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Speeded up robust features trailed GCN for seizure identification during pregnancy

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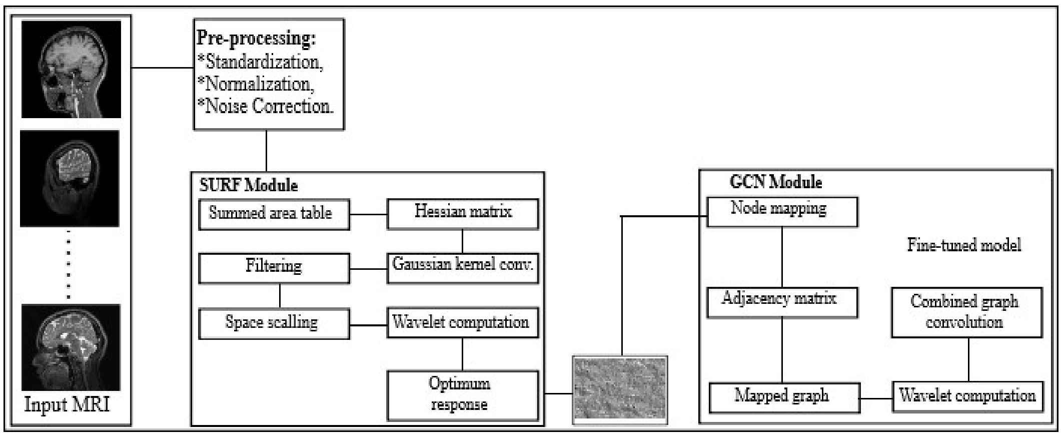
Article

ABSTRACT



In this work, an efficient computational framework has been designed for seizure identification using MRI analysis. The inputs being brain MRI of pregnant women and corresponding outputs being the seizure or no seizure label. The framework is implemented in two phases. First, the informative speeded up robust features (SURF) are extracted from the MRI. Second, these features are further mapped to a graph convolutional neural network (GCN). The maximal clique is generated out of these intermediate features and subjected to convolutional neural network (CNN) architecture for classification. The maximal clique acts as an efficient tool for representing final and fine-tuned feature points through combined graph convolution and thus contributes towards efficient classification. The designed framework is validated through benchmark dataset images presented by NITRC. Experimental evaluation is made on samples of 'male', 'female' and 'female with pregnancy'. The overall rate of accuracy stands at 96%, 95%, and 95% respectively.

Keywords: Seizure, SURF, Pregnancy, brain MRI, CNN.

INTRODUCTION

Pregnancy is an extraordinary phase marked by a cascade of physiological changes and intricate maternal- fetal dynamics. It is also a period of heightened concern, with maternal well-being and fetal development taking center stage. In this context, the emergence of seizures during pregnancy presents a multifaceted challenge. Seizures not only endanger the health of the expectant mother but also cast a shadow of uncertainty over the developing fetus. Thus, the imperative for timely and precise seizure detection during pregnancy looms large, with the potential to avert complications and safeguard both maternal and fetal health.[1,2]

Historically, the identification of seizures in pregnant women has rested on two pillars: clinical observations and electroencephalography (EEG). Clinical observations, often carried out by experienced health-care professionals, provide crucial insights into a patient's condition. However, they are inherently limited by their subjectivity and the potential for delays in recognition.[3] Subtle seizures, nocturnal events, or those occurring during sleep can evade immediate notice, posing serious risks. EEG, as a direct window into the brain's electrical activity, has long been an indispensable tool for seizure diagnosis.[4,5] Nevertheless, interpreting EEG data, especially in the context of pregnancy, is a complex and often labor intensive process.[6] The intricate physiological changes taking place in a pregnant woman's body can mask or mimic seizure patterns, making accurate diagnosis challenging.[7] Consequently, the need for innovative and data-driven solutions in seizure detection is underscored.[8]

