EDM: A multiclassification support system to identify seizure type using K Nearest Neighbor

Shiza Shakeel[1], Niha Afzal[1], Gul Hameed Khan[1], Nadeem Ahmad Khan[1], Mujeeb ur Rehman Abid[2], and Muhammad Awais Bin Altaf[1]
Electrical Engineering Department, Lahore University of Management Sciences, Lahore, Pakistan[1]
Department of Neurology, Shalamar Hospital Lahore, Pakistan [2]
awais.altaf@lums.edu.pk

2021 28th IEEE International Conference on Electronics, Circuits, and Systems (ICECS) | 978-1-7281-8281-0/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICECS53924.2021.9665565

Abstract— **Seizure type identification plays a pivotal part in the diagnosis and management of epileptic seizure disorder. Unfortunately, did not get much attention in past decades due to the unavailability of databases with seizure type marking. Seizure types not only assists the neurologist in deciding the correct drug and its dosage but precaution the epileptic patients about the seizure attack and its severity. In the recent past, a significant contribution has been made by applying machine and deep learning algorithms to the binary classification of generalized seizures. This work proposes and implements an early diagnostic and management (EDM) system to assist the neurologist in type identification (5-classes) of the seizure activity at run time and also features an interactive graphical user interface (GUI). In the GUI, temporal, spectral (along with source localization) and spatial plots can be viewed along with the seizure data classified based on its types. The system utilizes a discrete wavelet transform (DWT) and k-nearest neighbour, (KNN) based on feature extraction and classification, respectively. The system is validated using 31 patients' recordings from Temple University Hospital (TUH) EEG Database. Our system achieves a 5-class classification accuracy, sensitivity and specificity of 97.7%, 92.9%, and 98.7%, respectively, for patient-wise cross-validation.**

Keywords— electroencephalogram (EEG), K-nearest neighbour (KNN), multi-classification, seizure detection, seizure types.

I. Introduction

Though significant advancement has been done in the healthcare and computation sector in past decades still the mysteries in diagnostic of chronic neurological disorders (CNDs), such as Autism [1] - [3] , epilepsy [4] - [7], migraine [8], etc., remain unsolved. Approximately >1% (65 million) people are affected by epilepsy [7], which makes it the most common CNDs worldwide [4]. According to the Pakistan Journal of Neurological disorder, the documented percentage of the population affected by epilepsy is around 1.5% and actual figures are way beyond reported ones. Moreover, the neurologist to patient ratio is significantly low in Pakistan (1 per 1.4 million people) [9]. Therefore, there is a dire need to automate the diagnostic and monitoring system for the CNDs to enable the patients at local health facilities to start getting benefits from the technology advancement around us. Even ~30% of epileptic patients have refractory symptoms and requires surgery. The remaining patients, in general, lacks the early diagnostic and monitoring (EDM) support system, as the epileptic seizures are highly customized to a specific individual and is a combination of multiple types. One of the main reasons of an alarming number of people being affected and remain unattended is the limitations of individual profiling. The databases mostly available does not take into account the types of the seizure, which is crucial in its detection and for medication type and its dosage.

Moreover, artificial intelligence (AI) has been utilized significantly in recent times in a lot of biomedical diagnostic systems. AI-based system for epileptic seizures has shown excellent detection results on seizure detection as a binary classification problem. The pain-problem in existing works is, 1) focus on seizure detection as binary classification, 2) complex AI classifier that requires optimization to achieve good results [dependency on support staff], 3) unavailability of electroencephalogram (EEG) data with seizure type information, and 4) the software solutions are not neurologist friendly. Generally, seizures are tracked by an EEG, which involves the recording of the electrical signal from multichannel electrodes separated spatially. Each channel depicts the superposition of the specific localized brain activity. The EEG is measured by placing the probes on the scalp it's called "scalp EEG" whereas when the probes are placed inside the head (surgically) it's called "intracranial EEG".

