AUTOMATIC DETECTION OF SCHIZOPHRENIA USING SPECTROGRAMS FROM EEG SIGNALS

A Project Report Submitted

by

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In Partial Fulfillment
of the Requirements for the award of the degree

BACHELOR OF TECHNOLOGY

DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY PATNA
May 2023

THESIS CERTIFICATE

This is to certify that the thesis titled **AUTOMATIC DETECTION OF SCHIZOPHRENIA USING SPECTROGRAMS FROM EEG SIGNALS**, submitted by **Maharshkumar Patel**, to the Indian Institute of Technology, Patna, for the award of the degree of **Bachelor of Technology**, is a bona fide record of the research work done by them under our supervision. This thesis is a genuine representation of the research work conducted by the author under our guidance. The entire content of this thesis, either in its entirety or in part, has not been previously submitted to any other institute or university to obtain any degree or diploma.

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Date: 8th May 2023

ACKNOWLEDGEMENTS

I extend my gratitude to Dr. P.K Tiwari, my supervisor, for providing continuous support and guidance throughout the project. I am also grateful to my colleagues who collaborated with me, exchanging ideas and thoughts, which greatly contributed to the successful execution of the project with accurate information. I extend my heartfelt thanks to my parents for their unwavering support and encouragement. Lastly, my are grateful to God for enabling me to complete this journey successfully.

ABSTRACT

KEYWORDS: Schizophrenia; EEG; Time-Frequency Representation

Schizophrenia, a chronic and severe mental disorder, affects millions worldwide. Early detection of this condition is critical for timely intervention and effective symptom management. Electroencephalography (EEG), a non-invasive procedure, has recently emerged as a promising tool for studying the brain's electrical activity and identifying neuro-physiological markers associated with schizophrenia. The proposed method in this research uses EEG signals from individuals to detect schizophrenia automatically. This method utilises Time-Frequency Representations or TFRs produced from the de-noised EEG signals to classify healthy and schizophrenic patients. The classifier used is a CNN model, which can achieve results of 95% in one dataset while 96% on another.

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CHAPTER 1

INTRODUCTION

Schizophrenia (Sz) interferes with an individual's mental ability, emotional traits, and social and personal well-being. It is a disorder characterised by symptoms such as unusual and inaccurate fixed beliefs (delusions). These hallucinations include hearing or seeing unreal sounds or images and experiencing strange feelings, thoughts, or speech. This illness has a significant impact on thought and mental development. Although the cause of Sz is not entirely known, most research shows that abnormalities in the brain could lead to its occurrence. According to the World Health Organisation (WHO), this condition affects over 21 million individuals globally. This condition manifests itself in youth; it is more prevalent in younger boys than females. The detection of Sz is untrustworthy because the expert can make mistakes in some circumstances, as its symptoms are often confused with those of other psychological diseases.

EEG is a very non-invasive, convenient and affordable functional neuroimaging technique. The brain's activity in this modality is recorded from the scalp with superb temporal and spatial resolution. This is very vital in Schizophrenia detection. Aside from the benefits already described, EEG signals are routinely recorded in many channels.

A Convolutional Neural Network model will be used in this scenario to study Sz diagnosis from EEG information. This work uses a dataset from the Institute of Psychiatry and Neurology in Warsaw, Poland, and a publically available EEG dataset from Lomonosov Moscow State University's Center for Neurophysiology and Neuro-Computer Interface at Lomonosov Moscow State University. The techniques of baseline removal, filtering, segmentation, normalising, and creating time-frequency representations from the EEG data will be used in the preprocessing step.

The Literature Survey is done in Chapter II, while Chapter III explains the Motivation behind the project. Chapter IV contains the explanation for the proposed method, and Chapter V discusses the Results obtained at the end, followed by the Conclusion in Chapter VI.

CHAPTER 2

LITERATURE SURVEY

Researchers have recently demonstrated many strategies for detecting anomalies in the electrical activity in the brain for Sz diagnosis. Most of the research used image data but not parameters derived from EEG signals to investigate the different abnormalities in Schizophrenia. EEG is far more convenient than imaging data for diagnosing brain disorders and has demonstrated promising outcomes.