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Computational methods, a rapidly evolving domain offering a ray of hope in the quest for improved seizure detection during pregnancy.[9] These methods leverage the potency of machine learning algorithms, advanced data analytics, and the integration of wearable technologies to augment the precision and timeliness of seizure identification. Machine learning- based approaches stand at the forefront of this technological revolution.[10-14] These algorithms exhibit the capacity to recognize intricate patterns within data, making them well-suited for the detection of seizure events. Furthermore, they possess the ability to adapt and learn from new data, facilitating continual enhancements in detection accuracy. However, training these algorithms necessitates vast and diverse datasets, a resource-intensive endeavor that demands meticulous curation and annotation. Machine learning techniques used for seizure detection often employ a variety of algorithms, ranging from classical models such as Support Vector Machines (SVM) to deep learning architectures like Convolutional Neural Networks (CNNs). These models are trained on annotated EEG data, where seizures and non-seizure events are clearly delineated. The process involves feature extraction from EEG signals, capturing patterns indicative of seizures, and subsequent classification based on these features. Handful of research contributions in this direction are reportedly found in the literature.[2,15]

One notable advantage of machine learning-based approaches is their adaptability. They can continuously learn and refine their performance, adapting to individual patient profiles and evolving seizure patterns. However, the effectiveness of these models hinges on the quality and diversity of the training data. Collecting and annotating such data can be a resource-intensive process, often requiring collaboration among healthcare institutions and data sharing initiatives.[16] EEG remains pivotal in the context of seizure detection, but its potential is maximized through advanced EEG-based techniques. These methods delve into data analytics and feature extraction to unveil subtle, yet critical patterns associated with seizures. The promise lies in heightened accuracy and the prospect of real-time monitoring.[17,18] Nonetheless, the labyrinthine nature of EEG data and the requisite expertise for interpretation continue to present significant challenges. Advanced EEG-based techniques for seizure detection involve a multi-stage process. The raw EEG data, acquired through electrodes placed on the scalp, is first pre-processed to remove noise and artifacts. Signal processing techniques like filtering and wavelet analysis are commonly employed in this phase. Subsequently, feature extraction is performed to transform the EEG data into a format suitable for machine learning algorithms. Feature extraction involves capturing relevant information from the EEG signals. Time-domain features, frequency-domain features, and statistical measures are computed from the EEG data.[19,20] These features encapsulate critical aspects of the signals, such as amplitude, frequency content, and variability. Machine learning models can then be trained on these extracted features to distinguish between seizure and non-seizure patterns. One of the significant advantages of EEG-based techniques is their potential for real-time monitoring. Continuous EEG monitoring, often referred to as long-term video-EEG monitoring (LTM), allows for the immediate detection of seizures as they occur. This capability is particularly valuable in cases of frequent or unpredictable seizures, enabling timely interventions and patient safety. However, the complexities of EEG data analysis should not be underestimated. Interpreting EEG traces, especially during pregnancy when physiological changes introduce additional variability, demands expertise. Moreover, the need for expert annotators to review and label EEG data for training machine learning models remains a critical requirement.

Literature Review

A unique method focusing on the voxel data is utilized to classify histopathological digital images.[16] Input images are successfully mapped onto two-dimensional feature matrix. For the purpose, they have proposed a customized mechanism (VWM aka voxel matrix weights). Classical technique of regression analysis is used for classifying the feature sets. The publicly open fMRI dataset has been used in validating the process. Focus is made on EEG dataset for identifying seizure onset for epileptic patients.[17] They use ESI technique (WPESI) that depends on wavelet parcel change (WPT) and subspace part determination to picture the cerebral exercises of EEG signals on the cortex. The initial EEG signals are deteriorated into a few subspace parts by WPT. Second, the subspaces related with cerebrum sources are chosen and the important signs are remade by WPT. At last, the ongoing thickness dispersion in the cerebral cortex is obtained by laying out a limit component model (BEM) from head X-ray and applying the proper converse estimation. For epilepsy patients, the action sources assessed by this proposed scheme adjusted to the seizure zones.