To aid the neurologists, we aim to develop a system that should fulfil the local requirements, focus on multiple seizure types, be trainable to neurologist's style of diagnosis, and be user friendly to enable/upgrade according to the expert's self-use. The features of this support tool should include analysis, assistance and summarization of the EEG signal for specific CND. A couple of years back, the international league against epilepsy (ILAE) published the revised seizure type classification, shown in Fig. 1. The purpose was to unify the terminologies and make them more descriptive regarding the patient experience. Broadly, the seizure is categorized into two types, i.e., generalized seizure and partial seizure. A generalized seizure is irrespective of the location of the neuron and ideally can be detected from any EEG scalp location. Whereas, the partial seizure is specific to a certain area or location of the scalp and can't be identified from all scalp locations. A generalized seizure is subcategorized further into non-convulsive and convulsive. The convulsive involves the whole body whereas the non-convulsive might include some specific body part that gets affected during the seizure onset.

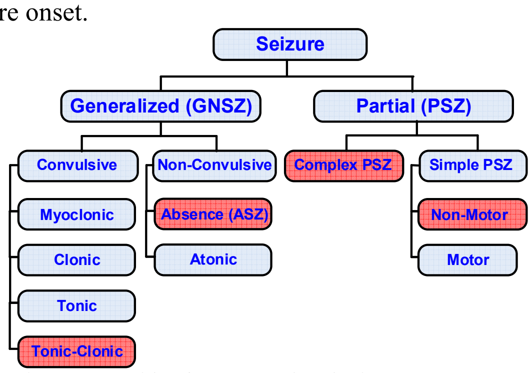

Fig. 1: Seizure types with a focus on analyzed seizure types.

The convulsive includes the tonic-clonic, which are considered to be most fatal as it involves loss of consciousness, muscle jerking, falling on the ground, etc. The other common type is absence seizure (ABSZ), which is common in small children and most of the time is an early symptom for refractory epileptic seizure if remain untreated. In the partial seizure (PSZ) complex PSZ (CPSZ) are the most common and it involves an epileptic person being dazed during the seizure onset and will remain unconscious about his surroundings. The simple PSZ involves non-motor and motor effects during the seizure onset. The non-motor involves emotional distress and mood swings. In the work, we have incorporated the four most common seizure types, i.e., Tonic-Clonic (GNSZ), ABSZ, CPSZ and focal non-specific seizure (FNSZ). In general, seizures arise as the neurons in the brain fire, unwarranted and unrestrained electrical signals are generated. In FNSZ, only specific nerve cells are involved in the firing, and the action of the patient during seizure onset depends on the affected area. In principle, the right side of the brain controls the left side of the body, and vice-versa, and hence the seizure in the specific area will affect the body in the other area.

II. Seizure Database With Multiple Types

In the work, we have utilized the Temple University Hospital (TUH) EEG seizure database [10], that is the largest publicly available EEG dataset which includes the type of seizure information and the timestamp of each seizure event. The database contains overall eight (8) different type of seizures, i.e., FNSZ, GNSZ, simple PSZ (SPSZ), CPSZ, ABSZ, tonic seizure (TNSZ), tonic clonic seizure (TCSZ), and myoclonic seizure (MYSZ). The data was released on Oct. 2018 with a revised release on 2020 having total of 3050 seizure events. We included 4 types in this study (shown in Fig. 2), which are considered most common among the patients, therefore, it makes a 5-class seizure classification.

Fig. 3 shows the EEG pattern of seizure types used in this study. The plot shows the seizure patten for all four types, i.e., ABSZ, FNSZ, GNSZ, and CPSZ. Its apparent the seizure pattern is different for each type and the profiling based on seizure type is very much important in both diagnosis and management of the epileptic patients.

Ref [11], [12] identifies two types of seizure detection algorithms. The first is a “seizure onset detector” which recognizes a seizure with a very small latency but with a midcore accuracy. Such a system can be useful for seizure prediction where early warning can help to mitigate the harmful effects. Whereas, the second type of algorithm is a

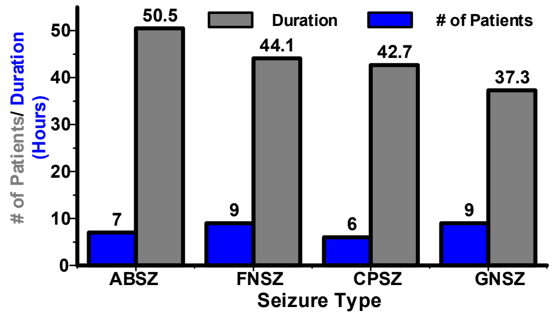

Fig. 2: Measurement showing the working of the implemented system.

seizure event detector which detects a seizure accurately but with a delay. This type of algorithm is especially useful for neurologists. Since they can check the number of occurrences, type and severity of the seizure to prescribe essential medication.

