Undergraduate Conference on Intelligent Computing and Systems (UCICS 2025)
26-27 February, 2025; Varendra University, Rajshahi, Bangladesh

The Detection and Classification of Schizophrenia using DL and ML Methods: An Overview of the Recent Works

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***Abstract*— Schizophrenia (SZ) is a psychotic disorder in which people face delusion, hallucinations, and various behavioral problems. It is tough to identify a patient with this disease by only observing the external physical features. Therefore, advanced technology should be introduced to identify and classify the problem. Recently, Machine Learning (ML) and Deep learning (DL) methods have manifested a great improvement in the field of detection and classification of this disease. Magnetic Resonance Imaging (MRI) and Electroencephalography (EEG) data could be effectively classified using these methods. This review paper includes the evaluations of the ML and DL methods, datasets, limitations, and distinctions of the models, a description of the models, and future scope in this field. The comparative study between used models, their effectiveness, and future scopes will help the researchers to explore this field of research. Researchers can have knowledge about the pros and cons of the methods used in state-of-the-art which will help them to improve the existing methods and also establish a novel practically useable model to ensure an early detection of the disease. This paper would help as a foundation for future research directions in this sector.**

Keywords*— Schizophrenia, detection, classification, transfer learning, EEG signals, MRI

I. Introduction

Schizophrenia (SZ) is a long-standing mental disorder that has an impact not only on individuals but also on their families and society at large. For a variety of factors, the number of persons afflicted by this illness is growing daily. Around the world, 24 million individuals, or 1 in 300 people (0.32%), are affected with schizophrenia. At this rate, adults account for 1 in 222, or 0.45%. It is not as usual as many other mental disorders [1]. Throughout their lives, 0.3% to 0.7% of persons get a diagnosis of schizophrenia. Males are more sensitive to SZ than the females [2].

For the early detection and classification of SZ, various ML and DL methods are used. The detection and classification can be done either by image data or signal data.

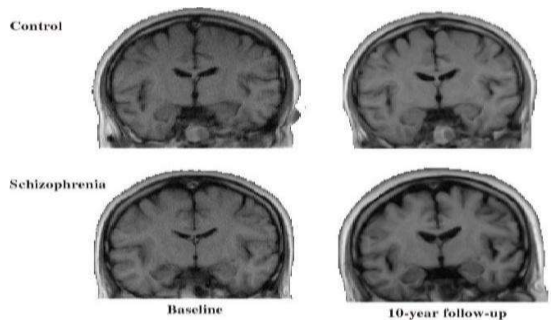

Fig. 1. a) healthy control, b) Schizophrenia patient [4]

Structural imaging methods were taken into consideration when changes in the gyrification index, volume of grey matter, the density of grey matter, and thickness of the cortex have been interpreted as representing synaptic loss in SZ [3].

Fig. 1 illustrates the image of a healthy control and that of a SZ patient. The main factor limiting the practical use of computer-aided diagnosis is the low generalizability of handmade feature-based machine learning, which results from the possibility of inaccurate feature selection [5].

Another data type is Electroencephalogram (EEG) data which is brain signal data that is used by converting to 2D images or by extracting the features using various methods. EEG is one of the most useful and popular functional neuroimaging modalities, which especially appeals to specialized medical professionals.

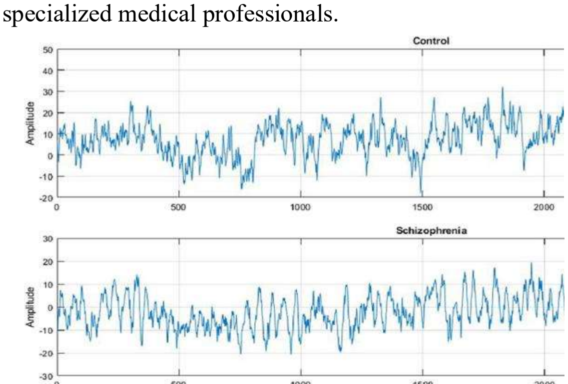

Fig. 2. a) healthy control, b) Schizophrenia patient [6]

Fig. 2 illustrates the EEG signals of a healthy control above and that of an SZ patient below. The extremely complicated EEG signal is divided into several components to obtain information from it. Some transform techniques are Fourier transform, wavelet transform, SPWVD, etc. Recently, this disease has caused a great threat to the people. So, a faster and more reliable method to detect and classify SZ is necessary. For this, this review paper will help a lot to analyze the works upon the detection of this disease.