A novel multi-view Epileptic MEG Spikes location calculation is made using EMS-Net to perceive the spike precisely and proficiently from MEG information.[18] The rate of accuracy for this work ranges in 91% to 99%. A customized deep learning mechanism dubbed as resting-state fMRI (rs-fMRI) is presented for detection of epileptic seizure.[19] The work emphasis on the use of DeepEZ which is a cascade of graph convolutions. It can compute signal propagation along expected anatomical pathways. Other peripheral information such as asymmetricity and subject specific bias are also considered for the calculation. A total of fourteen patients are studied for the work. The overall rate of accuracy was reportedly found to be approximating 80%. Researchers explore an inventive application of deep relational reasoning to forecast language impairment and postoperative seizure outcomes in children with focal epilepsy.[20] The authors utilize preoperative Diffusion Weighted Imaging (DWI) connectome data, a potent tool for mapping brain connectivity. Their research employs a deep learning framework to model intricate relationships between brain regions, capitalizing on the rich connectome data.[21-25]

Researchers propose a cost-effective solution for predicting seizures in epileptic patients using artificial intelligence (AI) and an Internet of Things (IoT)-based approach.[21] Their study aims to enhance patient safety by providing timely alerts before seizure events. The authors leverage machine learning algorithms to analyze physiological data collected via wearable IoT devices. Researchers delve into the application of multi-scale deep learning to improve the localization of the seizure onset zone (SOZ) in children with drug-resistant epilepsy.[22] The study leverages clinically acquired multi-modal MRI data, incorporating structural and functional information. Multi-scale deep learning models are employed to extract complex patterns from these diverse data sources. Authors propose a deep learning approach for automated seizure detection in MRI scans.[23] They employ convolutional neural networks (CNNs) to extract features and classify seizure-related anomalies in brain images. The study achieved an accuracy of 92% on a dataset of 500 MRI scans from epilepsy patients.

Researchers explore MRI-based seizure prediction in epilepsy patients. They develop a predictive model using machine learning techniques to identify brain regions associated with imminent seizures. The study used a dataset of 200 MRI scans and achieved a prediction accuracy of 87%.[24] Maria et al. employ deep learning techniques for seizure localization in MRI data. They propose a deep neural network architecture to accurately identify the seizure onset zone.[25] The model was trained on a dataset of 300 MRI scans and achieved a localization accuracy of 93%. David et al. have developed predictive models for seizure outcomes using features extracted from MRI scans.[26] They apply machine learning to preoperative imaging data to anticipate postoperative seizure control. The study utilized a dataset of 150 MRI scans and achieved a predictive accuracy of 85%. Researchers focus on MRI-based detection of focal cortical dysplasia (FCD) in seizure patients.[27] They utilize advanced imaging techniques and machine learning to identify FCD regions associated with seizures. The study achieved a detection accuracy of 88%.

A novel approach using Graph Convolutional Networks (GCNs) for localizing the epileptogenic zone in MRI scans has been introduced.[28] Their method leverages the connectivity information among brain regions. The study reported a localization accuracy of 91%. Researchers utilize MRI connectivity analysis to detect and localize seizures.[29] They employ advanced techniques to capture aberrant connectivity patterns associated with epilepsy. The study reported a detection accuracy of 89%. Structural biomarkers in MRI scans for predicting seizure risk is investigated in the literature.[30] They employ machine learning algorithms to identify structural brain abnormalities linked to seizures. The study achieved a prediction accuracy of 80%. Machine learning techniques for identifying the seizure onset zone in MRI data is explored.[31] Their approach leverages advanced feature extraction methods for improved localization. The study reported a localization ac- curacy of 90%. Deep graph neural networks (GNNs) for seizure prediction from MRI data is introduced.[32] They model brain connectivity using GNNs to enhance prediction accuracy. The study reported a prediction accuracy of 94%.