The focus of the presented work is more towards the seizure event detection approach but targeting multiple seizure types and reducing the complications involved during the processing. In the last 2-3 years, there is some focus on types of seizure identification.

Ref [11] evaluated the big amount of EEG data to cater for the performance of multiple classifiers using the TUH database. They utilized a leave-one-out approach to enhance the training data and find accuracies using a gradient boost classifier for multiclassification. The GNSZ showed good classification accuracy compared to the FSHSZ, and the implemented system was a 3-class classification. The achieved classification accuracy was 89.2% but was limited to fewer seizure types. Ref [7] adapted multi-class seizure classification while utilizing multiple classifiers and reported gradient boosted as the optimal choice, but the average accuracy was in the mediocre range (~80%).

III. Proposed Multi Classification Algorithm

The proposed multi-class seizure classification system is shown in Fig. 4. The data is loaded in the system along with initially marked labels for the prior unknown data in the learning phase. After preprocessing, features are extracted based on discrete wavelet transform (DWT), since incoming EEG data is non-stationary. Overall “22” features are extracted and they are reduced to “10” using the feature selection method by incorporating the principal component analysis (PCA) technique. The extracted and selected features are used to train the multi-classifier K Nearest Neighbor (KNN), and during the validation stage, the same selected features are utilized to compute the performance and evaluate the seizure type and location at run time. To assist the

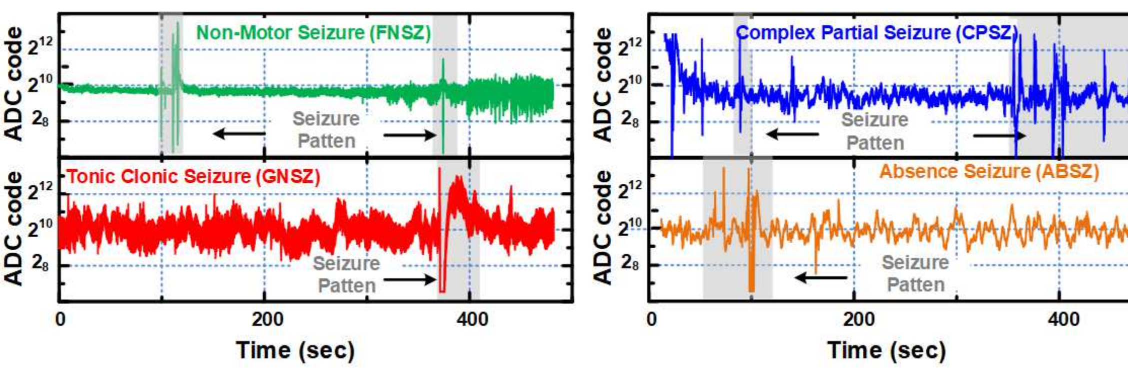

Fig. 3: Seizure types with focus on analyzed seizure types.

neurologist, the seizure information and complete display are provided to the neurologist in the run time. The graphical user interface (GUI) details and features are explained and detailed in the next section. The GUI system is termed an intelligent neural support system (INSS) and can provide assistance to the neurologist at run time for seizure tracking and type identification along with neurologist feedback and marking facility to auto-correct and re-train the correct seizure patterns.

