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A Modified Gated Recurrent Unit Approach for Epileptic Electroencephalography Classification

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ABSTRACT

Epilepsy is one of the most severe non-communicable brain disorders associated with sudden attacks. Electroencephalography (EEG), a non-invasive technique, records brain activities, and these recordings are routinely used for the clinical evaluation of epilepsy. EEG signal analysis for seizure identification relies on expert manual examination, which is labour-intensive, time-consuming, and prone to human error. To overcome these limitations, researchers have proposed machine learning and deep learning approaches. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have shown significant results in automating seizure prediction, but due to complex gated mechanisms and the storage of excessive redundant information, these approaches face slow convergence and a low learning rate. The proposed modified GRU approach includes an improved update gate unit that adjusts the update gate based on the output of the reset gate. By decreasing the amount of superfluous data in the reset gate, convergence is speeded, which improves both learning efficiency and the accuracy of epilepsy seizure prediction. The performance of the proposed approach is verified on a publicly available epileptic EEG dataset collected from the University of California, Irvine machine learning repository (UCI) in terms of performance metrics such as accuracy, precision, recall, and F1 score when it comes to diagnosing epileptic seizures. The proposed modified GRU has obtained 98.84% accuracy, 96.9% precision, 97.1 recall, and 97% F1 score. The performance results are significant because they could enhance the diagnosis and treatment of neurological disorders, leading to better patient outcomes.

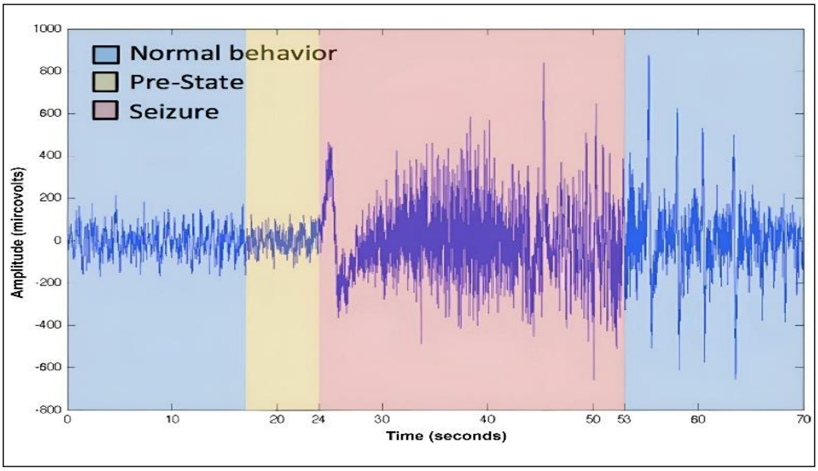
Keywords: Epileptic seizure detection, recurrent neural network, long short-term memory, modified-gated recurrent unit.

INTRODUCTION

Epilepsy is a chronic neurological disorder that affects more than 50 million people worldwide (World Health Organization, n.d.). The neurons in the brain fire the message using electrical pulses in a normal state. Still, in an epileptic condition, the sudden extensive discharge of neurons leads to life-threatening consequences such as involuntary movement, unconsciousness, and even death (Sajobi et al., 2021). The brain's electrical activity is recorded by electrodes placed on the scalp to record electroencephalography (EEG) signals, which are used to diagnose epilepsy. Epilepsy is a neurological disorder that causes unpredictable seizures, which can lead to social difficulties and an increased risk of mortality (Fisher et al., 2014). Figure 1 presents a comprehensive depiction of EEG signals associated with both normal, pre-state and epileptic seizure states (Alotaiby et al., 2014). The epileptic seizure varies from person to person; sometimes, the patient rarely experiences the attack, but in other cases, a patient may have hundreds of seizures per day. Not every seizure can be an epileptic seizure, as correctly identifying the signals is required to diagnose it as an epileptic seizure. Without EEG, it is often impossible to obtain a solid diagnosis of a brain-related disease. However, for detecting epileptic seizures and spikes, the traditional method of visual inspection of the EEG is a time-consuming and error-prone procedure.

Figure 1

An Example of Normal, Pre-state and Seizure EEG Recordings



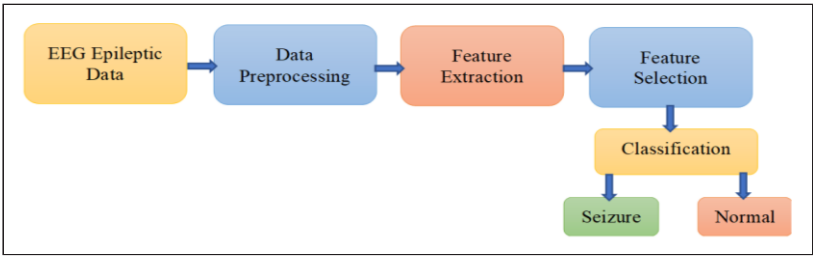
Therefore, an automated epileptic seizure detection system can enable doctors to diagnose patients with epileptic seizures. Various machine learning (ML) and deep learning (DL) techniques have been developed to detect epileptic seizures using frequency, time, time-frequency domain, and other parameters (Alickovic et al., 2018). DL techniques are used to overcome the limitations of automated epilepsy detection systems (Orosco et al., 2013). Researchers have evolved and analysed many convolutional models to see how effective they are in automatic epilepsy detection structures (Gotman, 1982; Siuly et al., 2016).

DL models such as the Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long-short term memory (LSTM), Gated Recurrent Unit (GRU), and Autoencoders (AEs) are widely used for the automatic detection of an epileptic seizure (Natu et al., 2022). Chen et al. (2016) reviewed the LSTM model as a distinguished technique with the best performance measures (Ismail & Yusof, 2022). RNNs with a gated mechanism have emerged as useful for modelling sequential inputs such as speech or EEG.

The amount of data that needs to be manually assessed by trained neurologists has created a workflow bottleneck; neurologists are overwhelmed by the volume of data (Fisher et al., 2014). Combining DL with EEG and Magnetic Resonance Imaging (MRI) modalities to effectively detect automated epileptic episodes is discussed. Figure 2 depicts the framework of an automatic epileptic detection system with EEG to classify seizures as normal or epileptic. The proposed work aims to address the slow convergence of GRU by using a modified GRU architecture that has fewer gating mechanisms.