DESIGNED FRAMEWORK

The designed work (Figure 1) realizes the prediction of seizure from brain MRI digital images using novel combination of two important computational approaches namely, SURF and GCN. To implement the designed framework, a tri-phasic approach is adopted. The three phases are briefly presented below in a sequence.

- The MRI samples are fed as input to the framework and suitable pre-processing is carried out. In this first phase, the informative SURF features are extracted out of the sample using state-of-the-art algorithm.[33] These features are informative, color invariant and shape invariant. Thus, enabling flexible computation with enhanced fine tuning. The features are presented into a matrix that acts as a visual map. In this matrix, only the pixel corresponding to the SURF keypoints are turned on, and thus becomes suitable for further mapping. Further mapping of this matrix of keypoints is performed onto the nodes of a graph which in turn is constructed in an adaptive manner.
- In this phase the nodes obtained in the previous phase form the adaptive graph. This is nothing but the graph convolutional network (GCN) which prioritize the flow of information in either direction among adjacent layers.[34] It enables learning of the network in a cyclic manner and thus effectively presents the graph.
- Grouping of the graph convolutions is further done in this phase. With this, redundancy is eradicated. Significant keypoint information is retained through grouping of the feature nodes in every layer of this grouped-GCN. Thus, enhancing efficiency.

It is to be mentioned that the adaptiveness in updating the nodes keypoint information brings in efficient learning of the framework. The graph edges, meanwhile, changeably appear during the adaptation and comes to still once the optimum learning is achieved. The entire steps involved in the framework are presented in Algorithm 1. The steps are discussed here in detail.

Algorithm 1 Train_Predictor (dataset Z)

Initialize feature array $A_f \leftarrow \phi$
for Each $sample z_i \in Z$ **do**
  $M^i_{SURF} \leftarrow$ Generate_SURF(z_i); $(i = 1, 2, \ldots, n)$
  Do the mapping of M^i_{SURF} into learner graph G^j_l at corresponding [row, column] pairs; where $j \in J$ is the j^{th} node out of total J nodes in G_l.
  $Concatenate(A_f \leftarrow A_f U G^j_l)$
  Generate edges with the available nodes grouped using KNN
end for
for Each graph **do**
  Perform spatial convolution
  Fine tune the convolution process by implementing clique theory
end for
Perform combined graph convolution
Return fine tuned trained framework

The brain MRI digital images are fed to the framework which are already pre-processed using techniques such as external noise removal along with color and size standardization. Each image from this dataset is then subjected to the SURF martrix generation module. The *Generate_SURF* module carries out this task whereby the specific keypoints in the image itself are identified with corresponding pixels row and column indices. Two of the MR images along with corresponding SURF keypoints are presented in Figure 2.