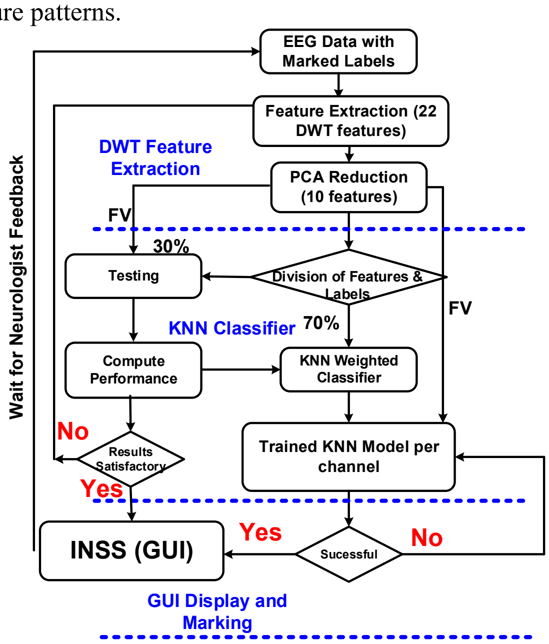

Fig. 4: Flow diagram of the proposed EDM multi-seizure classification

In the implemented system, KNN showed the best classification results for both binary and multi-classification. KNN is non-parametric and lazy learning algorithm, meaning it's based on the input data and training part is not complicated. Therefore, KNN is fundamental and east to implement machine learning algorithm. The working principle is shown in the Fig. 5. The class of any new feature vector (FV) is decided based on the Euclidean distance of the incoming FV with neighboring elements. The final class identification will be based on the majority vote (minimum distance).

IV. Proposed Neurologist Support GUI

INSS is an interactive MATLAB GUI for processing EEG data incorporating 1) view all channels together, 2) view selected channels, and 3) spectral and head plot of the specific channel for seizure localization. Moreover, to display the EEG data clearly it has zoom and pan functionality where zoom/pan speed can be set. Comments can also be added to a patient's file. Furthermore, the predicted seizure, its type and location can be also be viewed (Fig. 6). The spectral and head plots for the data can also be viewed (any number of head plots at any frequency can be viewed simultaneously). The head plots give the relative power for all channels at a particular frequency, the highest power is represented by yellow and the power decreases towards blue (Fig. 7). Currently, four types of seizures can be predicted through INSS. INSS also offers a mark/unmark seizure option thus the neurologist can update the seizure marking if required. Lastly, the system can also be updated according to local needs.

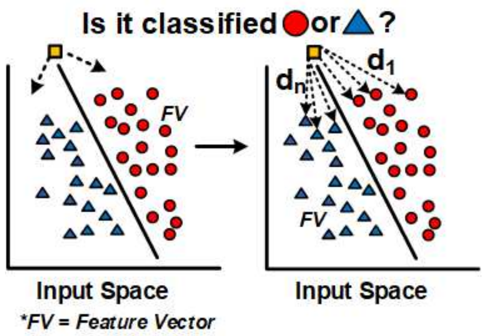

Fig. 5: KNN classifier and working principle.

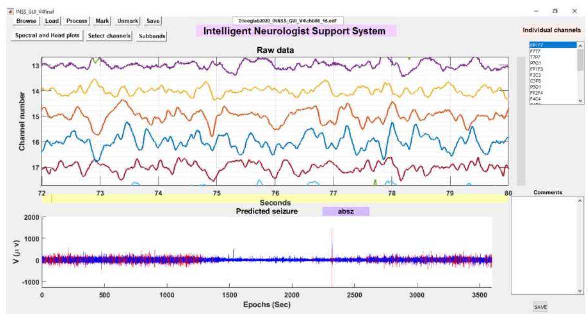

Fig. 6: GUI of the implemented INSS system with multiple EEG channels.

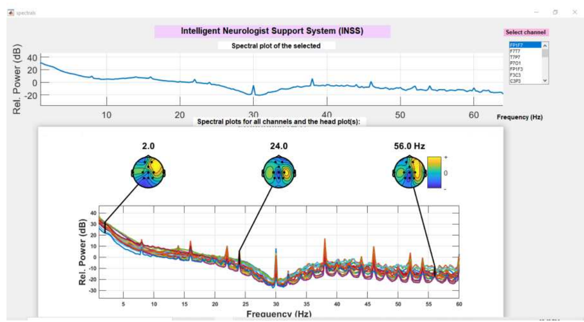

Fig. 7: GUI of the implemented INSS system with spectral plot and source localization of EEG channels.