This paper's structure is set up as follows: A basic introduction of SZ in section I. Related work is covered in Section II, while the methodology of the used methods is covered in Section III. Discussion in Section IV and lastly, the conclusion and future scope are covered in Section V.

II. Related Works

In this section, different research works for the detection and classification of SZ are discussed.

Using resting-state functional MRI (rs-fMRI) data, Zhu et al. [7] introduced Temporal-BCGCN, an advanced graph convolutional network, for lateralization analysis and SZ classification. In their work, they used two public datasets COBRE and UCLA, and achieved the accuracy of 83.62% and 89.71% respectively. Cattarinussi et al. [8] in their work, examined the diagnostic significance of regional homogeneity (ReHo) and fractional amplitude of low-frequency fluctuations (fALFF) as determined by resting-state functional magnetic resonance imaging (rs-fMRI) in a group of healthy controls (HC) with SZ. The ReHo features showed higher classification accuracy. Lastly, they used a stacking model to improve accuracy up to 87.4%.

Siuly et al. [9] used an EEG dataset which was collected from Kaggle. Average filtering was used for signal pre-processing, and deep ResNet was used to extract hidden patterns from EEG signals. Deep ResNet, SVM, and KNN classification performances were compared. In terms of performance, the SVM classifier outperformed the ResNet classifier, with an accuracy of 99.23%. Ahmad et al. [10] aimed to classify SZ patients from healthy controls using ML techniques and rs-fMRI data, focusing on the correlation of brain regions' activation and functional connectivity. Among various linear and nonlinear ML models, SVM with radial basis function (RBF) performed best with an accuracy of 95%.

Hu et al. [11] proposed a better model with more accuracy with multimodal inputs. Two datasets NUSDAST and IMH were used. Both linear and non-linear SVM were applied to this dataset. Next, the sequential models, inception models, and inception_resnet models were applied. Here, 3D CNN and 2D CNN were also used for the classification. However, the 3D CNN model outperformed the others. The accuracy was improved up to 81.02% by utilizing complicated topologies and multimodal input incorporating dMRI and sMRI data. The accuracy could be improved more by using a larger dataset and data augmentation. Lei et al. [12] introduced the graph neural network (GCN) model. In the study, rs-fMRI data from 1412 subjects—505 SZ patients and 907 controls—from 6 sites were used. A harmonization technique known as ComBat is used to eliminate the undesired side effects and reveal the patients' true functional problems. The adjacency matrix was found using the KNN technique. Using class activation mapping (CAM), the most significant regions that contribute to GCN classification are identified. To evaluate the GCN model's efficacy, its salient features, clinical correlation, and model performance were compared to those of SVM (linear kernel) which is a traditional ML method that is commonly used in neuroimaging research of brain disorders.

Karthik et al. [13] proposed a DNN algorithm based on genetic phenotype. 102 participants are included among which 69 samples for SZ detection. Data was acquired from the GEO database. The RGBIC Framework was established to examine patient gene expressions. Initial efforts focused on identifying potentially high-risk biomarkers using the signal-induced feature ranking algorithm (SIFRA). Then a DNN model was used which outperformed all other models and acquired an accuracy of 95.65%. This model makes use of the Rectified Linear Unit (ReLU) activation function. The complexity of the suggested SIFRA model is reduced in all circumstances. To persuade the limitations of feature extraction-based techniques, Khare et al. [14] suggested a model that combines convolutional neural network (CNN) and time-frequency analysis. There are 81 participants in the Kaggle EEG dataset, which includes 32 healthy controls and 49 patients with SZ. Using continuous wavelet transform, short-time Fourier transform, and smoothed pseudo-Wigner-Ville distribution (SPWVD) techniques, the EEG data are converted into scalogram, spectrogram, and SPWVD-based time-frequency representation (TFR) displays. The models CNN, VGG16, AlexNet, and ResNet50 are fed 2D plots to compare the output. 93.33%, 93.09%, 93.34%, and 93.36% were their respective accuracy gains. Using the CNN and TFR model based on SPWVD produced the greatest accuracy of 93.36%. The Adam optimizer scales each weight's learning rate. The accuracy could be improved by using a larger dataset.

Hu et al. [15] proposed a naive 3D CNN model for the classification of SZ. Two datasets named NUSDAST and IMH were used here individually. Firstly, using the CAT12 toolset, the datasets were preprocessed and divided into components for gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). Following that, Personalized feature-based ML was implemented using Voxel-based Morphometry (VBM) as a feature and SVM as a classifier.