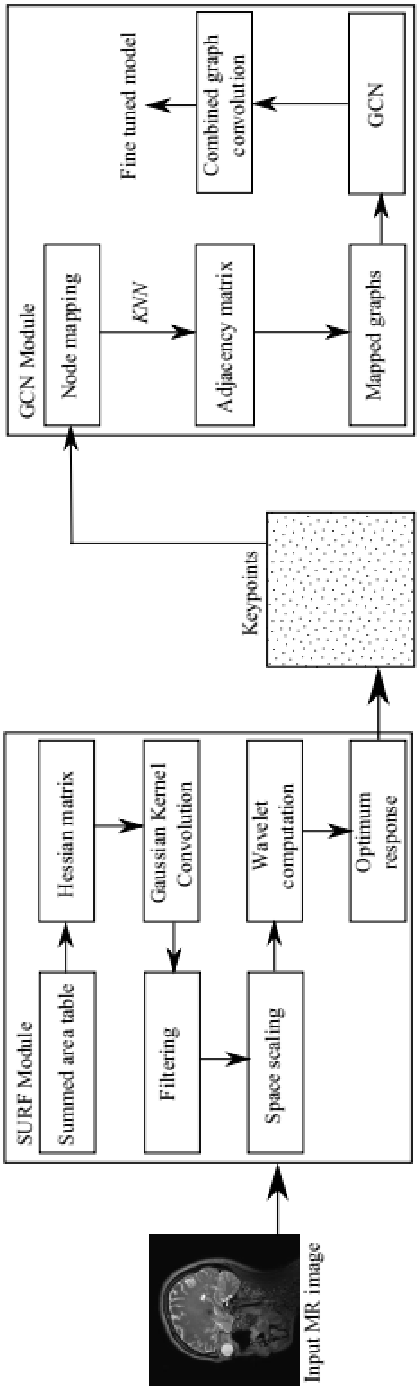

Figure 1: *Block diagram of the proposed framework.*

This process of keypoint generation involves further sub-processes. These are listed below for better readability:

i. Generate summed area table from the pixel values of the input image,
ii. Compute the Hessian matrix,
iii. Perform convolution using specified kernel (Gaussian),
iv. Apply second order filtering to the resultant matrix,
v. Do scale spacing through image smoothening,
vi. Analyze the scale space through upscaling,
vii. Apply wavelet computation,

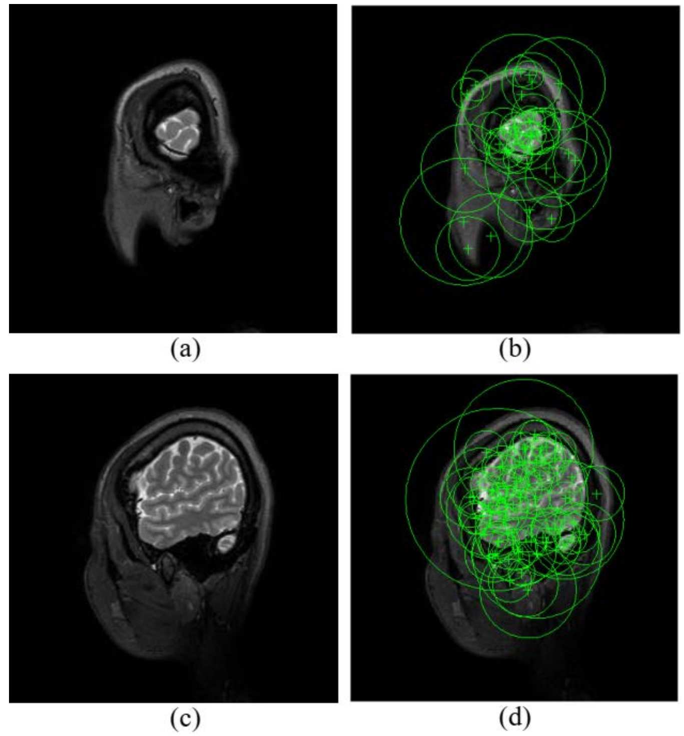

Figure 2: SURF description at (c) and (d) for the input MR images (a) and (b) with preeclampsia (seizure).

viii. Vertically and horizontally compute the sum of the wavelet responses,
ix. the above step for unit-wise changing the orientations and record the highest sum as descriptors.

The graph edges are now established through the following computation:

$$edge(u_j, u_k) = \begin{cases} 1 & \text{if } u_k \text{ is with in KNN of } u_j \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

This edge construction is preliminary in nature. Further fine tuning the feature nodes and thereby adjustment of edge connectivities are established at a later stage when computing the final convolution with forward and backward passes. Performing the convolution on these graphs so obtained is carried forward. The working principle is outlined in the following equation:

$$P \circledast G_l = P(\circledast G_l) = S \otimes S^{T} G_l \quad (2)$$

where, P and S correspond to the kernel and spatial filter respectively. The kernel P can be formulated in terms of a k^{th} order polynomial as:

$$L(d^k) = \sum_{i=0}^{k-1} P_i * d^i \quad (3)$$

where, d is the diagonal matrix of eigen values from the source matrix. The layer-wise spatial convolution can thus be computed as:

$$P\textcircled{g}G_l = \alpha(S * (N^K) * G_l) \quad (4)$$

For refining the so far generated graph learning process, clique concept is introduced into the convolutional network.