V. Measurement Results and Discussion

The evaluation shows the proposed multi-class seizure classification system achieves an averaged accuracy, sensitivity and specificity of 97.7%, 92.9%, and 98.7%, respectively, based on 70/30 training/testing data distribution for 5-fold validation. The measurement of the system is shown in the performance is shown in Fig. 8, where the detected seizure is highlighted as the red pattern and type is identified as ABSZ. The INSS system allows the neurologist to further investigate the seizure source localization and its spectral pattern. Moreover, can add specific comments and feedback for later follow up.

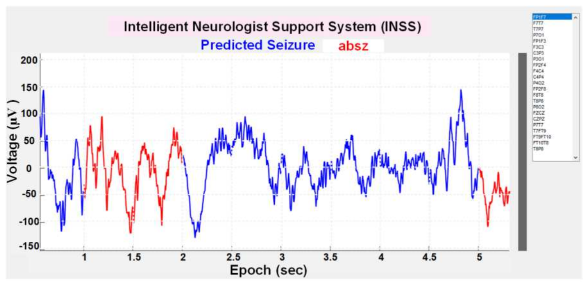

Fig. 8: Measurement showing the working of the implemented system.

Fig. 9 shows the averaged binary classification results of sensitivity, specificity and accuracy for all four types of seizures analyzed in this study. The good thing about the implemented system is that it shows good results across all four (4) seizure types. Moreover, the proposed system can be easily extended to incorporate further seizure types without enhancing the design complexity. Fig. 10 shows the multi-classification results of all the 4-seizure types averaged across each measured channel. To evaluate and compare with prior works related to TUH and multi-class seizure, we are having tabulated our results with the state of the artworks in Table I. The proposed and implemented work achieves the highest classification accuracy for the multi-class seizure identification task using DWT and KNN for feature extraction and classification.

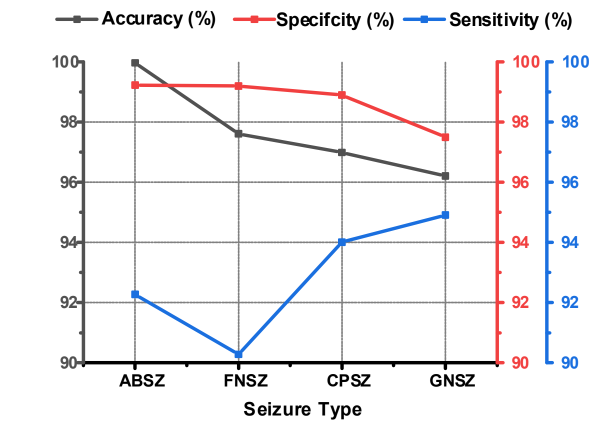

Fig. 9: Measurement results of individual binary classification.

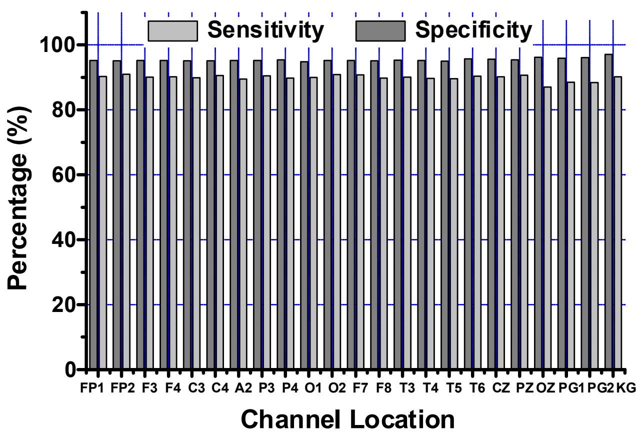

Fig. 10: Results showing the averaged multi-classification results of all channels.

VI. Conclusion

In this work, a seizure diagnostic and monitoring system is proposed and implemented. The purpose of the system is to assist the neurologist in the identification of seizure type, temporal and spectral pattern, source localization, and patient information with high accuracy. Moreover, the implemented system incorporates a KNN based multiclassification approach for multiclass seizure identification. The evaluation shows the proposed multi-class seizure classification system achieves an averaged accuracy, sensitivity and specificity of 97.7%, 92.9%, and 98.7%, respectively.