Figure 2

The Framework of Automatic Epileptic Seizure Detection System



The content of this paper is organised into different sections. The related work section provides a literature review of various epileptic detection models currently employed. The following section, i.e., preliminary concepts, provides an overview of DL models such as RNN, LSTM, and GRU. The proposed method is described in the Proposed Modified GRU Approach section. Further, the experimental study section illustrates the implementation details of the proposed model having experimental setup, UCI EEG dataset description, and training and implementation of the proposed modified GRU (M-GRU) model. The Results and Discussion section evaluates the results obtained from the proposed model in terms of performance measures and their comparison with existing neural network models. The conclusion section summarises the proposed research and provides recommendations for future research endeavours.

RELATED WORKS

Deep learning techniques enable early-stage epilepsy detection using EEG signals and exhibit great potential in accurate treatment and expedient medical decisions for individuals. Nigam and Graupe (2004) proposed a method for the automatic detection of epileptic seizures using the neural network large memory storage and retrieval (LAMSTAR). The method resolves the limitations by pre-processing long-term EEG data using the spike's relative spike amplitude and rhythmicity attributes to train the LAMSTAR ANN. The proposed method obtained a significant classification accuracy of 97% in a specific dataset. Güler and Übeyli (2005) investigated how wavelet coefficients can be used to classify EEG information. An adaptive neuro-fuzzy inference system (ANFIS) is applied to classify EEG signals. The proposed model takes wavelet transformation coefficients as input. The model obtains an accuracy of 98.68%.

Golmohammadi et al. (2018) proposed two LSTM architectures with a combination of 3 and 4 layers with a softmax classifier and obtained satisfactory results with an accuracy of 96.82%. Kannathal et al. (2005) provide correlation metrics for EEG indicators and actual data. Various entropy estimators have been used for the EEG alerts of epileptic seizure signals. The proposed entropy-based method achieved 95% classification accuracy. Further, Srinivasan et al. (2007) proposed a neural network (NN)-based automatic epileptic seizure detection system with approximate entropy (ApEn) as an input feature. Two types of classifiers, Elman Network (EN) and Probabilistic Neural Network (PNN), are implemented, and using the EN classifier, an overall accuracy of 95.45% is obtained. Güler and Übeyli (2007) created an eigenvector feature withdrawal method for EEG sign detection primarily based on pattern recognition, and Polat and Güneş (2008) proposed a unique hybrid automatic identity mechanism based on Artificial Immune Recognition System (AIRS). The proposed method has three stages: first, Welch Fast Fourier Transformation (WFFT) for feature extraction, then Principal Component Analysis (PCA) for dimensionality reduction of features. Finally, AIRS is implemented as a classifier. The proposed method obtained 100% accuracy with 10-fold cross-validation with two classes (A and E).

Orhan et al. (2011) proposed a multilayer perceptron neural network-based classification model to diagnose epileptic seizures using Discrete Wavelet Transformation (DWT) and the K-means algorithm for each frequency sub-set. Wang et al. (2017) provided a multi-domain characteristic withdrawal technique for seizure detection. Gajic et al. (2015) presented a new method for detecting epileptiform activity in EEG signals using time, frequency, and non-linear analysis and achieved an overall accuracy of 98.7% when tested on three sets of EEG signals. Wang et al. (2011) demonstrated entropies from Wavelet Packet Decomposition (WPD) to have a powerful ability to represent the intrinsic characteristics of electroencephalogram (EEG) signals for the seizure detection method. Fergus et al. (2015) adopted an advanced AI approach to picking out automatic epileptic seizures using EEG signals.

Hsu and Yu (2010) proposed sub-band non-linear parameters for seizure detection using EEGs. In recent times, Sharmila et al. (2018) suggested DWT with the adequate-NN classifier to discover epilepsy. Alickovic et al. (2018) hired the discrete wavelet to redecorate and wavelet packet fragmentation to conduct automated epileptic seizure diagnosis and prognosis. At the same time, Satapathy et al. (2016) reviewed different techniques for categorising EEG indicators to find epileptic seizures. Subasi et al. (2019) introduced hybrid device learning strategies for detecting epileptic seizures, whereas Hussain (2018) presented a study approach with a linear kernel support vector machine and K-Nearest Neighbour that showed an accuracy of 99.5%. Rosas-Romero et al. (2019) proposed CNN for epileptic seizure prediction.

In recent years, various DL methods (Roy et al., 2018) have been developed that significantly increase the performance of epileptic seizure detection from EEG datasets. CNN is a popular DL model that allows extracting numerous features by implementing filters in different convolutional layers (Radenović et al., 2019). The result from these layers improves the performance significantly. Yet, CNN is unable to retain the memory of previous time stamps, which leads to a downscaled performance in time series data patterns such as EEG. Therefore, a specific type of neural network, the recurrent neural network (RNN), uses previous outputs as inputs and is able to retain the previous time stamp information (Choi et al., 2017). Bhanusree et al. (2023) demonstrate the efficiency of the proposed time-distributed attention-layered CNN (TDACNN) model in extracting spatiotemporal features from time-series speech signals, enabling accurate classification of emotions. Due to the vanishing gradient problem, RNN faces a short-term memory problem.

An alternate gating mechanism with a mechanised GRU to resolve this issue was proposed (Chung et al., 2014), incorporating two gate operating mechanisms, the Update and Reset gates. The update gate eliminates the risk of vanishing gradient problems, whereas the reset gate allows for the continuous discarding of stored redundant information. It is frequently impossible to eliminate enough redundant state information in a single screening due to GRU's ongoing issues with a sluggish convergence rate, limited learning efficiency, and the complicated state of time series data (Wang et al., 2019). Table 1 summarises some prominent DL epilepsy detection approaches in the available literature.

