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RESEARCH ARTICLE

TLENet-Transformer for Epilepsy Detection with Futuristic IoMT Plans

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ABSTRACT

Temporal Lobe Epilepsy (TLE) is the most prevalent subtype of focal epilepsy, often posing diagnostic difficulties due to its complex clinical features. To address these challenges, this study proposes TLENet-Transformer, a novel deep learning architecture tailored for precise TLE identification. The study begins with skull stripping, bias field correction, z-score normalization, and Gaussian filtering; these methods are implemented to enhance image quality. Following this, a segmentation method based on an optimized Fuzzy C-Means clustering algorithm is employed, providing accurate delineation of regions. At this point, the segmented images are subsequently mapped to a pre-labelled Automated Anatomical Labelling (AAL) template to detect distinct segmented ROIs. Developing hybrid models that combine DL with Transformer and attention-based techniques could improve feature extraction. The classification module integrates a hybrid deep learning approach, combining 3D Convolutional Neural Networks for spatial feature extraction, Spatio-Temporal Long Short-Term Memory units for capturing temporal dynamics, and Capsule Networks to preserve hierarchical features. This multi-layered architecture allows the model to learn complex patterns associated with affected regions. TLENet-Transformer gives a high diagnostic accuracy of 98.16%, outperforming conventional models in both sensitivity and specificity. Furthermore, the study explores the integration of Internet of Medical Things (IoMT) technologies to enable real-time remote monitoring as the future scope of work.

Keywords: CNN, Fuzzy C means clustering, Long short-term memory, Internet of medical things, Temporal lobe epilepsy

Introduction

TLE is a major form of focal epilepsy categorized by recurrent seizures originating from the brain's temporal lobe. It affects memory, emotional regulation, and other cognitive functions. Besides, the most prevalent kind of medication-refractory epilepsy in adults is still TLE, which is characterized by seizures that start in the temporal.¹ Normally, diagnosis involves a combination of clinical assessment, such as electroencephalography (EEG),² and neuroimaging techniques such as Magnetic Resonance Imaging (MRI).³ Finding ictal EEG onset shapes restricted to the temporal lobe during seizure screening is the cornerstone of diagnosing TLE.^{4,5} Although it is not necessary for diagnosis, the neuro-radiological detec-

tion of a temporal lobe lesion is a strong confirmation of TLE. A histological anomaly such as Medial Temporal Sclerosis (MTS) characterized by gliosis and cell loss in the hippocampal and adjacent medial temporal regions, is linked to the majority of TLE patients.⁶ Finding neuroimaging indicators of TLE is essential for diagnostic assessment since MRI abnormalities are frequently linked to a higher chance of successful treatment.⁷ The study and management of epilepsies may therefore be directly impacted by methods that increase the diagnostic precision of neuroimaging. The fact that brain atrophy in TLE might differ from person to person but often follows a similar pattern within particular regions of grey matter tissue is an intriguing feature.⁸ Visual examination of pre-operative MRI can reveal signs

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of MTS, which often manifest as an amplified signal on T2-weighted images.⁹ It indicates underlying gliosis and hippocampus shrinkage on T1-weighted images, that are linearly correlated with hippocampal cell loss.¹⁰ However, MTS frequently cannot be seen on MRI and is only verified by histological examination of surgical materials.¹¹ Furthermore, the complexity of TLE makes early diagnosis challenging, which highlights the need for advanced tools to improve diagnostic accuracy and treatment outcomes.¹² DL algorithms have evolved as powerful tools for the diagnosis and classification of TLE.¹³ These algorithms, particularly CNNs¹⁴ and Recurrent Neural Networks (RNNs)¹⁵ can automatically extract patterns from complex EEG or MRI data, helping to identify subtle biomarkers associated with epileptic activity.¹⁶ DL models help in detecting the onset and localization of seizures. Also, they can predict seizure events by analyzing time-series data in EEG recordings. Such models enhance diagnostic precision and can assist clinicians in distinguishing between different epilepsy types.¹⁷ The primary advantage of DL in TLE classification is its ability to handle vast amounts of high-dimensional data and learn hierarchical representations without manual feature engineering. This allows DL algorithms to detect intricate and latent features in EEG, leading to more accurate and consistent diagnoses.¹⁸ Furthermore, DL models can be trained to improve with more data, refining their ability to predict seizure onset and progression. This scalability, along with their potential for real-time analysis, is crucial in TLE diagnosis and management.¹⁹ Despite the promise of DL in TLE

detection, numerous challenges remain. One significant problem is the need for large, annotated datasets to train DL models effectively, as TLE datasets are often limited and heterogeneous.²⁰ Additionally, DL models are computationally intensive and require significant processing power and expertise to implement in clinical settings. Interpretability is another issue, as DL models often act as black boxes which makes it complex for clinicians to understand the decision-making procedure behind a model's predictions.²¹ Additionally, variability in patient data such as noise in EEG signals affects the robustness and generalization of the model across diverse populations.²² For these reasons, this research aims to present an accurate TLE detection framework with optimal classification performance. The key contributions are:

- A tissue segmentation module is proposed to slice the ROI from TLE MRI using the proposed FCM.
- A robust classifier is designed to detect the TLE accurately via the proposed TLENet-Transformer which analyzes the complex brain structures and minimizes misclassification.

A rigorous investigation is carried out to evaluate the competence of the proposed TLENet-Transformer in detecting the disease. [Table 1](#) explains the limitations of the existing models.

Materials and methods

This model starts with a pre-processing phase that includes skull stripping, bias field correction, z-score normalization, and noise reduction using a Gaussian

Table 1. Limitations of existing Epilepsy detection models.

Authors/Year	Methods	Aim	Achievements	Limitations
Suh et al. in 2023 ²³	DLR	To enhance the image quality and accuracy in MRI	91% accuracy	Optimizing the DL classifiers can help attain improved performance
Hu et al. in 2024 ²⁴	GSAM	To develop a vision-based TLE detection strategy	Exposed high computation speed and accuracy 89%	Limited data was employed for investigation
Tsai et al. in 2024 ²⁵	TLE	To extract features from T1-weighted MRI scans using Free Surfer software.2	92% accurate brain region segmentation, enhancing the calculation of lateralization indices (LI)	Variability and require expertise for accurate processing.
Yu et al. in 2024 ²⁶	TCN-LSTM	To develop a realistic simulated epilepsy detection model	Revealed minimized error for real and simulated data	Need to evaluate accuracy of investigation
Wang et al. in 2024 ²⁷	LSTM-NN	To detect epileptic seizures accurately	99% and 97% accuracy for different datasets	For larger datasets, exposed poor performance
Ficici et al. in 2024 ²⁸	MRI and EEG	assisting in surgery planning, diagnosis, and treatment of epilepsy.	diagnosis and personalized treatment planning with 94% accuracy	Challenges in ensuring consistency across diverse patient populations.
Huang et al. in 2025 ²⁹	TCN-SA	To develop automated detection of epilepsy	95% accuracy	Revealed poor performance on other datasets
Zhu et al. in 2025 ³⁰	CRCANet	Automating the lateralization of epileptogenic regions in mesial temporal lobe epilepsy using brain MRI scans,	improves accuracy Of 93% and efficiency in identifying epileptogenic areas.	Potentially limiting its applicability in resource-constrained settings.