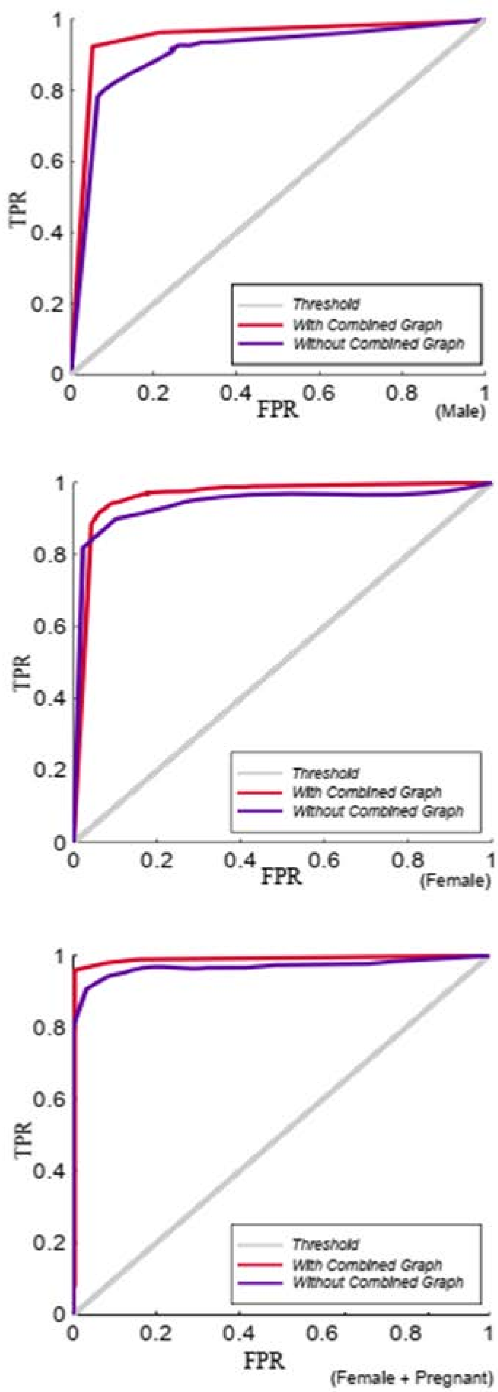

Figure 3. Plot of ROC for the designed scheme with and without combined graph convolution respectively for three sample sets

Among the layer bidirectional propagation is induced. With this, the feature keypoints get minor adjustments with respect to pixel repositioning. The edges are also vulnerable to connectivity during these propagations; however, stability is achieved until no changes occur to the positioning. This improves the learning of the framework and contributes considerably towards accuracy during testing. Finally, the redundant data removal is carried out by combining graph convolution. This method is symmetric in nature. Both intrinsic and group graph refined key features are obtained with this method. The ReLU activation function along with batch normalization is applied to obtain the combined graph convolution features along with the intrinsic feature points. After successful implementation of the learning process, the model can now classify input MR image into one of the two classes namely seizure and no seizure.