Table 1

Some of the Prominent Deep Learning Epilepsy Detection Approaches

Reference/ Year	Pre-Processing/ Feature Extraction Methods	Dataset	Epilepsy Detection Approach	Performance Matrices
Nigam and Graupe (2004)	Multistage non-linear filter	Real-time EEG data	LAMSTAR-ANN	Accuracy-97.2%
Güler and Übeyli (2005)	Wavelet transform	UCI epileptic dataset	ANFIS	Accuracy-98.68%
Srinivasan et al. (2007)	Approximate entropy (ApEn)	UCI epileptic dataset	Elman Network, Probabilistic NN (PNN)	Accuracy-99.6%
Orhan et al. (2011)	DWT and K-Means algorithm	UCI epileptic dataset	MPNN	Accuracy-95.6%
Chung et al. (2014)	Not defined	Ubisoft-Polyphonic music dataset	LSTM-RNN GRU-RNN	Learning rate validation
Gajic et al. (2015)	DWT, dimensionally reduction	University Hospital Bonn	Quadratic classifiers	Accuracy-98.7%
Satapathy et al. (2016)	DWT	UCI epileptic dataset	MLPNN, SVM, RNN	Average accuracy-98.3%
Talathi (2017)	Auto-correlation	Bonn University	GRU-RNN	Accuracy-98%
Choi et al. (2017)	Time series analysis	Sutter-PAMF data	RNN	Area under curve (AUC)-0.777
Chen et al. (2018)	Not defined	University Hospital Bonn	Double-DNN	Accuracy-97.28%
Alickovic et al. (2018)	EMD, DWT	Freiburg and CHB-MIT	Multiscale Principal Component Analysis (PCA)	Accuracy-99.70%

(continued)

Reference/ Year	Pre-Processing/ Feature Extraction Methods	Dataset	Epilepsy Detection Approach	Performance Matrices
Yao et al. (2019)	Not defined	CHB-MIT	Independently RNN (IndRNN)	Avg. Acc -87% Avg. Sens-87.3%
Gramacki and Gramacki (2022)	Not defined	Helsinki University Hospital	CNN	Accuracy-97% (window_size-5)
Li et al. (2023)	Short-time Fourier Transformation (STFT)	Kunming Children's Hospital	Bi-GRU	Accuracy-92%
Bhanusree et al. (2023)	Not defined	RAVDESS and IEMOCAP data corpora	TDACNN	Accuracy-92.19%

PRELIMINARY CONCEPTS

Recurrent Neural Network

An RNN is a form of neural network with a traditional design that can handle variable-length inputs. In a conventional feed-forward network, the output is based on the current input data, whereas in an RNN, the output at time-step t depends on the previous time-step *t-1*. Because of the limitations of learning information from past data sequences, RNNs provide solutions having two input sources: the current and recent past input. Instead of the unidirectional connection of neurons in the traditional feed-forward network, RNNs have a flow of information that is directed as cycles within connected neurons. Figure 3 illustrates the architecture of the RNN, where the RNN layer comprises a single layer and unfolds according to the number of steps or time stamps. In RNN, each node has a function to produce current hidden state S_t and output y_t with current input x_t and previous hidden state h_{t-1} (Murad & Pyun, 2017). The conventional RNN model is depicted in Equations 1 to 3 (Pascanu et al., 2014):

$$S_t = \tanh\left[(Wh_{t-1} + Ux_t)\right] \tag{1}$$

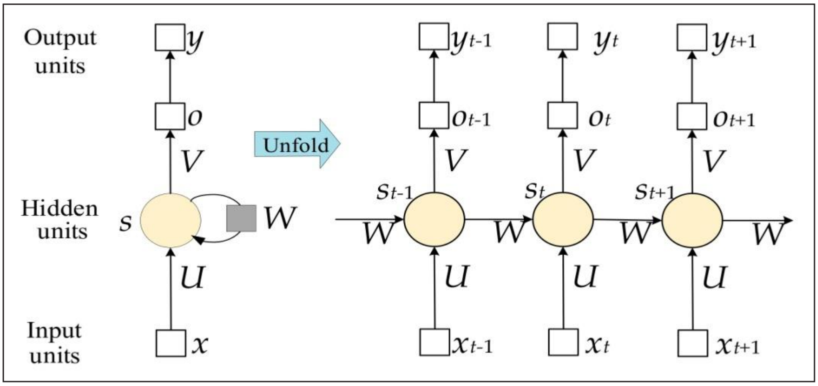
$$O_t = V_{st} \tag{2}$$

$$y_t = \text{sigmoid}(O_t) \tag{3}$$

where W, U and V are the weight matrix for hidden, input and output units. Non-linear activation functions such as hyperbolic *tangent* for hidden state and logistic *sigmoid* for output state are used.

Figure 3

A Structural Representation of a Recurrent Neural Network (Li et al., 2019)



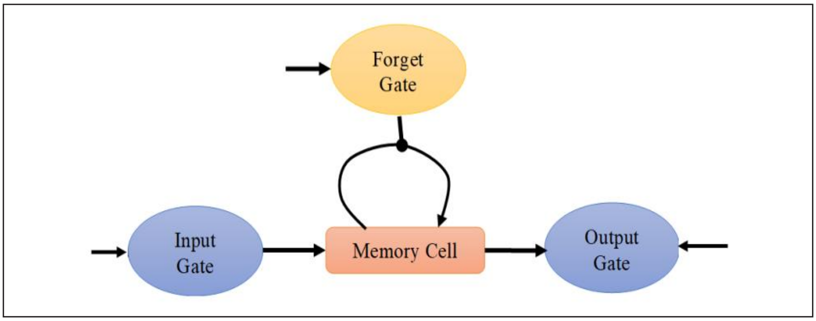
RNNs often suffer from the "Vanishing" and "Exploding" gradient problems (Hochreiter & Schmidhuber, 1997), which lead to the failure of learning long-range dependencies due to this gradient becoming too small or too large (Rosas-Romero et al., 2019). Gated recurrent network topologies such as the LSTM unit (Gao & Wang, 2019) and Gavvala et al. (2014) proposed GRU to circumvent the vanishing gradient problem.

Long Short-term Memory (LSTM)

LSTM was introduced in 1997 (Hochreiter & Schmidhuber, 1997) to resolve the problem of vanishing or exploding gradients. RNNs may overlook important processed data because they have difficulty transferring information from earlier time stamps to succeeding stages in a long sequence (Yuen et al., 2018). The LSTM network can store previous information for an extended period of time using unique memory cells. LSTM gates are not only addressing the issue of short-term memory but can also be used to regulate the flow of data. The gates can store a long succession of required data while discarding superfluous information. In Figure 4, instead of a single gate block in the RNN, an LSTM memory block contains three gates: an input gate, an output gate, and a forget gate. The forget gate helps to remember or forget the information that is not necessary to retain. The detailed architecture of LSTM is shown in Figure 5.