In their paper, Kim et al.[1] detected Sz with a classification accuracy of 62.2%. FFT was used to determine the spectral power for the frequency bands. The diagnostic test was then evaluated using ANOVA and ROC methodologies. Laksono et al.[2] used the raw EEG signals as input in SVM and CNN to classify Sz, achieving the accuracies of 79.2% and 76%, respectively. Oh et al. employed a Deep CNN Model on the unprocessed EEG data, achieving accuracy rates of 81.26% for subject-based testing and 98.07% for non-subject-based testing, respectively. Wu et al.[3] implemented the Recurrent Auto-Encoder model to discriminate EEG data into Sz and healthy subjects, which received 81.81% accuracy. Brain Vision Analyzer was utilized by Johannesen et al.[4] to diagnose EEG signals, and the feature selection was made using the wrapper technique. Two SVM models were implemented to categorize individuals as healthy or Sz. SVM Model 1 provided an accuracy of 84%, whereas SVM Model 2 showed a classification accuracy of 87%. The Pearson Correlation Coefficient (PCC) was used by Naira et al.[5] to generate the relation between the channels. This was used as the input CNN achieving 90% accuracy.

Phang et al.[6] developed a distinct parallel ensemble of 1D and 2D CNNs that achieved 91.69% accuracy to include data from several domains and dimensions. Khare et al.[7] used TFRs to discriminate between Sz and healthy subjects. The TFRs are fed into a CNN model resulting in an accuracy of 93.36%. A CNN was used as a method that allowed automatic extraction of the main characteristics by Lillo et al.[8] to classify Sz subjects with an accuracy of 93%. Aslan et al.[9] used Spectrogram representations to classify Sz individuals beforehand without any noise removal steps. This

method yielded an accuracy of 95% on one dataset while 97% on another. Kumar et al.[10] used an electroencephalogram (EEG) signal and a local descriptors-based automated method to identify Sz using an Adaboost classifier. This method reached an accuracy of 92.85% on one dataset while 99.36% accuracy on the other. EEG signals were learned using Recurrence Plot and Gramian Angular Field with CNN models for Ko et al.[11], getting to an accuracy of 90% and 93.2%. Time-frequency transformation was used for the EEG for Sz disorder by Dvey-Aharon et al.[12], who obtained accuracy ranging from 92.0% to 93.9%. Combined frequency domain and time-domain features were used by Santos-Mayo et al.[13] and then classified using an SVM model yielding 93.43% accuracy and a Multilayer Perceptron, giving 92.233% classification accuracy for Sz. Sun et al.[14] suggested an accuracy of 99.22% using a hybrid neural network for Sz discrimination. This article offered a system for manually extracting and transforming time and frequency information into RGB images. Supakar et al.[15] constructed a model employing RNN-LSTM to assess the EEG data and provide a 98% accurate diagnosis of schizophrenia. Shalbaf et al.[16] fed Scalogram representation images into popular transfer learning models. Their convolutional network output was further fed into an SVM classifier yielding an accuracy of 98.60%. A multitaper and 1D-convolutional producing an accuracy of 98.76% using a neural network-based approach was implemented by Göker et al.[17]. Shoebi et al.[18] employed a method which was 99.25% accurate using z-score and L2-combined normalized EEG signals with a CNN-LSTM model. Aslan et al.[19] used Scalogram representation images on the VGG16 model to classify Sz individuals from healthy ones on two datasets with accuracies of 98% and 99.5%. In contrast, Bagherzadeh et al.[20] used a connectivity matrix extracted from the EEG signals on pre-trained transfer learning networks to get an accuracy of 99.9%. Şeker et al.[21] used SPWVD time-frequency representation images with a Vision Transformer to achieve the accuracies of 87% for subject-independent and 100% for subject-dependent testing. Another detection technique of Sz using electroencephalogram data utilising innovative relaxed local neighbour difference pattern (RLNDiP) approach with an artificial neural network for categorization was suggested by Sairamya et al.[22], earning a 100% accuracy rate.

CHAPTER 3

MOTIVATION

A type of signal processing technique known as time-frequency representations (TFRs) enables the display of changes in a signal's frequency domain over time. The study's purpose stems from the fact that TFRs can be utilised to investigate the temporal dynamics of brain activity in distinct frequency bands in schizophrenia detection using EEG.

One of the most prominent characteristics of schizophrenia is aberrant brain activity in many frequency bands across time. Those with schizophrenia, for example, have lower alpha and beta power and higher delta and gamma power than healthy people, according to studies. These variations can occur at various moments throughout the EEG recording. TFRs can be used to visualise variations in the frequency domain of EEG data across time, allowing specific temporal patterns associated with schizophrenia to be identified. Deep learning algorithms can be trained to distinguish individuals as healthy or having schizophrenia based on their EEG TFRs by studying these patterns.