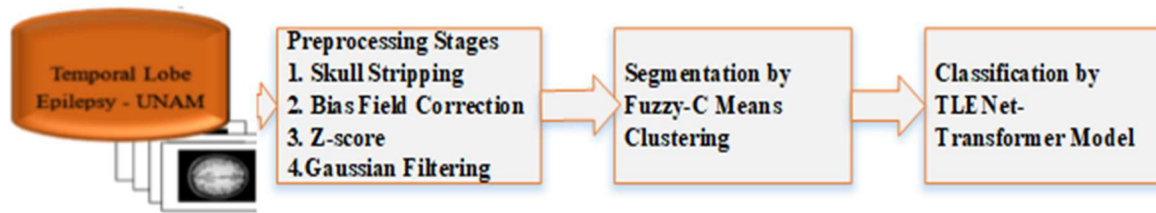


Fig. 1. Proposed methodology of TLE-Net-transformer model.

filter. Subsequently, a segmentation phase is used to utilize the proposed FCM to accurately segment the ROI. Finally, the classification phase is carried out with TLE Net-Transformer, a DL-based detector that integrates a 3D CNN with an attention mechanism, ST-LSTM, and CapsNet. Fig. 1 explains the proposed methodology.

Dataset details

Temporal Lobe Epilepsy-UNAM MRI Dataset was employed for detection, which is available in the link <https://openneuro.org/datasets/ds004469/versions/1.1.3/download>. The dataset has MRI scans from 400 individuals with epilepsy and healthy images. Training set of images 320 individuals, and testing set of images 80 individuals. The dataset contains manually inspected surface reconstructions and volumetric analysis.

Pre-processing methods

Normally, pre-processing is applied to attain noise-free data from the raw images. In the case of brain MRI, the complex structures need to be pre-processed to enhance image quality and highlight the significant areas. It includes:

Skull stripping: It is a crucial pre-processing step in medical image analysis, particularly in MRI scans. The goal of skull stripping is to remove the skull and non-brain tissues from the images, isolating the brain itself.³¹ It obtains the 3D image of the brain MRI and convert the image into a binary format where the pixels representing the skull and non-brain tissue are set to zero (background), and the pixels representing the brain are set to one (foreground). Here, Otsu thresholding³² is used, which is an automatic, non-parametric method used for determining the optimal threshold.

Bias field correction: It is a pre-processing method employed in MRI to address intensity non-uniformities created due to different attributes like magnetic field inhomogeneities.³³ This correction enhances the uniformity of tissue intensities, allowing for more accurate segmentation and analysis. The

process typically involves estimating the bias field and applying a correction algorithm such as Non-parametric Non-uniformity Intensity Normalization (N4ITK) to adjust the intensity values across the image. By removing these biases, image quality is improved and facilitates better detection and analysis of anatomical structures.

Z-score Normalization: It is a statistical technique³⁴ used to standardize the values of a dataset by transforming them into a common scale with a mean μ of 0 and a standard deviation σ of 1.

Gaussian Filter Method: It is a type of linear filter employed in image processing for reducing noise and smoothing images.³⁵ It functions by convolving the image with a Gaussian function, which gives more weight to pixels near the center of the kernel and less weight to those further away. The filter is defined by its standard deviation, which controls the amount of blurring, with a smaller standard deviation resulting in less blurring, while a larger one increases the blur effect.

Tissue segmentation phase

Tissue segmentation is a critical step for isolating anatomical structures in medical imaging, such as GM, WM, and CSF, from MRI images. A soft clustering method and a common approach called FCM³⁶ clustering, which is based on its intensity and spatial context, where each voxel in the image is assigned a membership value to multiple clusters or tissues.

Proposed FCM clustering

FCM works by assigning pixels or voxels to clusters based on intensity similarity while allowing partial membership of a pixel to multiple clusters, which is particularly useful in cases where tissue boundaries are unclear. The objective of the proposed FCM is to minimize Eq. (1), where N denotes the total voxel counts, C denotes the cluster count (here $C = 3$), u_{ik} denotes the membership value of the voxel i to cluster k , satisfying $0 \leq u_{ik} \leq 1$ and $\sum_{k=1}^C u_{ik} = 1$, x_i and c_k signify the intensity value of i^{th} voxel and centroid of k^{th} cluster, respectively, and also $m > 1$ represents the

Algorithm of MRI Image Analysis with FCM and TLENet-Transformer model

1. Preprocessing for MRI Images

Enhance image quality and normalize input for segmentation and classification.

Skull Stripping: Otsu threshold method

Bias Field Correction: N4ITK algorithms to correct intensity non-uniformity.

Intensity Normalization: Normalize pixel intensities to a standard range [0, 1].

Noise Reduction: Gaussian filtering to suppress random noise.

2. Segmentation Algorithm Using FCM Clustering

Segment brain tissues using soft clustering.

Initialize: Number of clusters c , Fuzziness parameter $m > 1$, Membership matrix U randomly

Repeat until convergence: Update cluster centers, membership values and check convergence

Output: Segmented image with soft labels for each pixel

3. AAI Labeling and TLENet Classification

Classify segmented regions using TLENet with anatomical labels

AAI Label Mapping:

Anatomical atlases to assign labels to segmented regions.

Map FCM clusters to anatomical zones using spatial coordinates and intensity profiles.

Feature Extraction:

Extract region-wise features: texture, shape, intensity histograms.

Optionally use TLENet's convolutional layers to learn deep features.

4. TLENet Transformer Classification model:

Input: Preprocessed and segmented MRI image with AAI labels.

Architecture: Hybrid CNN-Transformer model (TLENet) with attention layers.

Output: Class probabilities for each anatomical region (normal vs abnormal).

fuzziness parameter controlling the degree of cluster overlap (i.e., $m = 2$). Randomly initialize the cluster centroids c_k and membership matrix as $U = \{u_{ik}\}$ ensuring the constraint as shown in Eq. (2). Calculate the cluster centroids using the weighted mean of voxel intensities as per Eq. (3). The membership u_{ik} for each voxel i and cluster k is mentioned as per Eq. (4). Eqs. (3) and (4) compute until the algorithm reaches a pre-defined threshold τ . Each pixel is assigned a fuzzy membership value to each of the three clusters. The pixel's final class is determined by Eq. (5).

$$J_m = \sum_{i=1}^N \sum_{k=1}^C u_{ik}^m \|x_i - c_k\|^2 \quad (1)$$

$$\sum_{j=1}^C u_{ik} = 1 \quad \forall i \quad (2)$$

$$c_k = \frac{\sum_{j=1}^N u_{jk}^m x_j}{\sum_{j=1}^N u_{jk}^m} \quad (3)$$

$$u_{ik} = \frac{1}{\sum_{j=1}^C \left(\frac{\|x_i - c_k\|}{\|x_i - c_j\|} \right)^{\frac{2}{m-1}}} \quad (4)$$

$$class = \arg \max_k (u_{ik}) \quad (5)$$

AAL labelling method

To map the processed images to a pre-labelled AAL template by aligning the segmented brain tissues with predefined ROIs in the temporal lobe regions as per the AAL atlas. This process ensures the anatomical localization and labelling of brain regions.