Figure 4

The Representation of Single LSTM Unit



Input gate: This gate calculates the amount of input that passes through it. Equation 4 represents the input gate.

$$i_t = \text{sigmoid}\ [(W_{xi}x_t + W_{hi}h_{t-1} + b_i)] \tag{4}$$

Forget gate: The gate analyses what and how much information may be retained from the previous level to pass to the next level. If the information is not required for the next level, the previously stored data is multiplied by a zero vector. In Equation 5, the sigmoid function is applied to the current and previous states of the weighted input of the forget gate with bias.

$$f_t = \text{sigmoid}\ [(W_{xf}x_t + W_{hf}h_{t-1} + b_f)] \tag{5}$$

Output gate: Equation 6 defines the output at each level.

$$O_t = \text{sigmoid}\ [(W_{xo}x_t + W_{ho}h_{t-1} + b_o)] \tag{6}$$

Cell state: This is a memory of LSTM, which provides the output to the next level. In Equation 7, content of memory cell is updated as a product of internal memory.

$$c_t = f_t \odot c_{t-1} + i_t + \tilde{c} \tag{7}$$

where $\odot$ represents elementwise multiplication and new content of memory cell state is obtained in Equation 8.

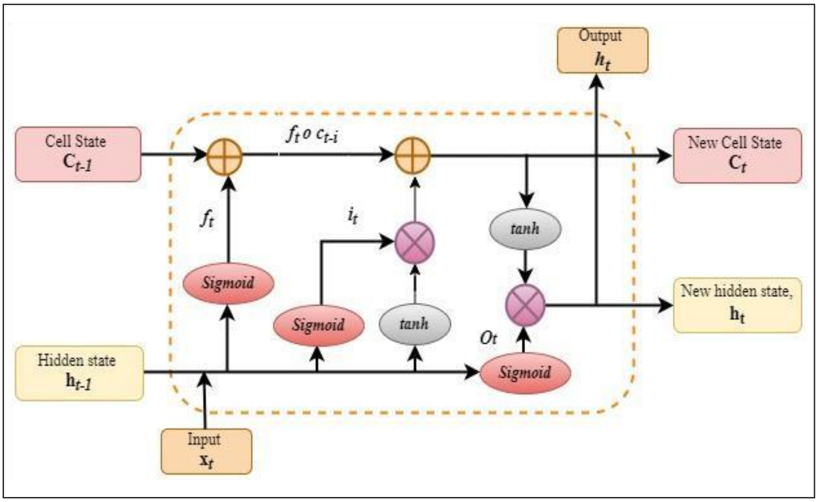
$$\tilde{C}_t = tanh[(W_{xc}x_t + W_{hc}h_{t-1} + b_c)] \tag{8}$$

Hidden state: This state is obtained by element-wise multiplication of the sigmoid layer and the *tanh* layer as per Equation 9.

$$\mathbf{h_t} = \mathbf{O_t} \odot \mathbf{tanh}\ (\mathbf{c_t}) \tag{9}$$

Figure 5

The Detailed Architecture of an LSTM Cell (Bengio et al., 1994)



Gated Recurrent Unit (GRU)

The GRU is a simplified structure of LSTM without explicit memory cell states. Introduced by Chung et al. (2014), GRU provides the solution for the vanishing gradient problem with a standardised RNN. The GRU uses the update and reset gates. It does not have separate internal memory. How much of the hidden state information to carry over to the next timestamp from previous timestamps is decided by the initial reset gate, while the update gate determines which data is supplied to the output (Laureys et al., 2015). Different gate-variants of GRU are also discussed with changes in gate mechanisms (Dey & Salem, 2017).

Reset gate: The reset gate r_t determines the quantity of past information to forget. The equation is as same as the update gate, but the difference lies in the weights and implementation of the gate. For example, in Equation 10, two inputs x_t and h_{t-1} are multiplied by their weights, and after point-to-point addition, the information is forwarded to the sigmoid function (Chung et al., 2014):

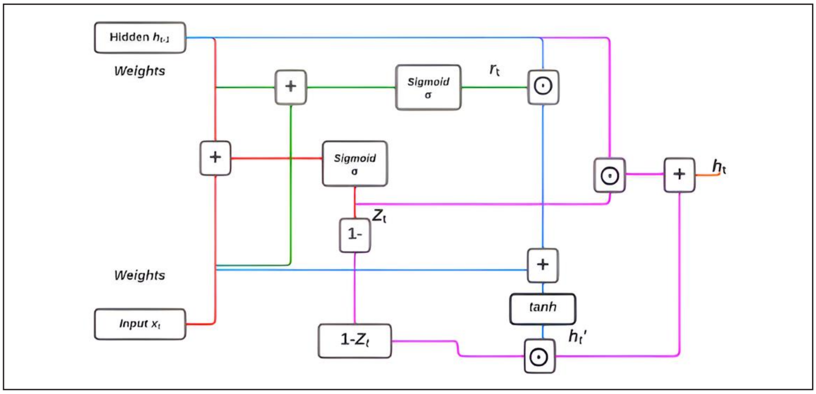
$$\mathrm{r_t} = \mathrm{sigmoid}\ (\mathrm{W_r}[\mathrm{h_{t-1}}, \mathrm{x_t}]) \tag{10}$$

Update gate: This gate is responsible for determining how much information is required to supply the next state (Wang et al., 2019). In Equation 11, update gate $z_{t,}$ where the current input x_t and output from the previous level/unit h_{t-1} are multiplied by the weight $W_{z,}$ and after the addition, the output lies between 0 and 1 by using the sigmoid function. Figure 6 explains the detailed structure of the GRU.