TFRs can also provide further information regarding the underlying mechanisms of schizophrenia. For example, abnormal gamma activity in the auditory cortex has been connected to auditory hallucinations in schizophrenia. On the other hand, reduced frontal cortex alpha activity has been associated with cognitive deficiencies such as attentional and working memory issues.

Because TFRs can be used to detect and visualise abnormal patterns of brain activity in the EEGs of patients with schizophrenia, this knowledge has been applied to develop more effective detection tools for this disorder. These TFRs were fed into a Convolutional Neural Network in the proposed method because CNNs are helpful in image analysis. Because of their ability to extract local features, they are well-suited for studying TFRs. Research has found that using CNNs for EEG categorization results in excellent accuracy.

CHAPTER 4

PROPOSED METHOD

4.1 Dataset

Dataset I

In this dataset, 14 males and girls between the ages of 27.9 and 28.3 years have recorded EEG signals. Additionally, 14 healthy people working in this facility and matched with the patients regarding age and gender carried out the data recording. A signal recording was done for 15 minutes for each case, and each of the 19 channels with the eyes closed. Standard 10-20 was used to record EEG data at a sampling rate of 250 Hz. Electrodes such as Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, C3, Cz, T4, T5, P3, Pz, P4, T6, O1, and O2 were employed in this investigation.

Most recordings here were not 15 minutes exact. Since considering 10-second segments further down the pipeline, we have taken the longest stretch of data that can be divided into 10-second segments perfectly for each class. For healthy subjects, it was 860 seconds or 14 minutes and 20 seconds of data, while for Sz subjects, it was 740 seconds or 12 minutes and 20 seconds.

Dataset II

This EEG dataset was made accessible to the public by the Lomonosov Moscow State University Laboratory for Neurophysiology and Neuro-Computer Interface. The dataset contains 84 patients with a mean age of 12.3 years, aged 11 to 14 (45 Sz subjects and 39 healthy control subjects). Participants were rested with their eyes closed while a multichannel (16 channel) EEG of 1-min length was taken from them. The following EEG channels were used: F7, F3, F4, F8, T3, C3, C3, Cz, C4, T4, T5, P3, P3, and Pz, P4, T6, O1, and O2.