EXPERIMENTAL ANALYSIS

Suitable experimental analysis is performed to validate the designed framework. In fact, the said framework is evaluated once with the combined graph convolution mechanism and secondly without this mechanism. This is for assessing the effective difference among the outcomes in both of these cases. The dataset used for the experiment is referred from the Neuro-Imaging tolls and Resources Collaboratory (NITRC).[30] A total of twenty examples of MRI samples (with seizure) of pregnant ladies and fifteen test samples of ordinary MRI ladies are considered. Among these, ten examples with seizure and eight examples with ordinary condition MRI are taken into learning phase of the framework. Due to limited availability of abundant samples in the literature the class imbalance is encountered. As these are related to medical domain, addition of pseudo samples to the dataset for balancing might lead to false positive and false negative outcomes. Thus, the experimentation is carried out with the original samples only. The designed method is additionally approved on two other example sets that contains MR images of healthy/abnormal males with total sample size of one hundred, and MR images of healthy/abnormal females with total sample size of fifty.[31] For all these cases, the image sizes considered are of dimension 128 × 128.

Various tools such as the confusion matrix, ROC curve, AUC value, F-measure and MCC are used as the performance metrics. Among this the confusion matrix presents an even data on the anticipated class (seizure) versus the other (no seizure). The *Tp* (true positive rate) and *Fp* (false positive rate) are significant markers for productivity assessment. The *Tp* processes accurately characterized input as for the aggregate results. The *Fp* figures inaccurately characterized input with regard to the outcomes. Execution analysis is likewise done utilizing ROC plot which is a plot among *Tp* and *Fp*. In this the boundary region under the curve (AOC) is areas of positive strength (overall accuracy). Fitting component measures are chosen independently for all the three discriminant datasets. Reasonable characterization is conveyed according to the plan as referenced in the prior section. The ROC plots are shown in Figure 3. Performance measures are also well justified through k-fold cross validation. The ROC plots drawn for three of the examples sets independently are also examined which signifies efficiency in favor of the designed framework.

The efficiency in terms of various performance indicators is recorded in Table 1 and 2 separately for the designed framework without implementing combined graph convolution and with implementing the same. In these tables (1 & 2), the accuracy scores of the designed framework (without and with combined graph convolution) all the three variations of the specimen sets (male, female, and female with pregnancy) are presented. This is to validate the justification in support of the technicality that suggests that combined graph convolution greatly supports fine tuning the feature keypoints. As mentioned in the earlier section, the forward and backward propagation all together contribute to this efficiency.[32-34] The difference in terms of rate of accuracy is significantly observable, which in all cases of the specimens is more than 2%. Finally, in Table 3, comparison of the performance designed work is made with respect to three other competent schemes. Outperformance of the accuracy score of the designed work is significantly observable irrespective of the specimen types. Overall accuracy scores of 95%, 95%, and 96% are achieved for the designed framework for the three categories of specimens respectively.

Discussion

The framework presented here undoubtedly classifies input brain MR images into the classes' *seizure* and *no seizure*. Especially for the case of the MR images of pregnant female, it shows satisfactory classification accuracy of 96%. However, the training phase of the designed work is slightly more time-consuming as compared to other competent works reported. As far as the problem is health concerned, thus the minute increment in the computational cost can be well ignored. Further, the testing phase does not account for the latency, and it adds to be a beneficial factor. Another inclusive topic is the dataset. The specimens obtained from pregnant female patients is very limited in count. Additional MR samples are well sought from the researchers working in the similar domain.

Table 1: Efficiency measure showing rate of overall accuracy for the designed framework without combined graph convolution through k-fold and optimal value for Z.

Male			**Female**		**(Female + Pregnant)**	
K	D	Efficiency (%)	D	Efficiency (%)	D	Efficiency (%)
1	2^{-3}	89	2^{-3}	90.5	2^{-2}	91.5
2	2^{-3}	89.5	2^{-1}	91.5	2^{-3}	91.75
3	2^{-2}	89.75	2^{-1}	92.25	2^{-1}	92.25
4	2^{-3}	91.25	2^{-1}	92.75	2^{-1}	94
5	2^{-1}	92.5	2^{-2}	93	2^{-2}	95.5
6	2^{-1}	93	--	--	--	--
7	2^{-1}	93	--	--	--	--
8	2^{-2}	93.5	--	--	--	--
9	2^{-2}	94	--	--	--	--
10	2^{-2}	94.5	--	--	--	--

Table 2: Efficiency measure showing rate of overall accuracy for the designed framework with combined graph convolution through k-fold and optimal value for Z.