The processed brain MRI images I_{seg} are aligned with the AAL template T_{AAL} using a spatial transformation model. This process minimizes the difference between the two datasets to ensure accurate mapping. The transformation is defined in Eq. (6), where R indicates the rotation matrix for aligning orientations, t states the translation vector to align positions, and x points to coordinate in the input image space. The registered image I_{reg} is obtained by applying T to I_{seg} as shown in Eq. (7). After registration, the AAL template T_{AAL} has predefined ROIs labelled as ROI_k for $k = 1, 2, \dots, 90$ and is overlaid onto I_{reg} . Each voxel v in I_{reg} is assigned to a specific ROI_k based on its correspondence in T_{AAL} . Eq. (8) defines the mapping function, in which $AAL(v)$ provides the ROI label for the voxel v in the temporal lobe regions. To isolate temporal lobe regions, only the labels corresponding to temporal lobe ROIs are retained. Let $S_{temporal}$ represent the set of temporal lobe labels as represented in Eq. (9). The segmented temporal lobe region is attained as shown in Eq. (10)

Finally, each temporal lobe ROI is quantified for volumetric analysis. For a specific ROI_k , Eq. (11) is applied to attain the temporal lobe region, in which $\delta(a, b) = 1$, if $a = b$, otherwise 0, and V_k gives the volume in ROI_k .

$$T(x) = Rx + t \quad (6)$$

$$I_{reg}(x) = I_{seg}(T(x)) \quad (7)$$

$$Label(v) = AAL(v) \text{ for } v \in I_{reg} \quad (8)$$

$$S_{temporal} = \{ROI_k | ROI_k \in Temporal \text{ Lobe}\} \quad (9)$$

$$I_{temporal}(v) = \begin{cases} I_{reg}(v) & \text{if } Label(v) \in S_{temporal} \\ 0 & \text{o.w} \end{cases} \quad (10)$$

$$V_k = \sum_{v \in I_{temporal}} \delta(Label(v), ROI_k) \quad (11)$$

Deep learning-based detection via Proposed TLENet-transformer

The proposed TLENet-Transformer is created using multiple stochastic models such as 3D CNN, ST-LSTM and CapsNet with a transformer network. The segmented V_k is given as input to 3D CNN, ST-LSTM and CapsNet and then concatenated to attain the desired output. The combination of 3D CNN, ST-LSTM, and CapsNet employs spatial, temporal, and hierarchical feature extraction to capture volumetric, sequential, and detailed part-to-whole relationships in the MRI brain images. Let $V_k \in \mathcal{R}^{N \times M}$ represent the segmented features, where N specifies the number of samples, and M signifies the number of selected features. These features serve as input to the 3D CNN, ST-LSTM, and CapsNet.

3D CNN

It is an extension of standard 2D CNNs that operate on three-dimensional data, making them particularly well-suited for tasks involving volumetric data like MRI scans.³⁷ The segmented feature set V_k is reshaped into a 3D format suitable for volumetric data input to the 3D CNN. Assume the reshaped data is represented as $\in \mathcal{R}^{H \times W \times D \times C_{in}}$, where H , W , and D refer to height, width, and depth, and C_{in} addresses the number of input channels. A 3D convolution applies a 3D kernel across this input as defined in Eq. (12), where $\mathcal{Y}_{i,j,k,c}$ refers to the output of the 3D convolution, $\mathcal{K}$ states the

3D convolutional kernel, and B_c addresses the bias.

$$\mathcal{Y}_{i,j,k,c} = \sum_{a=1}^{k_H} \sum_{b=1}^{k_W} \sum_{u=1}^{k_D} \sum_{v=1}^{k_{C_{in}}} \mathcal{X}_{i+a,j_b,k+u,v} \cdot \mathcal{K}_{a,b,u,v,c} + B_c \quad (12)$$

Here, the 3D CNN module is used to capture the spatial features F_{3dcnn} .

ST-LSTM

These networks extend traditional LSTMs to capture both spatial S and temporal τ dependencies in sequential data.³⁸ At this point, the F_{3dcnn} from 3D CNN is given as input to ST-LSTM layer as shown in Eq. (13).

$$F_{stlstm} = ST_LSTM(F_{3dcnn}) \quad (13)$$

The ST-LSTM retains the basic LSTM architecture which includes gates (input $\mathfrak{T}_t$, forget $\mathfrak{F}_t$, and output $\mathfrak{O}_t$ gates) and a cell state $\mathfrak{C}_t$, allowing it to learn long-term dependencies as shown in Eqs. (14) to (19) in which b , w , x , and T indicate bias, weight, and input vectors, and time correspondingly. Furthermore, σ indicates the sigmoid function and $\odot$ refers to element-wise multiplication.

$$\mathfrak{T}_t = \sigma(w_i \cdot [\mathcal{H}_{t-1}], x_T + b_i) \quad (14)$$

$$\mathfrak{F}_t = \sigma(w_f \cdot [\mathcal{H}_t - 1], x_T + b_f) \quad (15)$$

$$\mathfrak{O}_t = \sigma(w_o \cdot [\mathcal{H}_t - 1], x_T + b_o) \quad (16)$$

$$\mathfrak{C}_t = \tanh(w_m \cdot [\mathcal{H}_t - 1], x_T + b_m) \quad (17)$$

$$\widehat{\mathfrak{C}}_t = \mathfrak{F}_t \odot \widehat{\mathfrak{C}}_{t-1} + \mathfrak{T}_t \odot \mathfrak{C}_t \quad (18)$$

$$\mathcal{H}_t = \mathfrak{O}_t \tanh \odot (\widehat{\mathfrak{C}}_t) \quad (19)$$

From ST-LSTM, the spatiotemporal features F_{stlstm} is attained.

CapsNet

It is a novel type of neural network architecture designed to improve upon traditional CNNs by addressing some of their limitations, particularly in recognizing patterns and understanding spatial hierarchies.³⁹ Now, the features from ST-LSTM F_{stlstm} is fed to CapsNet as expressed in Eq. (20).

$$F_{final} = CapsNet(F_{stlstm}) \quad (20)$$

$$S_j = \sum_i C_{ij} \hat{U}_{ji} \quad (21)$$

$$V_j = \text{Squash}(S_j) \quad (22)$$

$$C_{i,j} = \frac{\exp(B_{i,j})}{\sum_k \exp(B_{i,k})} \quad (23)$$

The CapsNet's objective is to capture and preserve the spatial relationships between features, which can improve the model's performance from several perspectives. Each capsule in a layer is a vector pointing to the parameters used to instantiate the feature. The primary and digit capsule layers make up a CapsNet. Eqs. (21) to (23) deliver the dynamic routing process for the capsule layer, in which U_j indicates the output of a capsule of layer L , V_j means to output of a capsule in layer $L + 1$, $\hat{U}_{ji}$ denotes the prediction vector from the capsule i to capsule j , $C_{i,j}$ stands for coupling coefficient, S_j points to weighted sum of predicted vectors, and $B_{i,j}$ signifies log prior probabilities that capsule i should be coupled to capsule j .

$$\text{Squash}(S_j) = \frac{\|S_j\|^2}{1 + \|S_j\|^2} \frac{S_j}{\|S_j\|^2} \quad (24)$$

Eq. (24) shows the squash function, which ensures that the output vector length is between 0 and 1. The hierarchical relationship $F_{capsnet}$ is captured via CapsNet. After processing the segmented feature set V_k through the 3D CNN, ST-LSTM, and CapsNet, extracted the learned feature set F_{final} is obtained.