$$z_t = sigmoid\ (W_z[h_{t-1}, x_t]) \tag{11}$$

Figure 6

An Illustration of GRU's Detailed Architecture



h_t' is a new memory content that uses the reset gate to store the past relevant information. This can be seen in Equation 12, where x_t is multiplied by weight *W* and r_t is multiplied by h_{t-1} element-wise Hadamard product. An activation function, *tanh*, is applied to the summation. h_t is the memory unit in GRU, which stores the final information to pass down to the network.

$$h_t j = \tanh[W(r_t \odot h_{t-1}, x_t)] \tag{12}$$

h_t is the hidden-layer vector that stores the information for the current unit and passes this to the network. The update gate decides how much information is needed to collect from the current $h_t j$ and the previous memory content, h_{t-1}.In Equation 13, the element-wise multiplication of the update gate z_t and h_{t-1} is performed. Then, the element-wise multiplication of (1- z_t) and $h_t j$ and the summation of both provides h_t.

$$h_t = (z_t \odot h_{t-1}) \tag{13}$$

In Equation 14, is the predicted output of GRU at time t, where W and b represent weight and bias.

$$y_t = sigmoid\ (W_o \odot h_t + b) \tag{14}$$

Algorithm 1 outlines the steps involved in the GRU process.

Algorithm 1

The Pseudo-Code of a Gated Recurrent Unit

Algorithm 1: Gated Recurrent Unit

Input: EEG Data Set

Output: Class Label: (1) *Epileptic Seizure* or (2) *Normal Seizure*.

Begin

For each (EEG signal) input *x* at time *t*:

Do

Reset gate $r_t = \sigma(W_r.[h_{t-1}, x_t])$*# Determines how much of the past information needs to forget.*

Update gate $z_t = \sigma(W_z.[h_{t-1}, x_t])$*# How much information is required to supply for the next level.*

Current memory $h_{t'} = tanh\ tanh\ (W.[r_t \odot h_{t-1}, x_t])$ *# Stores the past information.*

Hidden-layer vector $h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h_{t'}$ *# Stores the information for the current unit.*

Output $y_t = \sigma(W_0 \odot h_t)$

End for

Output: Apply ***SoftMax*** function on yt to find the label for the class.

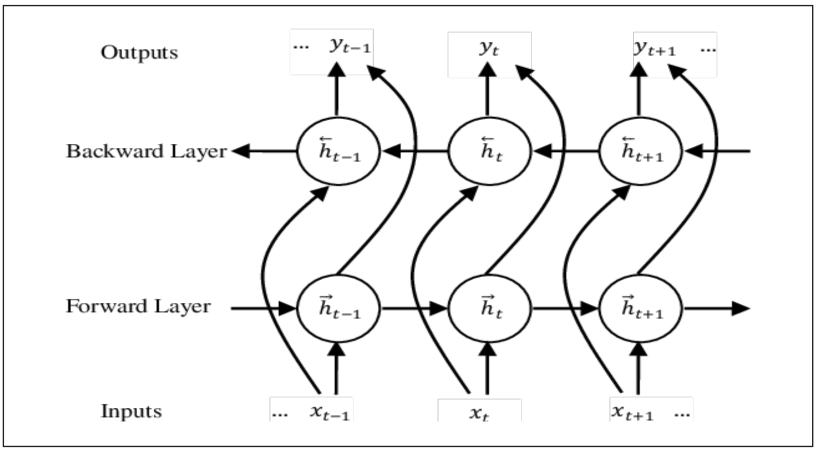
Bidirectional LSTM (BLSTM)

BLSTM is used to learn the internal relationship of the whole sequence of data. While the LSTM neural network can only process historical information for forward propagation to get a future prediction, the

BLSTM network can extract the relationship of the whole data sequence from both directions (Mousa & Schuller, 2016). The author utilises Gaussian filtering, downsampling, and Fourier transform to remove redundant information, extracting high-dimensional features, and combining sequence information with a Gate Recurrent Unit (GRU) for improved model detection accuracy (Li et al., 2023). Figure 7 explains BLSTM, where the input layer is connected with both the backward and forward LSTM layers, and to obtain the final output, both layers' outputs are combined. Through this, historical and future information are integrated (Mousa & Schuller, 2016).

Figure 7

The Basic Architecture of BLSTM



Bidirectional GRU (Bi-GRU)

Unidirectional GRU allows learning only from past information supplied through the input layer. It only preserves the information obtained from previous time steps. In some cases, to better understand the context and eliminate the ambiguity that occurred due to learning only one-way future context information is also required. BGRU provides information from two directions: from previous time steps to future time steps and from future time steps to last time steps. Using this, BGRU can preserve information from the past and future and help to understand the context in a better way (Tran et al., 2019).

THE Proposed Modified-GRU approach

The paper presents a modified GRU-based strategy for dealing with multivariate time-series imaging records that address slow convergence and occasional knowledge of performance. The improved update gate z_t of the GRU neural network is implemented in the proposed model. The output of the reset gate is utilised to adjust the update gate. Due to this, the irrelevant information contained in the reset gate is decreased, resulting in a larger volume and faster convergence. At time t, update the gates, reset them, and compute the output through the proposed Equations 15 to 19.

$$r_t = sigmoid\,[W_r(h_{t-1}, x_t)] \tag{15}$$

$$z_t = sigmoid\,[W_z(h_{t-1}, r_t)] \tag{16}$$

$$h_t j = tanh\,[W(r * h_{t-1}, x_t)] \tag{17}$$

$$h_t = (1 - z_t) * \ [h_{t-1} + z_t * h_t j] \tag{18}$$

$$y_t = sigmoid\,(W_o * h_t) \tag{19}$$

The proposed modified-GRU approach is explained in Algorithm 2.

Algorithm 2

The Pseudo-Code of a Modified Gated Recurrent Unit for Seizure Classification

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Algorithm 2: Modified-GRU

Input: EEG Data Set
Output: Class Label: (1) *Epileptic Seizure* or (2) *Normal Seizure*

Begin

Step 1. **Modified GRU Initialization**
i. Let x_1, x_2, …. x_n be the input sequence.
ii. Let t be the time sequence.
iii. Let r_t and z_t be the reset gate and update gate at time sequence i.

