder (HACA) framework for epileptic seizure detection. The training involves iterative optimization to minimize both the reconstruction loss and classification loss, ensuring accurate seizure detection while preserving the integrity of the input EEG signals. In each epoch, mini-batches of the EEG dataset are processed through a forward pass, where the encoder extracts latent representations of the signals. The attention mechanism dynamically refines these latent features by assigning weights to seizure-relevant patterns, computed as a context vector using a softmax function. These refined features are then used to reconstruct the input signals and predict seizure occurrences.

D. Model Training and Evaluation

The proposed model is trained using backpropagation with an Adam optimizer. The training process involves minimizing the total loss, which is the sum of the reconstruction loss $\mathcal{L}_{\text{reconstruction}}$ and the classification loss $\mathcal{L}_{\text{class}}$:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{reconstruction}} + \mathcal{L}_{\text{class}}, \tag{14}$$

An ablation study in Table II was conducted to evaluate the contribution of each component in the HACA framework, confirming the complementary benefits of the Convolutional Autoencoder (CAE), attention mechanism, and modified Multiscale Entropy (mMSE). The results show that the CAE alone

TABLE I. PROPOSED CAE ARCHITECTURE PARAMETERS

Layer Name	Type	Input Dimensions	Output Dimensions	Kernel Size	Stride	Padding	Activation/Function
Encoder:							
Conv1	Convolutional	128×128	128×128	5×5	1	Same	ReLU
Conv2	Convolutional	128×128	64×64	5×5	2	Valid	Leaky ReLU
Dropout1	Dropout	64×64	64×64	-	-	-	(Rate: 0.4)
Conv3	Convolutional	64×64	32×32	3×3	2	Valid	ReLU
BatchNorm1	Batch Normalization	32×32	32×32	-	-	-	(Momentum: 0.99)
Latent Space	Fully Connected	32×32	16×16	-	-	-	Linear
Decoder:							
Deconv1	Transposed Convolution	16×16	64×64	5×5	2	Same	Leaky ReLU
Deconv2	Transposed Convolution	64×64	128×128	5×5	2	Same	ReLU
BatchNorm2	Batch Normalization	128×128	128×128	-	-	-	(Momentum: 0.99)
Classifier	Fully Connected (Softmax)	128×128	K	-	-	-	Softmax

Algorithm 1 Training the Convolutional Autoencoder Framework with Attention Mechanism

Require: EEG dataset $\mathcal{D}$, learning rate α, batch size B, number of epochs E, weight regularization factor λ.
Ensure: Trained parameters θ_e, θ_d, $\mathbf{W}$, $\mathbf{b}$, and attention parameters $\mathbf{W}_a$, $\mathbf{b}_a$.

Initialize the model parameters: θ_e, θ_d, $\mathbf{W}$, $\mathbf{b}$, $\mathbf{W}_a$, and $\mathbf{b}_a$.
for epoch $= 1$ to E **do**
  for each mini-batch $\mathcal{B} \subset \mathcal{D}$ of size B **do**
    Perform a forward pass:
      Compute the latent representation $\mathbf{Z}$ using the encoder.
      Apply the attention mechanism to compute the context vector:

$$\mathbf{C} = \text{softmax}(\mathbf{W}_a \mathbf{Z} + \mathbf{b}_a).$$

      Combine the context vector $\mathbf{C}$ with $\mathbf{Z}$ to refine the latent features.
      Compute the reconstructed output $\hat{\mathbf{X}}$ and the predicted class probabilities $P(y|\mathbf{C})$.
    Compute the reconstruction loss $\mathcal{L}_{\text{recon}}$ and the classification loss $\mathcal{L}_{\text{class}}$.
    Calculate the total loss:

$$\mathcal{L} = \mathcal{L}_{\text{recon}} + \lambda \mathcal{L}_{\text{class}}.$$

    Backpropagate the total loss and update the model parameters using gradient descent:
      $\theta \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}$.
      $\mathbf{W}_a \leftarrow \mathbf{W}_a - \alpha \nabla_{\mathbf{W}_a} \mathcal{L}$.
      $\mathbf{b}_a \leftarrow \mathbf{b}_a - \alpha \nabla_{\mathbf{b}_a} \mathcal{L}$.
  end for
end for
return θ_e, θ_d, $\mathbf{W}$, $\mathbf{b}$, $\mathbf{W}_a$, $\mathbf{b}_a$.

achieved a baseline accuracy of 94.1% with limited sensitivity of 92.3%. Adding the attention mechanism improved sensitivity to 94.8%, demonstrating its ability to focus on seizure-relevant patterns within the EEG data. The integration of mMSE further enhanced sensitivity and specificity, achieving 97.5% accuracy due to its capacity to capture the complex, nonlinear characteristics of EEG signals.