Transformer module

Integrating a transformer module in TLENet helps the model focus on the most relevant parts of the input data. At this point, the input $F_{final} \in \mathcal{R}^{N \times M}$ is fed to the Transformer encoder. The transformer module⁴⁰ represents the features as a sequence of tokens suitable for the Transformer by embedding and positionally encoding them. Each feature vector $f_i \in F_{final}$ is embedded into a higher-dimensional space via a learnable embedding matrix $\mathcal{M}_e$ as defined in Eq. (25).

$$\text{Token}_i = f_i \mathcal{M}_e \quad (25)$$

$$\text{Input}_i = \text{Token}_i + P_i \quad (26)$$

$$P_{i,2j} = \sin\left(\frac{i}{10000^{\frac{2j}{d_{model}}}}\right), P_{i,2j+1} = \cos\left(\frac{i}{10000^{\frac{2j}{d_{model}}}}\right) \quad (27)$$

These tokens are augmented with positional encodings P_i to capture sequential information as specified in Eq. (26). Positional encodings P_i are defined using sinusoidal functions for each dimension j of the embedding as formulated in Eq. (27), where d_{model} defines the embedding space.

Attention mechanism

The Transformer Encoder applies self-attention to enhance feature representation by computing relationships between tokens. The input tokens are transformed into a query (Q), key (K), and value (V) matrices using learnable weight matrices W_q , W_k , W_v as expressed in Eq. (28).

$$Q = F_{final} W_q; K = F_{final} W_k; V = F_{final} W_v \quad (28)$$

$$\text{Att}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \quad (29)$$

$$\text{Softmax}(z_i) = \frac{\exp(z_i)}{\sum_j \exp(z_j)} \quad (30)$$

$$\text{MultiHead}(Q, K, V) = \text{Concat}[h_1, \dots, h_h] W_o \quad (31)$$

$$h_i = \text{Att}(QW_q^i, KW_k^i, VW_v^i) \quad (32)$$

$$\text{FFN}(x) = \text{ReLU}(xW_1 + B_1)W_2 + B_2 \quad (33)$$

$$O_{\text{Att}} = \text{LayerNorm}(\text{Input} + \text{MultiHead}(Q, K, V)) \quad (34)$$

$$O_{\text{ffn}} = \text{LayerNorm}(O_{\text{Att}} + \text{FFN}(O_{\text{Att}})) \quad (35)$$

$$P_{final} = \text{Softmax}(F_{transformer} W_{fc} + B_{fc}) \quad (36)$$

Eq. (29) expresses the calculation of attention scores, in which d_k refers to the dimensionality of the key vector. The Softmax ensures that the attention scores across all keys sum to 1 as given in Eq. (30). To capture diverse relationships between features, Multi-Head Attention is applied. Multiple self-attention heads are computed in parallel, and their outputs are concatenated as indicated in Eq. (31), in which W_o states output projection weights, and h_i points to heads and is estimated using Eq. (32). The output of the Multi-Head Attention module is passed through a position-wise Feed Forward Neural Network (FFN) to capture complex patterns. The FFN consists of two linear layers with a ReLU activation as illustrated in

Table 2. Hyper parameter settings of the proposed TLE Net model.

Module	Component/Layer	Parameters	Values
3D CNN	3D Convolution	Kernel Size	$3 \times 3 \times 3$
		Filters	64
		Stride	1
	Max Pooling	Pool Size	$2 \times 2 \times 2$
CapsNet	Activation	Stride	2
		Type	ReLU
	Convolution	Kernel Size	9×9
		Filters	256
	Primary Capsules	Activation	ReLU
		Capsule Size	3
ST-LSTM	Digital Capsules	Capsule Size	10
	Routing Iterations	Iterations	3
	Spatial Attention	Attention N/w	Softmax
	LSTM Layer	Hidden Units	128
		Activation	Tanh
Transformer Module	Temporal Attention	Attention N/w	Softmax
	Multi-Head Attention	Number of Heads	8
	Positional Encoding	Encoding N/w	Sinusoidal
	Feedforward Layer	Hidden Units	2048
	Activation	Type	ReLU
	Dropout	Rate	0.1
Dense Layers	FC	Units	64
	Dropout	Rate	0.5
Output Layer	Dense	Units	2
	Activation	Type	Softmax

Eq. (33), where W_1 , W_2 and B_1 , B_2 signify learnable weight matrices, and biases in order. Residual connections and Layer Normalization are applied after both the Multi-Head Attention and FFN modules to stabilize training and preserve information as formulated in Eqs. (34) and (35). The output from the Transformer Encoder, $F_{transformer}$ is passed through Fully Connected (FC) layers for classification. The FC layer computes the class probabilities using Eq. (36), where W_{fc} and B_{fc} address weight matrix and bias for the FC layer, and *Softmax* ensures the output represents a probability distribution over the possible classes.

Table 2 delivers the hyper parameter settings of the proposed TLENet-Transformer model. Fig. 2 displays the architecture of the feature extraction phase in the proposed TLENet-Transformer. Fig. 3. depicts the overall architecture of the proposed TLENet-Transformer.

The model's ability to capture spatial, temporal, and hierarchical features in the dataset is well supported by its design. Spatial features are addressed through, allowing the model to learn patterns across different regions. Temporal dynamics are captured using time-stamped entries. Hierarchical structures are represented in layered representations that reflect relationships across scales. Together, these components allow the model to extract meaningful insights from complex, multi-dimensional data, enhancing its predictive capabilities.

Results and discussion

Simulation setup

The proposed TLE detection model using the suggested TLE-Net-Transformer approach was implemented in Python on an Intel core®core i3 processor 7020U@2.3 Ghz, with 8 GB RAM and a 64-bit operating system.

The simulation of the proposed TLE-Net-Transformer was compared with baseline models such as 3D CNN, ST-LSTM, and CapsNet, and recent DL models like CNN-LSTM,⁴¹ and multi-channel Deep CNN (MDCNN).⁴² The proposed detection model using the suggested TLE-Net-Transformer and the attained results are discussed here. Fig. 4 represents the corresponding skull-stripped images. Besides, Fig. 4(b) explains the bias field correction results. Fig. 4 shows the Z-score normalized images. Additionally, Fig. 4 shows the Gaussian-filtered images. Fig. 5 explains the FCM-clustered segmented images.

Fig. 6 gives the model performance graph of the training and testing data split, along with the accuracy and loss graphs. Table 3 presents the performance of the model compared with the hybrid baseline mode (70:30). Table 4 presents the performance of the model compared with the hybrid baseline mode (80:20). Table 5 gives the k-fold accuracy performance of the TLE-NET model. Table 6 gives comparison of the proposed model with the baseline model. Table 7 gives the comparison of the proposed FCM model with the baseline models.