(continued)

Algorithm 2: Modified-GRU

Step 2. **Create Modified GRU model**

i. Add hidden layers (Modified GRU layers) in the network

Step 3. **Train and validate the results of model**

i. Compute the reset gate r_t: $r_t = \sigma(W_r . [h_{t-1}, x_t])$

ii. Compute the update gate z_t: $z_t = \sigma(W_z . [h_{t-1}, x_t * r_t])$

iii. Compute the candidate state: $h_{t'} = tan\,h\,(W . [r_t * h_{t-1}, x_t])$

iv. **while** stopping criteria did not match do

v. **while** training for all instances do

vi. Prepare a mini batch feature set as model input.

vii. Calculate categorical cross entropy loss function.

viii. Update weights

ix. **end** while

x. **end** while

Step 4. Test model

Step 5. Return evaluated results

End

EXPERIMENTAL STUDY

This section examines the features of the dataset used to implement the suggested Modified GRU approach and evaluates the model's performance in comparison to other existing approaches on the UCI EEG dataset.

Dataset Description

The experiments are conducted on an epileptic seizure recognition dataset that has been retrieved from a publicly available database of the UCI machine learning repository, and its description is detailed by Andrzejak et al. (2001). The dataset is a pre-processed and re-structured version featuring epileptic seizure detection. Five target classes of patients are shown in Table 2. Each subset class includes 100 single-channel EEG segments with a duration of 23.6 seconds.

Table 2

The EEG UCI Epileptic Dataset Class Description

Classes	Class description	Patient state	No of cases
5	Eyes opened	Healthy	2,300
4	Eyes closed	Healthy	2,300
3	EEG data recorded from a healthy brain area	Partial Epilepsy	2,300
2	EEG data from identified a tumour-located area	Partial Epilepsy	2,300
1	EEG data during Seizure activity	Epilepsy with seizure	2,300

The data set is divided into five classes. Class 1 represents seizure activity, whereas class 2 helps in identifying the tumour in the brain. Class 3 denotes the healthy brain area except for the tumour region, while class 4 denotes the closed eye and class 5 denotes the open eyes. All the subjects falling in classes 2, 3, 4, and 5 are non-epileptic, whereas the subjects in class 1 are epileptic.

The EEG dataset was recorded by a 128-channel amplifier system having an average common reference. The whole dataset comprises 11,500 instances with 179 feature attributes, of which 178 variables are called the explanatory variables as explained in Table 3, whereas the last column indicates the target class variable labelled as y = {0,1}, where

0- No seizure activity is recorded
1- Seizure activity is recorded

Table 3

The Features Description of the UCI Dataset

Attributes	Description
X1 to X178	Explanatory variables that contain the features of patient data with ranging values from -1415 to 2047.
X179	It is the response variable *y* having values 0 and 1. 0 indicates no seizure activity, whereas 1 indicates the presence of seizure activity.

Experimental Setup

The results are compared with existing neural network models to determine the proposed model's accuracy. The experiment was conducted on a computer powered by an 11th Gen Intel(R) Core (TM) i7-11370H @ 3.30 GHz with 16 GB RAM for data processing. An open-source machine learning library, SciKit-learn, in the Python programming language is used. Jupyter Notebook, an open-source web application, is utilised to develop and share results for coding, visualisation of results, and narrated text.

Training of Modified-GRU

The proposed model is trained using default values to assign the weights of hidden layers and fully connected layers in stateful mode. The internal memory state for each GRU unit is initialised to 0. The GRU value is also set to 0, and the model is trained using the Adam optimiser. The learning rate of the proposed model is 0.001 with 20 epochs using k-fold cross-validation. Due to the abundance of features in datasets and the presence of some duplicate data, model fitting for neural networks will be hindered and take a lot of time. As a result, the datasets need to be pre-processed, which includes dimensionality reduction, cleaning, and normalisation. Following pre-processing, the first 80% of each dataset is used as the training set, while the remaining 20% is used as the verification set.

Evaluation Measures

The results obtained with NN models are compared with each other in terms of some performance evaluation metrics such as Precision, Accuracy, Recall, and F1 score. These metrics are calculated based on the confusion matrix, as explained in Table 4.

Table 4

A Confusion Matrix

		Predicted Class	
		Seizure	**Normal**
Actual Class	**Seizure**	True Positive (TP)	False Negative (FN)
	Normal	False Positive (FP)	True Negative (TN)

In the study, the parameters were extensively used for evaluating the performance of the proposed approach. The comparative study of performance is evaluated by the following measures in Equations 20 to 23.

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \tag{20}$$

Accuracy defines the ratio of correctly classified samples to total samples. TP and FN represent the number of correctly classified and incorrectly classified seizure recognition tasks, respectively. TN represents the number of seizure predictions not belonging to a given class and not classified in this class, whereas FP represents an incorrect classification of seizure recognition.

$$Precision = \frac{TN}{TN+FP} \tag{21}$$

$$Recall = \frac{TP}{TP+FN} \tag{22}$$

Precision and recall are both important for information retrieval, with positive class mattering more than negative. Precision is the ratio of actually positive seizure samples to all predicted positive samples, whereas recall or sensitivity is the ratio of predicted positive to total positive values.

$$F1\ score = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{23}$$

The F1 score represents the harmonic mean of precision and recall that takes into account both false positive and false negative predictions. It is more useful as a seizure and normal subject prediction tool in cases of uneven class distribution.

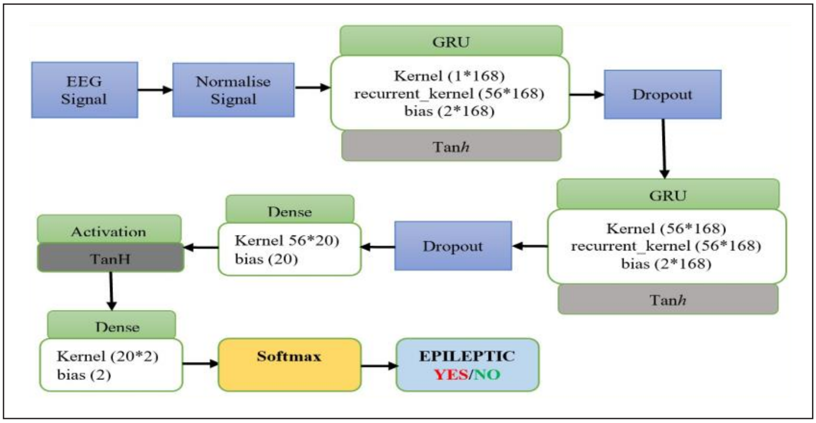
IMPLEMENTATION OF THE PROPOSED MODIFIED GRU

EEG signals are provided as input to the proposed M-GRU approach to detect epileptic seizures. The proposed deep learning-based system goes through normalisation (*ReLU*), a fully connected dropout layer that classifies epileptic seizures automatically. The dropout technique is used to improve generalisation performance and also resolve the overfitting problem.