TABLE I. OVERVIEW OF DIFFERENT RECENT WORKS

Author	Best Model	Data Set	Accuracy	Merits	Demerits
Zhu et al. [7] – 2024	Temporal-BCGCN	COBRE	83.62%	Outperformed the baseline models and the results also revealed that the left hemisphere of the brain in SZ patients shows a critical role in classification prediction	Only one modality is used in classification. They did not give a detailed analysis of the computational complexity and training time of the model
		UCLA	89.71%		
Cattarinussi et al. [8] – 2024	SVM + Stacking model	CNP	87.4%.	The multivariate integration and ensemble methods	Relatively small sample size and they cannot deny the effect of treatment on patients
Siuly et al. [9] – 2023	SVM	EEG from Kaggle	99.23%	Novel approach for feature extraction, improved ML performance.	Poor performance of DL classifier
Ahmad et al. [10] – 2023	RBF SVM	Brain Multimodality	95%	Extraction of the most discriminatory brain regions and a wide range of ML models	Small sample size, lack of evaluation on a larger dataset, and further model optimization are needed
Hu et al. [11] – 2022	inception_resnet_1	NUSDAST	79.27%	Improved performance for using multi-modal over single-modal	Increased cost, GPU memory limit, and modest dataset
	Multimodal & inception_resnet_1	IMH	81.02%		
Lei at el. [12] – 2022	GCN	Local dataset	85.8%	Better fitted for brain network and improved accuracy	Overfitting occurred and replication is required for clinical application
Karthik et al. [13] – 2021	DNN	GEO database	95.65%	Cost-effective and applicable for automated medical diagnosis	The proposed SIFRA model is complex

Author	Best Model	Data Set	Accuracy	Merits	Demerits
Khare at el. [14] – 2021	CNN	EEG from Kaggle	93.36%	Robust, simple, fast, and completely automated	Tangible selection of parameters and increased memory required
Hu et al. [15] – 2020	inception_resnet_1	NUSDAST	79.27%	Outperformed the manually constructed ML methods	Small sample size and absence of a multi-channel model
		IMH	70.98%		
Li et al. [16] – 2020	DCCSAE+SVM	SNP from MCIC	95.65%	The connection of both SNP and fMRI data produced great accuracy reducing overfitting	Need more computational time for the model and biological interpretation is also a promising task
		fMRI from MCIC	80.53%		

Different architectures of 3D CNN like sequential, Inception, and Inception_resnet models were used to classify. The testing results were obtained and the hyperparameter selection was done using nested cross-validation. With consideration of the NUSDAST dataset, inception_resnet_1 achieved the maximum accuracy, which was 79.27%. The inception_resnet_1 model likewise attained the greatest testing accuracy for the IMH dataset, at 70.98%. The major limitation of the work was the small sample size. Li et al. [16] represented a comprehensive study of SZ combining the exploration of single nucleotide polymorphisms (SNP) and functional magnetic resonance imaging (fMRI) data. They proposed a deep canonically correlated sparse autoencoder (DCCSAE) combining the deep canonical correlation analysis (DCCA) and sparse autoencoder (SAE) for better handling of both SNP and fMRI data. The DCCSAE model with SVM gave the best accuracy of 95.65% for the SNP dataset. Table I gives an overview of all the recently summarized works.

III. Materials and Methods

A. Dataset

Schizophrenia detection and classification evolved based on data or signals collected from the human brain. Data from the human brain can be collected as either MRI images or EEG signals. Data can be collected from various open or local sources. Some open-source datasets are discussed in Table II.

Table II. Some Publicly Accessible Datasets

Dataset	Publisher	Modality	Number of samples
NUSDAST [17] – 2013	National University of Singapore (NUS)	sMRI	SZ = 171 HC = 170 Strict SZ = 44 No disorder = 6
COBRE [18] – 2012	Mind Research Network and the University of New Mexico	sMRI and fMRI	SZ =72 HC = 75
RepOD [19] – 2017	Institute of Psychiatry and Neurology in Warsaw, Poland	EEG	SZ = 14 HC = 14
UCLA [20] – 2013	OpenfMRI project	sMRI, fMRI, and DWI	SZ = 50 HC = 130 Patients with ADHD = 43 Bipolar illness = 49
MCIC [21] – 2013	Mind Research Network (MRN)	sMRI and fMRI and DWI	SZ = 162 HC = 169

B. Methods for MRI data

MRI data contains the sMRI and fMRI data. The structural MRI data contains the structure of the brain and contains GM, WM, and CSF which helps to have more detailed information about the brain. The functional MRI records the blood flow to measure brain activity. Data collection and conversion into useful information constitute data processing. For image data, the processing includes image preprocessing, segmentation, etc. The feature was collected from the image using various feature extraction methods such as autocorrelation, mean, variance, etc. These extracted features are fed to the classification models which produce the final classification of SZ. Different ML and DL methods like SVM, LR, KNN, RF, CNN, and different pre-trained models are used in classification.