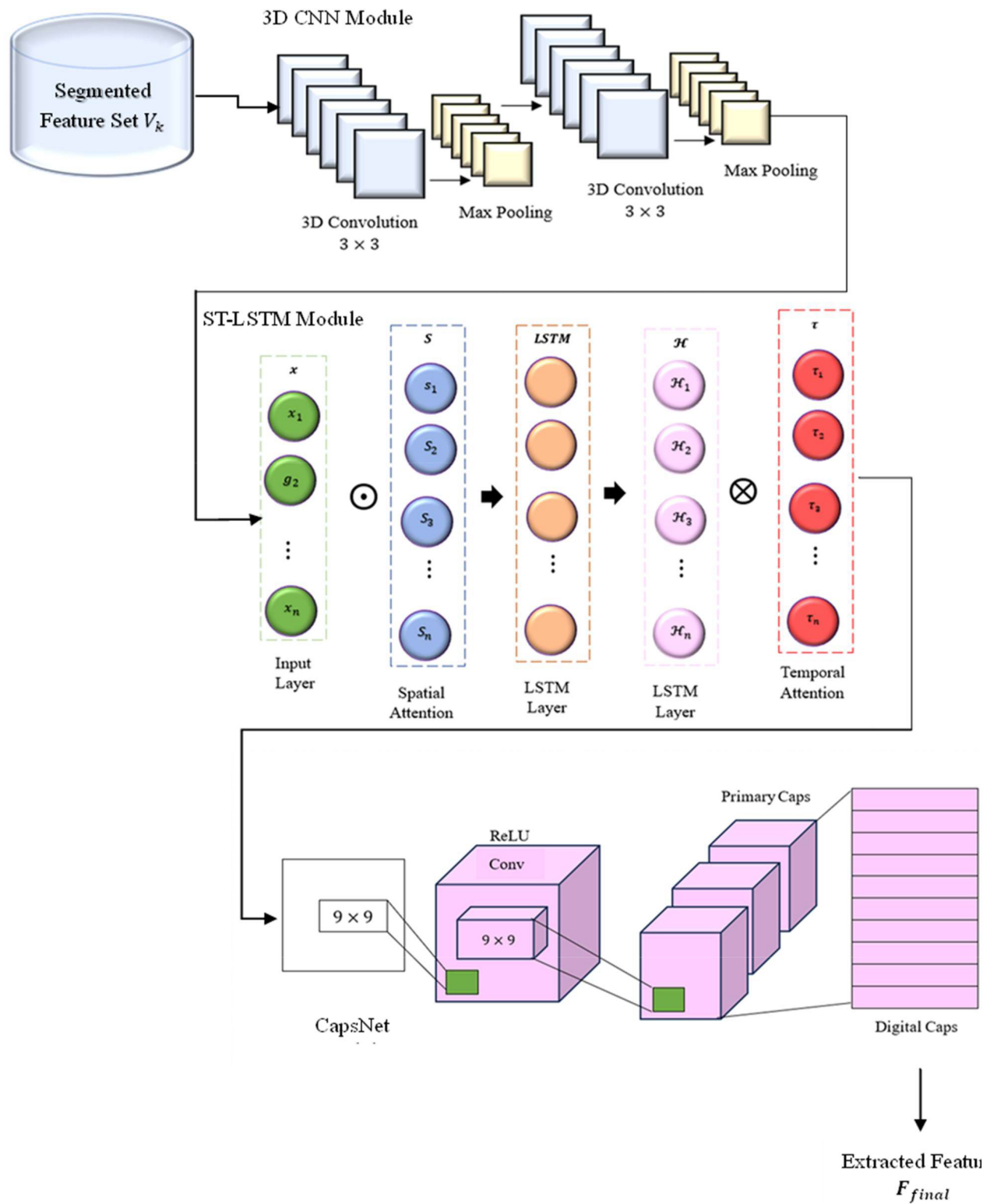


Fig. 2. Architecture of the feature extraction phase in the proposed TLE-Net-transformer model.

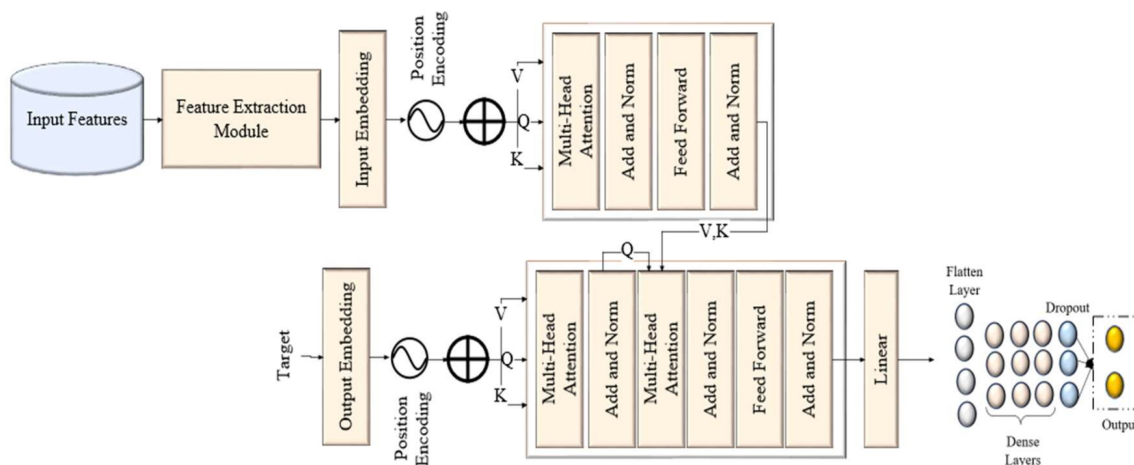


Fig. 3. Architecture of the feature extraction phase in the proposed TLE-Net-transformer model.

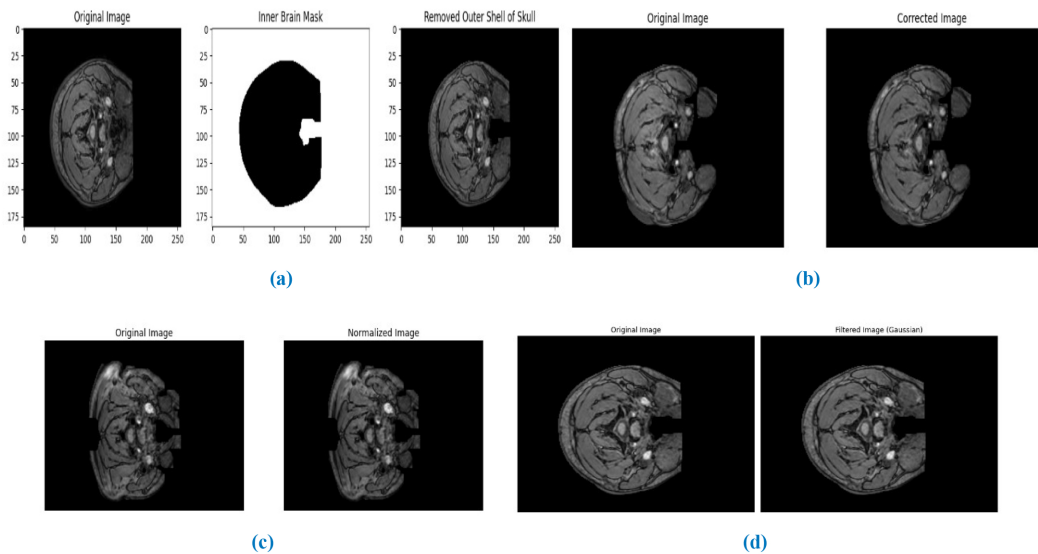


Fig. 4. Sample MRI images displaying (a) Skull-stripped, (b) Bias field corrected, (c) Z-score normalized, and (d) Gaussian filtered images.