The proposed model has a convolutional layer (CNN) with a feature map. Firstly, the normalised EEG signal value is first-level GRU, which has a kernel (1*168), recurrent kernel (56*168) and bias (2*168) with *TanH* activation function. Further, at the second level, kernel (56*168), recurrent kernel (56*168), and bias (2*168) with *TanH* activation function. Dropout is applied after the first and second layers of CNN. Here, two fully connected layers are used: kernel (56*20), bias (20), and kernel (20*2), bias (2), respectively. The activation function *TanH* is also applied between both fully connected layers. As a result, it is supplied to the output layer in the softmax classifier. At the end of the process, the system detects the final result, whether the epileptic seizure is present or not. Convolutional and FC layers are learnable to learn low to high-level values from EEG signals. Figure 8 illustrates the functionality of the modified GRU.

Figure 8

The Working Model of the Proposed Modified GRU Approach



Results and Discussion

This section provides a comparative analysis of the results obtained from different neural network models in terms of performance measures. The experiment is performed on a publicly available UCI dataset. The training and testing accuracy results of the existing neural network model are compared with the proposed modified GRU model, as illustrated in Figures 9 and 10.

Figure 9

Training Accuracy of Different DL Approaches on UCI Dataset

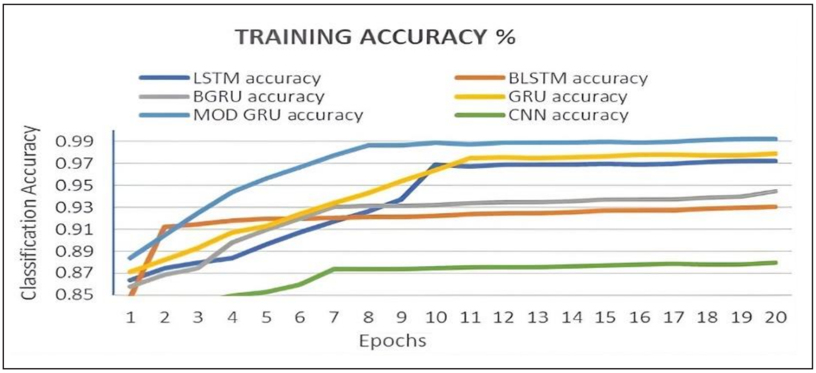
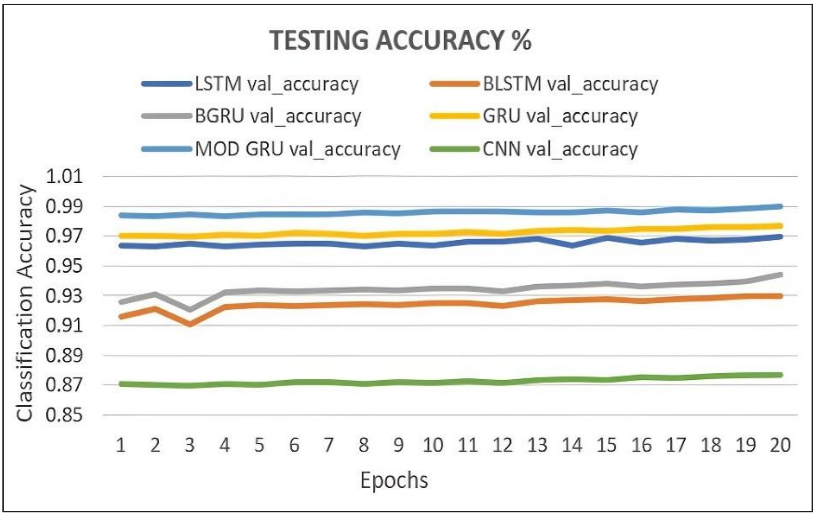


Figure 10

Testing Accuracy of Different DL Approaches on UCI Dataset



The F1 score is more valuable than accuracy based on the harmonic mean of parameters. Here, the F1 score shows nearly similar scores with slight variations. Table 5 illustrates the results of evaluation measures on different NN models. The proposed modified GRU model obtained 97%, the highest among other models, whereas CNN obtained 78%, the lowest. LSTM and GRU show scores of 95% and 95.4%, respectively. On the other hand, in the case of BLSTM and BGRU, BGRU was 0.7% more than BLSTM, whereas BLSTM was 93.5%. The recall percentage of the models shows slight variations; all the models occupy a percentage above 74%, which is the lowest proposed by the CNN model. An increasing trend is observed in the graph and the series of models, with 94.1%, 94.2%, 95.8%, 95.9%, and 97.1% for BGRU, BLSTM, LSTM, GRU, and proposed modified GRU, respectively. The graph for the models with different percentages explains the accuracy percentile, as shown in Figure 11. The maximum percentage is 98.8%, the highest for the modified GRU. The LSTM and GRU models are the ones in which the allocation is varied by 0.8%, where the LSTM model is 96.8% and the GRU model is 97.7%. Therefore, the BGRU model shows 1.4% more than the BLSTM model, holding 93%.