Male			**Female**		**(Female + Pregnant)**	
K	D	Efficiency (%)	D	Efficiency (%)	D	Efficiency (%)
1	2^{-3}	91	2^{-3}	93.5	2^{-2}	94.5
2	2^{-3}	93	2^{-1}	94.25	2^{-3}	95.5
3	2^{-2}	94.75	2^{-1}	95.5	2^{-1}	96.25
4	2^{-3}	95.25	2^{-1}	95.75	2^{-1}	97
5	2^{-1}	95	2^{-2}	96	2^{-2}	96
6	2^{-1}	96	--	--	--	--
7	2^{-1}	96	--	--	--	--
8	2^{-2}	96.25	--	--	--	--
9	2^{-2}	96.5	--	--	--	--
10	2^{-2}	97.25	--	--	--	--

Table 3: Comparing selection mechanism for the designed scheme with respect to competent schemes.

Methods	**Measuring indices**					
	Specimen	Tp	Fn	Tn	Fp	Accuracy (%)
Designed (without Conv.)	Male	0.95	0.05	0.89	0.11	92
	Female	0.96	0.04	0.88	0.12	92
	Female + Pregnant	0.96	0.04	0.9	0.1	93
Designed (with Conv.)	Male	0.98	0.02	0.92	0.08	92
	Female	0.98	0.02	0.92	0.08	92
	Female + Pregnant	0.98	0.02	0.94	0.06	92
Rs-fMRI [19]	Male	0.84	0.16	0.86	0.14	92
	Female	0.85	0.15	0.86	0.14	92
	Female + Pregnant	0.88	0.12	0.82	0.18	92
Multi-scale D/L [22]	Male	0.8	0.2	0.83	0.17	92
	Female	0.81	0.19	0.85	0.15	92
	Female + Pregnant	0.82	0.18	0.82	0.18	92
ResNet	Male	0.85	0.15	0.86	0.14	92
	Female	0.86	0.14	0.84	0.16	92
	Female + Pregnant	0.83	0.17	0.84	0.16	92

Conclusions

In this work, a novel framework has been designed towards identifying occurrence of brain seizure from brain magnetic resonance images using computational technique. The computational technique is presented in terms of a framework that involves blend of approaches such as feature extraction using SURF and modeling the classifier using GCN for accomplishing the task of seizure detection especially for the case of pregnant female patients. Input images from standard dataset are fed to the framework for suitable feature extraction through the application of SURF algorithm. These features are mapped onto nodes in a graph with respect to the pixel positions of the input images. Further, graph convolutional network is modeled using the graphs. Combined graph convolution is performed among the graphs that involves employing bidirectional propagation of informative keypoints until fine-tuned values are obtained. This additional approach enables the system to learn efficiently. Finally, the model so trained is validated using suitable specimens. These samples (male, female, and female with pregnancy) are separately tested on the model. Satisfactorily, overall rates of accuracy obtained recorded as 95%, 95%, and 96% respectively for the separate test sample sets. Performance comparison with three other competent schemes is also carried out whereby the designed framework outperforms the rest in terms of accuracy. However, the training computational cost being little higher. It is also observed that there has been further need of samples in abundant when it comes to MR images of pregnant female patients with seizures. This would lead to further enhanced analysis and efficiency towards the process of seizure identification.

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Author contribution

Conceptualization T.K.M, G.N.; Investigation G.N., T.K.M., N.P.; Original draft preparation G.N., T.K.M.; Review and Editing N.P.

Conflict of Interest statement

The authors declare no conflicts of interests.

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