Table 3. The proposed TLE Net model performance compared with another hybrid model (70:30).

Model	Accuracy	Precision	Sensitivity	Specificity	F1-Score	MCC	NPV	FPR	FNR
3D-CNN	0.9589	0.9469	0.9716	0.9462	0.9591	0.91	0.97	0.05	0.02
CAPESNET	0.9583	0.9478	0.9695	0.9473	0.9585	0.91	0.96	0.05	0.03
CNN-LSTM	0.954	0.9457	0.9632	0.9448	0.9544	0.90	0.96	0.05	0.03
MDCNN	0.9491	0.9412	0.9576	0.9407	0.9494	0.89	0.95	0.05	0.04
ST-LSTM	0.9469	0.9411	0.9534	0.9405	0.9472	0.89	0.95	0.05	0.04
Proposed TLE-Net-Transformer	0.9789	0.9784	0.9794	0.9783	0.9789	0.957	0.9794	0.0217	0.0206

Table 4. The proposed TLE Net model performance compared with another hybrid model (80:20).

Model	Accuracy	Precision	Sensitivity	Specificity	F1-Score	MCC	NPV	FPR	FNR
3D-CNN	0.9653	0.9532	0.9782	0.9527	0.9656	0.931	0.977	0.047	0.021
CAPESNET	0.9616	0.95	0.9738	0.9495	0.9618	0.923	0.973	0.050	0.026
CNN-LSTM	0.9567	0.9479	0.9664	0.947	0.957	0.913	0.965	0.053	0.033
MDCNN	0.9524	0.9455	0.9599	0.9449	0.9526	0.904	0.959	0.055	0.040
ST-LSTM	0.9491	0.9433	0.9555	0.9427	0.9494	0.898	0.955	0.057	0.044
Proposed TLENet-Transformer	0.9816	0.9827	0.9805	0.9826	0.9816	0.9632	0.9805	0.0184	0.0195

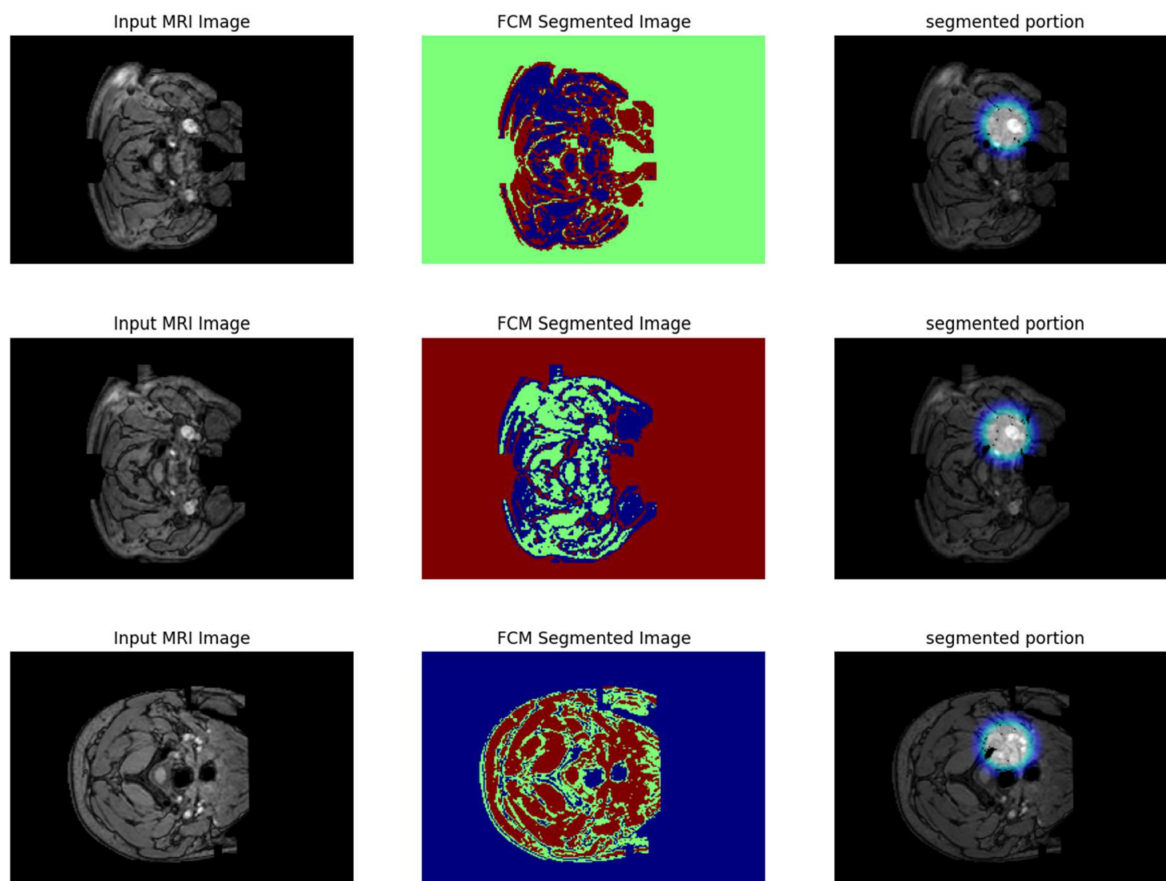


Fig. 5. Sample MRI images displaying FCM clustered segmented images.

Table 5. The proposed TLE Net model performance compared with the K5 validation.

Fold (K)	Accuracy	Precision	Sensitivity	Specificity	F1-Score	MCC	NPV	FPR	FNR
K = 1	0.9752	0.9731	0.9804	0.9724	0.9840	0.9762	0.9750	0.0215	0.0135
K = 2	0.9803	0.9760	0.9865	0.9780	0.9874	0.9810	0.9793	0.0192	0.0112
K = 3	0.9765	0.9744	0.9811	0.9735	0.9855	0.9784	0.9760	0.0210	0.0121
K = 4	0.9791	0.9776	0.9842	0.9767	0.9881	0.9814	0.9790	0.0203	0.0118
K = 5	0.9783	0.9770	0.9872	0.9760	0.9870	0.9829	0.9811	0.0199	0.0108

Table 6. Proposed model comparison.

Model	Accuracy
Without Pre-processing	90.15
Without Segmentation	93.51
Without Feature Extraction	94.01
Proposed TLENet	99.16

Table 7. Proposed FCM model.

Model	FSI	DSC	IoU	HD
FCM	0.9461	0.9508	0.9599	0.9481
UNet	0.9614	0.9668	0.9684	0.9567
3D UNet	0.9528	0.9604	0.9691	0.9698
Proposed FCM	0.9917	0.9881	0.9827	0.9907

Fig. 7 shows the confusion matrix, which provides a detailed assessment of the model's classification performance for distinguishing between healthy and patient groups. A Receiver Operating Characteristic (ROC) curve with an Area Under the Curve (AUC) of 0.99 is an exceptional result. It indicates that the model is almost perfect at distinguishing between the positive and negative classes. In simpler terms, the model has a 99% chance of correctly classifying a randomly chosen positive instance as more likely than a randomly chosen negative instance.