Acknowledgement

This work was funded by the National Center of Artificial Intelligence (NCAI) Research Fund (RF-NCAI-030) and Higher Education Commission (HEC), Pakistan under Grant 7978/Punjab/NRPU/R&D/HEC/2017.

Table 1: Comparison with the state-of-art works for multi-classification.

Parameter	JBHI'20 [14]	SPMB'20 [7]	JBR'20 [13]	This work
Type of Classification	Binary	Multi (5 classes)	Multi (3 classes)	**Multi (5 classes)**
Classifier	SVM, RF, KNN	XGBoost	LSTM, CNN	KNN
Channel	22	-	-	22
Accuracy	80.5%	84%	89.2%	**97.7%**
Specificity	-	-	96.8%	**98.7%**
Sensitivity	-	-	81.5%	**92.9%**
Features/# of Features	Mean Square Error	FFT + F_{MAX}	-	DWT (10)

References

[1] A. R. Aslam and M. A. B. Altaf, "An On-Chip Processor for Chronic Neurological Disorders Assistance Using Negative Affectivity Classification," in *IEEE Transactions on Biomedical Circuits and Systems*, vol. 14, no. 4, pp. 838-851, Aug. 2020.

[2] A. R. Aslam, *et al.*, "A10.13uJ/classification 2-channel Deep Neural Network-based SoC for Emotion Detection of Autistic Children," *IEEE Custom Integrated Circuits Conference (CICC)*, 2020, pp. 1-4.

[3] A. R. Aslam, *et al.*, "An 8.62 μ W Processor for Autism Spectrum Disorder Classification using Shallow Neural Network," *IEEE 3rd International Conference on Artificial Intelligence Circuits and Systems (AICAS)*, 2021, pp. 1-4,.

[4] C. Zhang, M. Altaf, and J. Yoo, "A 16-channel, 1-second latency patient-specific seizure onset and termination detection processor with dual detector architecture and digital hysteresis," *2015 IEEE Custom Integrated Circuits Conference (CICC)*, 2015, pp. 1-4

[5] M. R. Khan, W. Saadeh and M. A. B. Altaf, "A low complexity patient-specific threshold based accelerator for the Grand-mal seizure disorder," *2017 IEEE Biomedical Circuits and Systems Conference (BioCAS)*, 2017, pp. 1-4

[6] M. Aftab, *et al.*, "Design of Energy-Efficient Electrocorticography Recording System for Intractable Epilepsy in Implantable Environments," *2020 IEEE International Symposium on Circuits and Systems (ISCAS)*, 2020, pp. 1-5.

[7] S. Roy, U. Asif, J. Tang and S. Harrer, "Seizure Type Classification Using EEG Signals and Machine Learning: Setting a Benchmark," *IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*, 2020, pp. 1-6.

[8] Z. Taufique, *et al.*, "A Low Power Multi-Class Migraine Detection Processor Based on Somatosensory Evoked Potentials," in *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 68, no. 5, pp. 1720-1724, May 2021.

[9] F. Siddiqui, *et al.*, "Epilepsy in pakistan: national guidelines for clinicians," *Pakistan Journal of Neurological Sciences (PJNS), vol. 10, no. 3,* 2015.

[10] V. Shah, *et al.*, "The temple university hospital seizure detection corpus", *Frontiers in neuroinformatics*, vol. 12, pp. 83, 2018.

[11] M. Altaf and J. Yoo, "A 1.83 uJ/Classification, 8-Channel, Patient-Specific Epileptic Seizure Classification SoC Using a Non-Linear Support Vector Machine," in *IEEE Transactions on Biomedical Circuits and Systems*, vol. 10, no. 1, pp. 49-60, Feb. 2016.

[12] A. Shoeb, *Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment*, 2009.

[13] P. Vanabelle, *et al.*, "Epileptic seizure detection using EEG signals and extreme gradient boosting", J Biomed Res., vol. 34, no. 3, pp. 228-239, Aug. 2019.

[14] X. Zhang et al., "Adversarial Representation Learning for Robust Patient-Independent Epileptic Seizure Detection," in *IEEE JBHI*, vol. 24, no. 10, pp. 2852-2859, Oct. 2020.