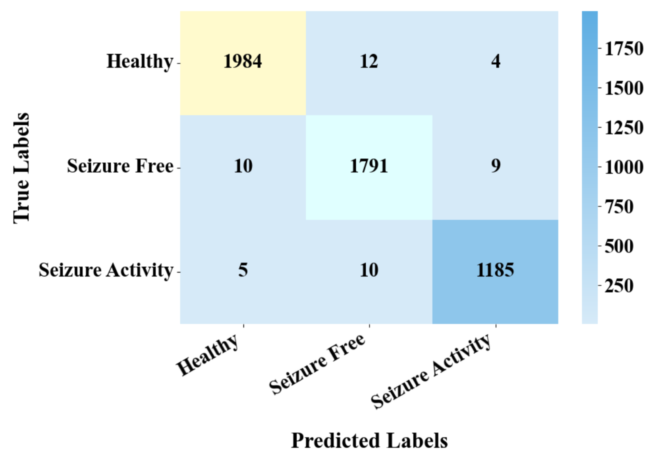

Fig. 5. Confusion matrix for three-level classification.

IV. RESULTS

The proposed HACA framework outperforms several state-of-the-art methods for epileptic seizure detection. Fig. 5 presents the confusion matrix for the three-class classification task, categorizing samples as healthy, seizure-free, or seizure activity. Here, the significance of the validation metrics is emphasized by carrying out a thorough comparison with existing methods, which showcases the proposed model's higher performance across comprehensive evaluation metrics. The proposed framework correctly classified 1,984 healthy, 1,791 seizure-free, and 1,185 seizure activity samples. Fig. 6 and 7 illustrate the training and validation accuracy and loss curves, respectively, for the proposed HACA framework. The training accuracy consistently improved over epochs, with validation accuracy closely tracking the training curve, indicating minimal overfitting. Fig. 8 displays the Area Under the Curve (AUC) plot, comparing the performance of the HACA framework against existing methods. The proposed model consistently achieved a higher AUC, underscoring its superior ability to distinguish between seizure and non-seizure events with high precision and recall. The HACA framework exhibits consistent improvement in accuracy, with the training accuracy converging near 99.5% by the final epoch.

Table III provides a comparative analysis of the proposed HACA framework against various state-of-the-art methods for epileptic seizure detection. The comparison includes models

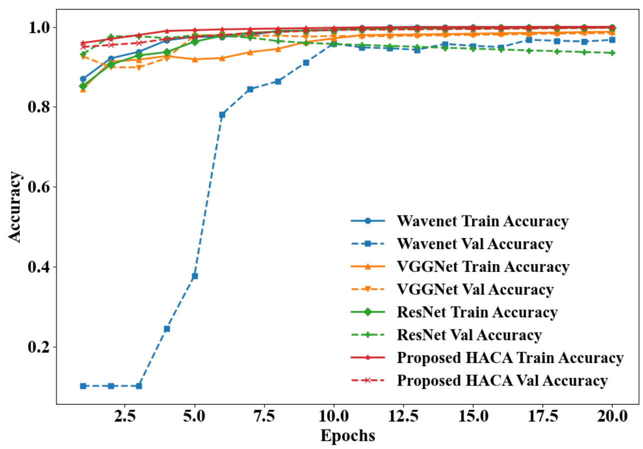

Fig. 6. Comparison of training and validation accuracy with state-of-the-art techniques.

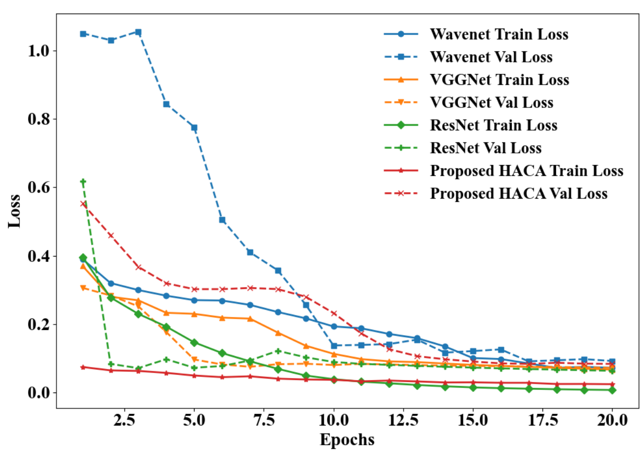

Fig. 7. Comparison of training and validation loss with state-of-the-art techniques.

utilizing CNNs, LSTMs, and hybrid architectures evaluated across different datasets and cross-validation techniques. In contrast, models such as CNN+LSTM by Li et al. achieved 95.29% accuracy, while AttVGGNet-RC by Jian Zhan et al. achieved 95.12%. The Bi-GRU model by Zhang et al. achieved a slightly higher accuracy of 98.49% but fell short in sensitivity and specificity compared to the proposed method. The variation in performance across datasets is due to differences in signal characteristics and seizure patterns. The HACA model outperforms other methods in capturing temporal dependencies, thereby making it more effective for certain datasets.