Future implementation of IoMT in the remote monitoring system

This future analysis utilizes an AI-based classification model integrated with the Internet of Medical Things (IoMT) to detect and categorize Epilepsy from MRI images. The medical images are sourced from hospital databases and transmitted through biosensors using Wi-Fi protocols. The data are processed using edge computing devices to reduce latency and enhance real-time analysis. A pre-trained AI

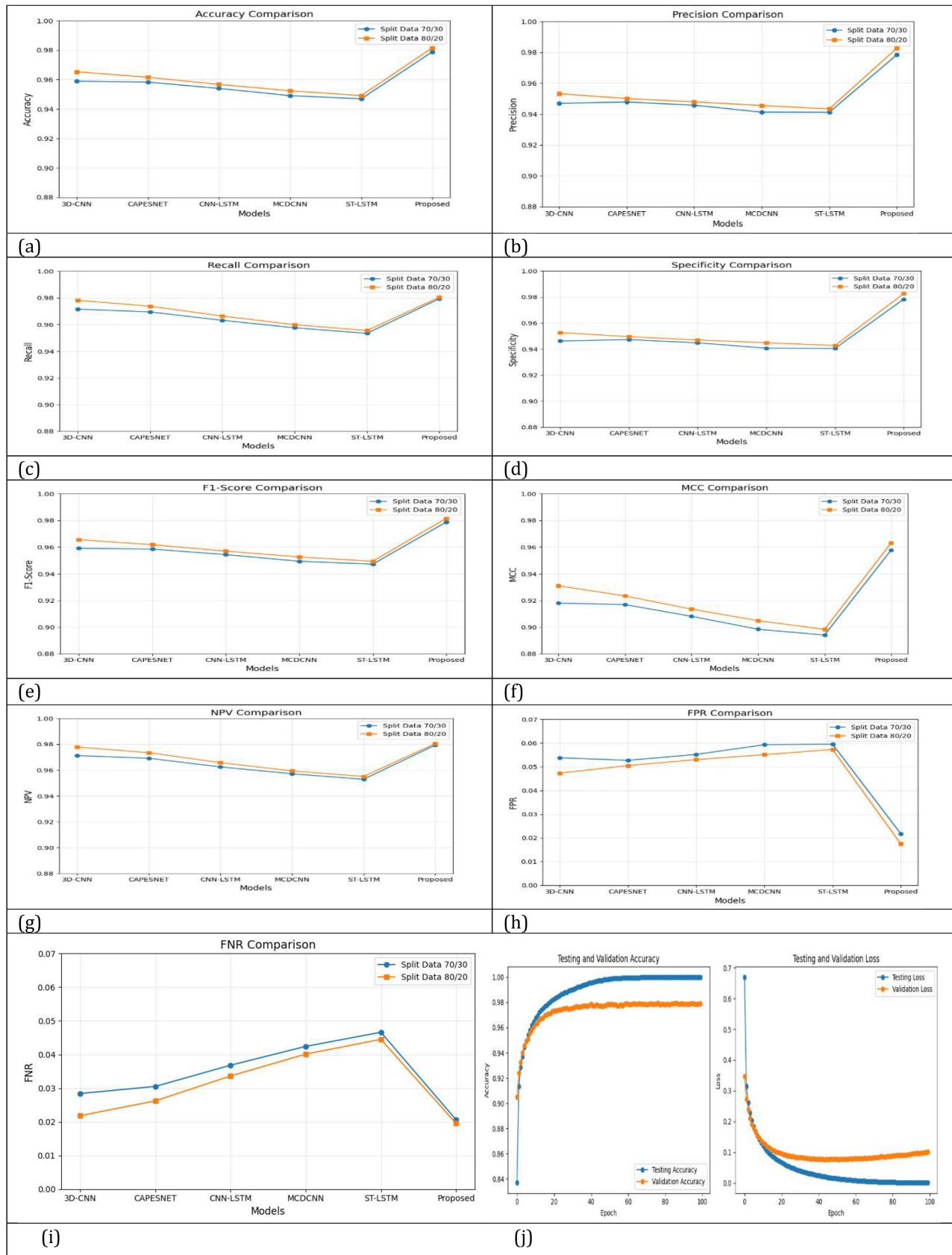


Fig. 6. Performance of the proposed model TLE Net Transformer from Fig (a) to Fig (i) and Fig (j) is the accuracy and loss graph.

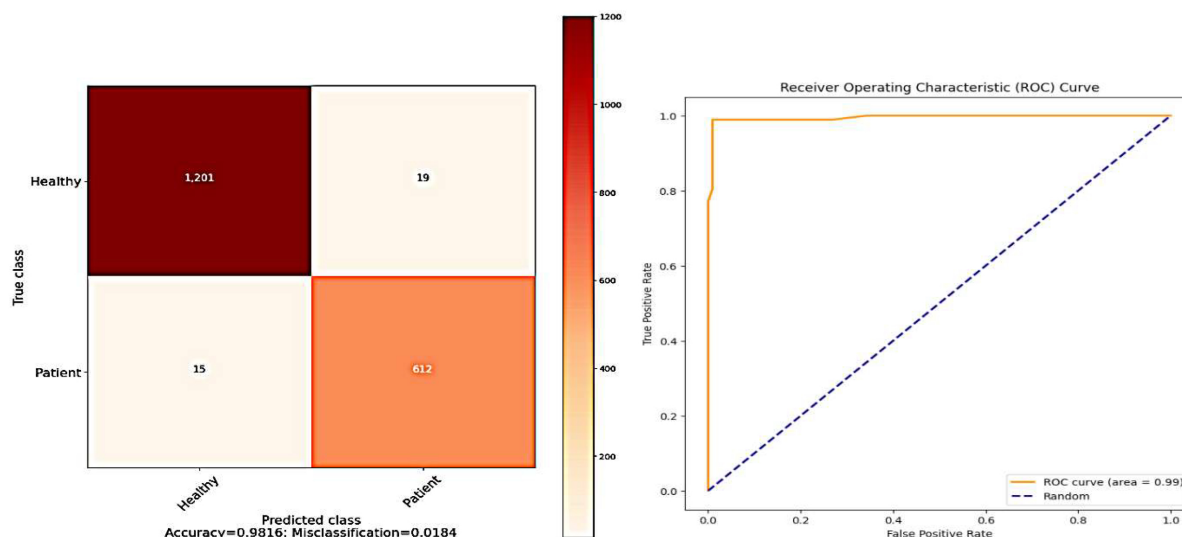


Fig. 7. Performance of proposed model TLE Net: Confusion matrix and ROC curve.