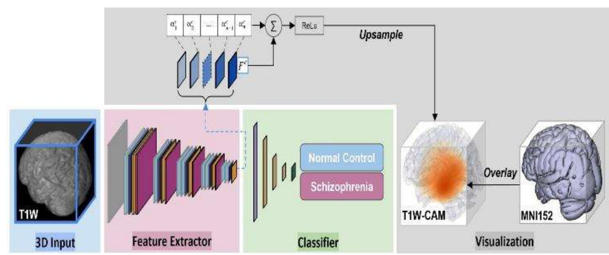

Fig. 3. Classification method proposed by Hu et al. [11]

C. Methods for EEG data

EEG signals are the brain signals collected in various conditions using a probe. For the processing of EEG signals, the transformation of signals to images or plots is done. The dimensionality reduction is done to divide and reduce an initial collection of raw data into more manageable groups using feature extraction. For feature extraction of image data fuzzy kernel, for EEG data FuzzyEn, FFT, etc. are used. After the feature selection and optimization, the selected features are fed to the ML and DL classification models.

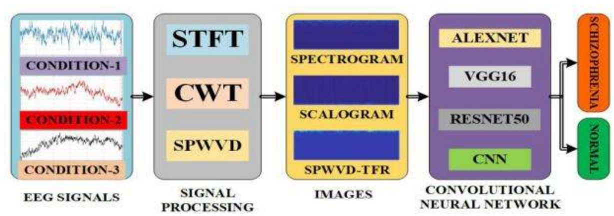

Fig. 4. Classification method proposed by Khare et al. [14]

IV. Discussion

The research works on psychiatric problems has increased recently. Detection and classification of SZ is also a very important issue now. This section covers some discussions on this detection and classification using ML and DL models. Various modalities are used now for SZ detection as EEG, sMRI, and fMRI data. EEG signals contain various artifacts and it is hard to collect signals without error signals. Again the EEG could not detect the specific brain location and function that causes SZ. fMRI could find the specific location more clearly and specifically than EEG. So, nowadays though the

EEG signals give better accuracies, the fMRI data are used more which improves the accuracy and the robustness of the model. Fig. 5 shows a comparison of recent works.

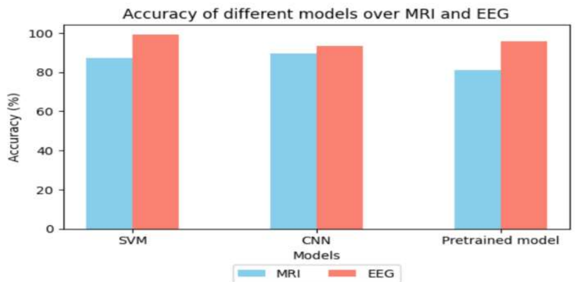

Fig. 5. Comparison of accuracy in data used in the recent works.

Both ML and DL models are used depending on the dataset and preprocessing of the data. However, DL models require a large dataset to extract the feature for detection. Most of the open-source datasets are small in size. In this case, ML models work better than the DL models. Again, some DL models are complex and need to be clarified in a more understandable way to increase their applicability.

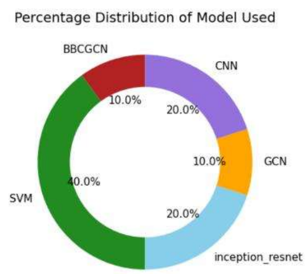

Fig. 6. Comparison of different ML and DL models used in the review.

V. Conclusion And Future Scope

Schizophrenia detection and classification is a very crucial topic in recent years. Recently, various researchers have been working on this topic and achieved great accuracy on the datasets. Though recent works have some noteworthy improvements, this area could be more developed in the future solving the limitations to implement in the real world. Large datasets should be introduced to work more efficiently. Most of the open-source datasets are small and with a single modality. Single modality could not gain the best outputs. The accuracy of the models could be increased by working with large datasets which could be made by merging datasets, and data augmentation. That's why, the researchers should be interested in the combinations of multimodal data to achieve a great outcome. The combination of multiple modalities is a bit more complex than a single. Upgraded processing techniques and classification models are needed to be built. These initiatives are going through the process but we are not wholly successful yet. Soon, these things will be achieved and practical medical implementation will be possible.

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