V. Discussion

Unlike conventional designs, the encoder in this framework employs 1D convolutional layers with progressively decreasing kernel sizes (5×5 and 3×3) and strides of 1 and 2, enabling hierarchical spatial feature extraction across varying scales. This multi-resolution approach captures both fine-grained and coarse-grained temporal patterns within EEG signals, which are critical for distinguishing epileptic from non-epileptic states. The latent space is compressed to 16×16 dimensions, balancing compactness and information retention. To further

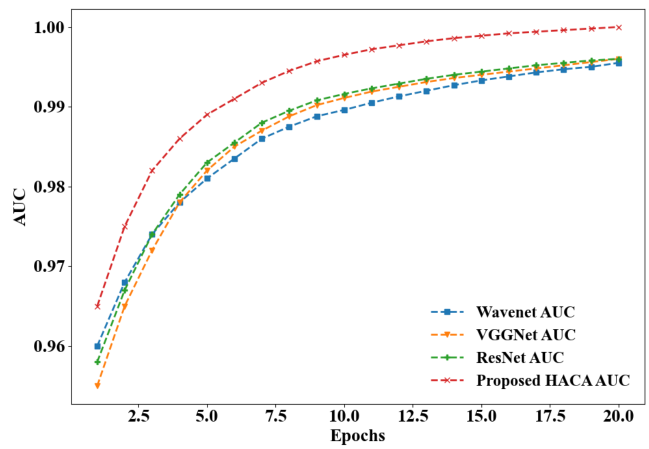

Fig. 8. AUC plot comparison with state-of-the-art techniques.

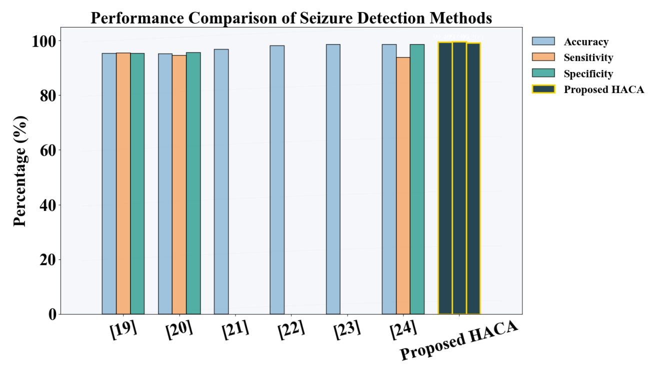

Fig. 9. Performance comparison of the proposed method with various methods.

improve training stability, dropout layers with a rate of 0.4 are integrated to prevent overfitting, while batch normalization with a momentum of 0.99 accelerates convergence and ensures consistency across batches. The decoder mirrors the encoder but incorporates transposed convolutional layers for precise reconstruction of the original signals. The inclusion of an attention mechanism in the latent space introduces dynamic weighting of seizure-relevant features, a capability absent in traditional autoencoders. Fig. 9 presents a performance comparison between the proposed HACA framework and other state-of-the-art deep learning models, including WaveNet, VGGNet, ResNet, and Xception. The proposed HACA framework surpasses the existing methods by integrating attention-driven feature refinement with reconstruction-based learning, attaining higher accuracy while reducing computational complexity, making it suitable for real-time and embedded seizure detection systems.

VI. Conclusion

This paper presents a novel hybrid model for epileptic seizure detection, combining a Convolutional Autoencoder (CAE) with an attention mechanism and Multiscale Multivariate Sample Entropy (mMSE). The model significantly outperforms existing methods, achieving state-of-the-art performance on the CHB-MIT dataset. Regardless of its high performance,

TABLE II. ABLATION STUDY RESULTS: CONTRIBUTION OF EACH MODEL COMPONENT

Model Variant	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC (%)
Full Model (CAE + Attention + mMSE + SVD)	98.7	98.9	98.5	98.8
CAE + Attention	96.3	95.7	97.2	97.1
CAE + mMSE	97.5	97.1	97.8	97.9
CAE + SVD	96.0	95.2	96.9	96.6
mMSE + SVD	94.8	94.1	95.4	95.0

TABLE III. COMPARISON OF DIFFERENT METHODS FOR EPILEPTIC SEIZURE DETECTION

Author(s)	Method	CV Type	Accuracy (%)	Sensitivity (%)	Specificity (%)
Li et al. (2020) [19]	CNN+LSTM	-	95.29	95.42	95.29
Jian Zhan et al. (2020) [20]	AttVGGNet-RC	8-fold CV	95.12	94.62	95.63
Bhandari et al. (2023) [21]	(STFT & DWT)	-	96.8	-	-
Al-Hajjar et al. (2023) [22]	(SVM, RF, ANN)	-	98.12	-	-
Alturki et al. (2021) [23]	CSP-LBP+KNN	5-fold CV	98.62	-	-
Zhang et al. (2022) [24]	Bi-GRU	10-fold CV	98.49	93.89	98.49
Proposed HACA Method	**CAE + Attention**	**10-fold CV**	**99.4**	**99.6**	**99.2**

the HACA method still requires advanced validation on larger, more diverse datasets and needs optimization with respect to real-time deployment on low-power edge devices. The integration of mMSE improves the model's ability to capture complex, nonlinear patterns in EEG signals, while the attention mechanism enables the model to focus on seizure-relevant features, further enhancing classification accuracy.

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