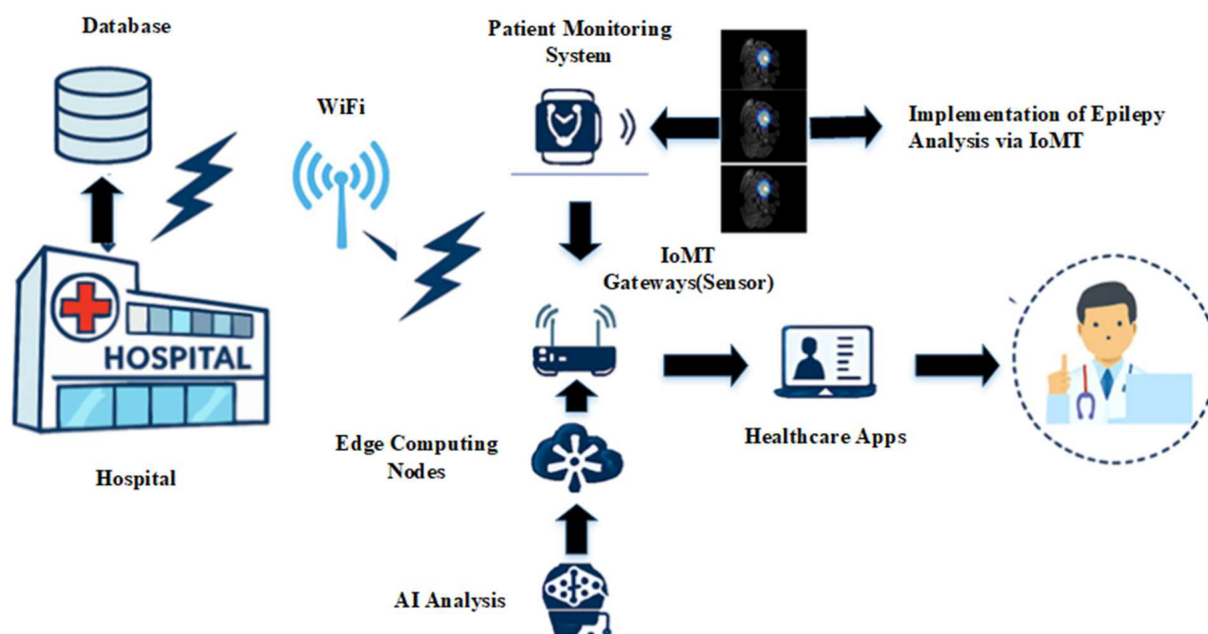


Fig. 8. Futuristic implementation of IoMT Epilepsy detection with remote monitoring.

model analyzes the MRI data to identify and classify Epilepsy. The results are then relayed to a medical application, allowing healthcare professionals to access diagnostic insights promptly. This workflow ensures improved decision-making accuracy and timely intervention, as explained in Fig. 8.

Conclusion

This paper has introduced a novel TLE detection algorithm using hybrid DL models. This model starts with a pre-processing phase that includes skull stripping, bias field correction, z-score normalization, and

noise reduction using a Gaussian filter. Finally, the classification phase was carried out with TLENet-Transformer, a DL-based detector that integrates a 3D CNN, ST-LSTM, and CapsNet. The input images were initially pre-processed and segmented using the proposed FCM. Then, the GM, WM, and CSF in the MRI brain image were processed using the AAL template to find the temporal lobe region. Once the labelling was carried out, the segmented image V_k was given as input to the proposed TLENet-Transformer to detect the disease. Future work of this study could involve exploring more advanced attention mechanisms to include feature selection and model interpretability. Expanding the dataset with diverse samples can en-

hance the model's robustness. Investigating transfer learning techniques could also accelerate training for similar tasks. Additionally, integrating optimization algorithms could fine-tune hyperparameters for better performance. The future implementation also plans to use IoMT remote monitoring methods.

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Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images that are not ours have been included with the necessary permission for republication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- Ethics Statement: This study used a publicly available dataset (Temporal Lobe Epilepsy-UNAM MRI), that is freely accessible for research purposes. No human participants were directly recruited, and no identifiable personal data were collected by the authors.
- Ethical Clearance: The project was approved by the local ethical committee at Vellore Institute of Technology.

Authors' contributions statement

J.V. designed the study, and J.V. performed the software simulations. S.S. analyzed the data. J.V. wrote the paper with input from all authors.

Data availability

Temporal Lobe Epilepsy-UNAM MRI Dataset was employed for detection which is available in the link <https://openneuro.org/datasets/ds004469/versions/1.1.3/download>. The dataset has MRI scans from 400 individuals with epilepsy and healthy images. Training set of images 320 individuals and testing set of images 80 individuals. The dataset contains manually inspected surface reconstructions and volumetric analysis.

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شبكة TLENet-Transformer للكشف عن الصرع مع خطط مستقبلية لإنترنت الأشياء الطبية

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الخلاصة

يُعد صرع الفص الصدغي (Temporal Lobe Epilepsy - TLE) أكثر الأنواع شيوعاً من الصرع البؤري، وغالباً ما يطرح تحديات تشخيصية بسبب تعقيد خصائصه السريرية. ولمواجهة هذه التحديات، تقترح هذه الدراسة نموذج TLENet-Transformer، وهو بنية جديدة للتعلّم العميق صُممت خصيصاً لتحقيق كشف دقيق لحالات صرع الفص الصدغي. تبدأ الدراسة بمجموعة من خطوات المعالجة المسبقة للصور الطبية، تشمل إزالة الجمجمة (Skull Stripping)، وتصحيح عدم تجانس المجال (Bias Field Correction)، والتطبيع باستخدام معيار Z-score، والترشيح الغاوسي (Gaussian Filtering)، وذلك لتحسين جودة الصور. بعد ذلك، تُستخدم طريقة للتجزئة تعتمد على خوارزمية التجميع الضبابي للمتوسطات (Fuzzy C-Means) المُحسّنة، مما يتيح تحديداً دقيقاً للمناطق المستهدفة. وفي هذه المرحلة، تُطابق الصور المُجزأة مع قالب التوسيم التشريحي الآلي (Automated Anatomical Labelling - AAL) المُعلّم مسبقاً، بهدف اكتشاف مناطق الاهتمام (Regions of Interest - ROIs) المميزة. كما أن تطوير نماذج هجينة تجمع بين التعلّم العميق (DL) وتقنيات المحولات (Transformers) والبيات الانتباه (Attention-Based Techniques) يمكن أن يساهم في تحسين استخراج السمات والخصائص. تدمج وحدة التصنيف نهجاً هجيناً للتعلّم العميق يجمع بين: الشبكات العصبية الالتفافية ثلاثية الأبعاد (3D CNNs) لاستخراج السمات المكانية، وحدات الذاكرة طويلة وقصيرة المدى المكانية - الزمانية (Spatio-Temporal LSTM) للنقاط الديناميكية الزمنية و شبكات الكبسولات (Capsule Networks) للحفاظ على السمات الهرمية والعلاقات البنوية بينها. وتتيح هذه البنية متعددة الطبقات للنموذج تعلّم الأنماط المعقدة المرتبطة بالمناطق المتأثرة بالمرض. وقد حقق نموذج TLENet-Transformer دقة تشخيصية مرتفعة بلغت 98.16%، متفوقاً على النماذج التقليدية من حيث الحساسية (Sensitivity) والنوعية (Specificity). علاوة على ذلك، تستكشف الدراسة إمكانية دمج تقنيات إنترنت الأشياء الطبية (Internet of Medical Things - IoMT) بهدف تمكين المراقبة عن بُعد وفي الوقت الحقيقي للمرضى، وهو ما يُمثل أحد التوجهات المستقبلية لهذا العمل البحثي.

الكلمات المفتاحية: الشبكات العصبية الالتفافية (CNN)، خوارزمية التجميع الضبابي للمتوسطات (Fuzzy C-Means)، الذاكرة طويلة وقصيرة المدى (LSTM)، إنترنت الأشياء الطبية (IoMT)، صرع الفص الصدغي. (Temporal Lobe Epilepsy).