Figure 11

The Training and Testing Accuracy of Each Approach on the UCI Epilepsy Dataset

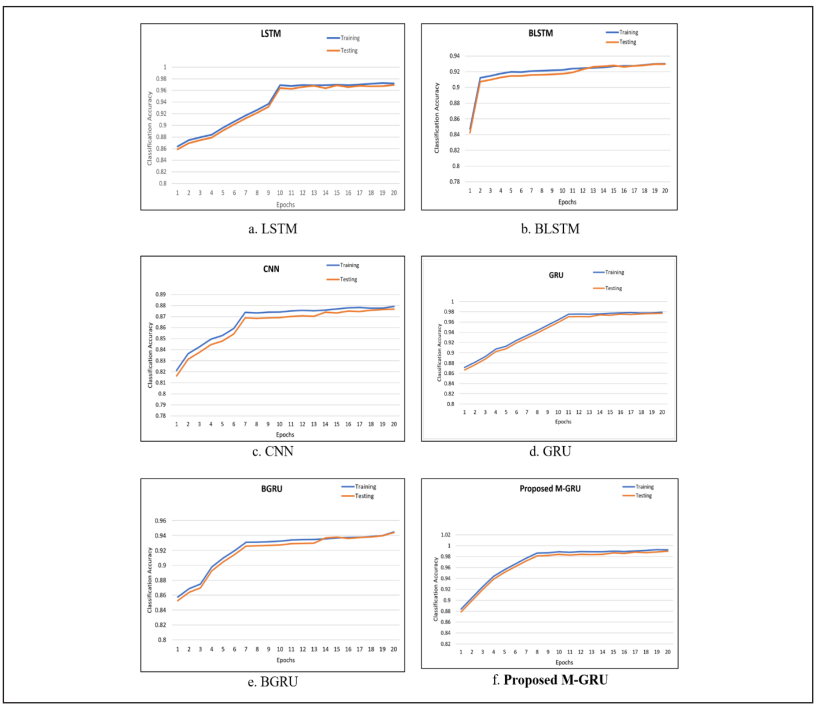


Table 5

Performance Metrics Achieved by Existing DL Methods

Model	*Precision*	*Recall*	*F1 Score*	*Accuracy*
CNN	95	74	78	88
LSTM	94.7	95.8	94.9	96.8
GRU	95.5	95.9	95.4	97.6
BLSTM	94.1	94.2	93.5	93.0
BGRU	95.2	94.1	94.2	94.4
Proposed M-GRU	96.9	97.1	97	98.84

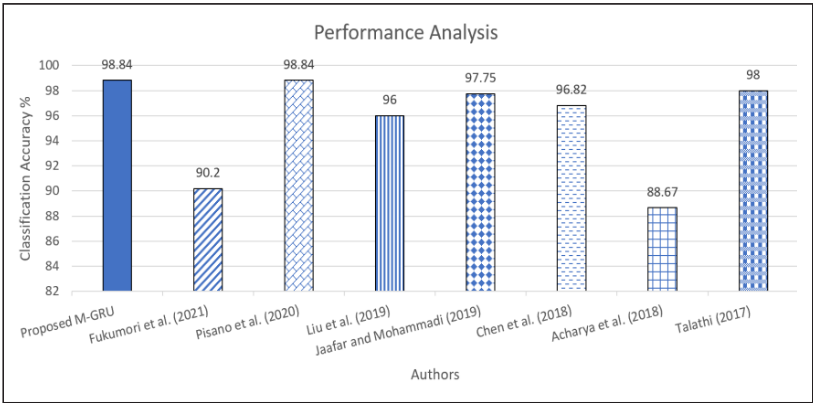
In conclusion, the CNN model shows the lowest recall percentage, F1 score, and accuracy of the other models. However, looking at the other models, the LSTM and GRU models show approximately similar percentages, nowhere less than 94%. BLSTM and BGRU are similar cases; they obtained about the same percentage of not less than 95%. However, modified GRU is the only approach that depicts the highest percentage in all conditions, whether precision, recall, or F1 score percentage. Moreover, its percentage remained the highest throughout the data on accuracy. Therefore, it is the most recommended one as it does not illustrate a lower percentage than 97%.

A Comparison of the Proposed Modified GRU Method with State-of-the-Art Methods

A comparative analysis of the proposed modified GRU model with existing models by different authors is provided in Figure 12. The proposed method classification results show an accuracy of 98.84%. Fukumori et al. (2021) claimed an accuracy of 90.2% with a neural network method, RNN. Pisano et al. (2020) achieved 98.84% accuracy with CNN. Liu et al. (2019) designed a model with an accuracy of 96% by using CNN, LSTM, and GRU. Further, Jaafar and Mohammadi (2019) presented an LSTM-based model with 97.75% accuracy. Two other models, 1D-CNN, LSTM, and GRU, were proposed by Chen et al. (2018) and Acharya et al. (2018) with 96.82% and 88.67% accuracy, respectively, in CNN. Talathi (2017) observed an accuracy of 98% with the GRU model.

Figure 12

A Comparative Analysis of Existing ML Methods for Seizure Classification with Proposed Modified GRU



CONCLUSION AND FUTURE RESEARCH

Epilepsy is the most common neurological illness, accounting for millions of deaths yearly. The brain neuron activities are captured using EEG, one of the most important tools for detecting epileptic seizures before they occur by capturing changes in EEG signals. Therefore, DL models for automated seizure detection can provide more accurate results in seizure detection and help provide better and on-time medical aids to the patient. The proposed M-GRU approach outperforms existing DL models in terms of various performance measures for predicting epileptic seizures. The effective prediction of epileptic seizures ensures patients a healthy and risk-free life. The model has achieved 98.84% accuracy, 96.9% precision, 97.1% recall, and 97% F1 score on the epileptic seizure dataset collected from the UCI ML repository. Earlier in the study, an accuracy of 98% was attained by Pisano et al. (2020). The proposed model improved accuracy to 98.84% with a reduced gated mechanism. The gated approach is much more efficient in terms of architecture and computational efforts. Thus, the proposed model has proven its competency as an efficient classifier for detecting epileptic seizures.

Some limitations of the study must be noted when analysing the results. In this paper, the proposed experiment has been implemented on the publicly available dataset, i.e., the UCI machine learning repository. The quantity of data and the number of patients might both be raised to improve the research even more. The classifiers would benefit from more data to train on because of the data used in this work. Data from more patients could result in a more thorough detection system due to the variety and variance surrounding epileptic seizures. Further, the experiment can be extended to a real dataset with more attributes and a larger size, especially applicable to brain-computer interface (BCI) applications. In addition, another important element, such as removing artefacts from EEG Epileptic data, could be studied before the data is delivered to the model, as the results with artefact-free data can make a difference.

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