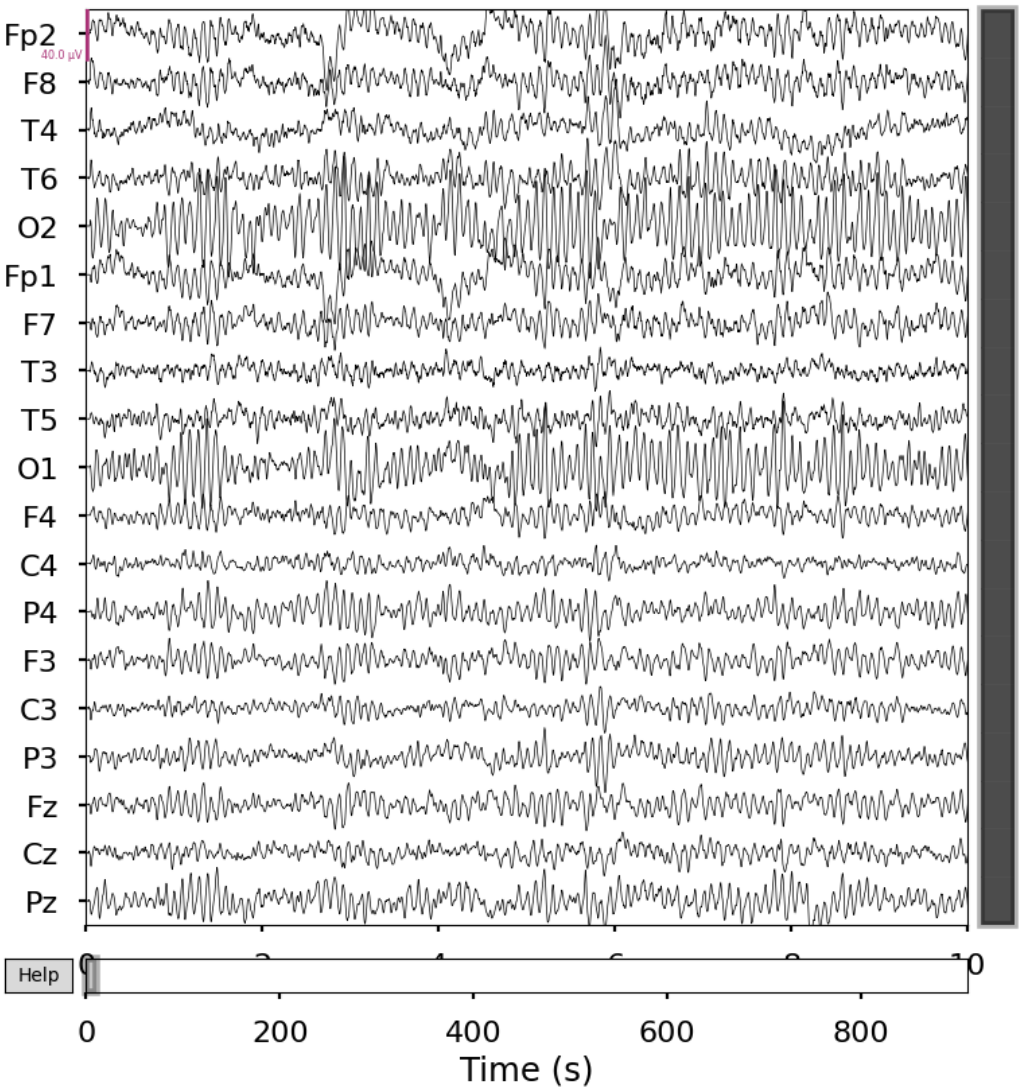


Figure 4.1: Raw EEG data from Dataset I

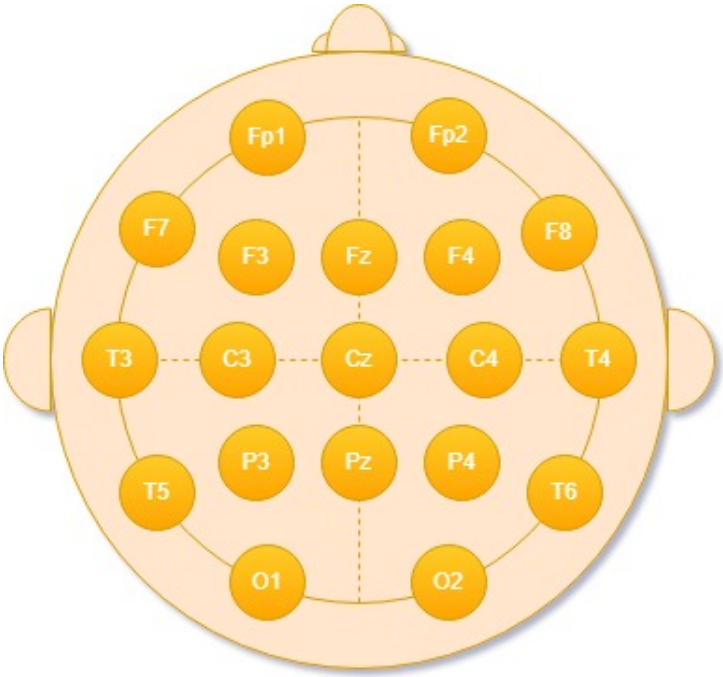


Figure 4.2: Electrode Placement for EEG Dataset I

4.2 Pre-processing

The EEG signals from the aforementioned datasets are pre-processed using several methods. These steps were common for both datasets. Baseline correction is done on the data to remove any influence from temporal shifts. This can be seen in Fig 4.6 as 4.6a) represents the raw signal while 4.6b) represents the signal after doing baseline correction. To eliminate power line interference, a 50 Hz notch filter was employed. The signal is then passed through a Buteerworth bandpass filter with a lower cutoff frequency of 4 Hz and a higher cutoff frequency of 45 Hz. Then the signals are segmented into 20-second segments. All the channels in the data are counted as individual signals and are individually normalized by z-score. The normalized signal can be seen in Fig 4.7b compared to the signal before normalization in Fig 4.7a. The data length at the end of this process is $sampling frequency \times 10$.

These signals are then further made into TFR images. Three kinds of TFR have been used in this study. They are,

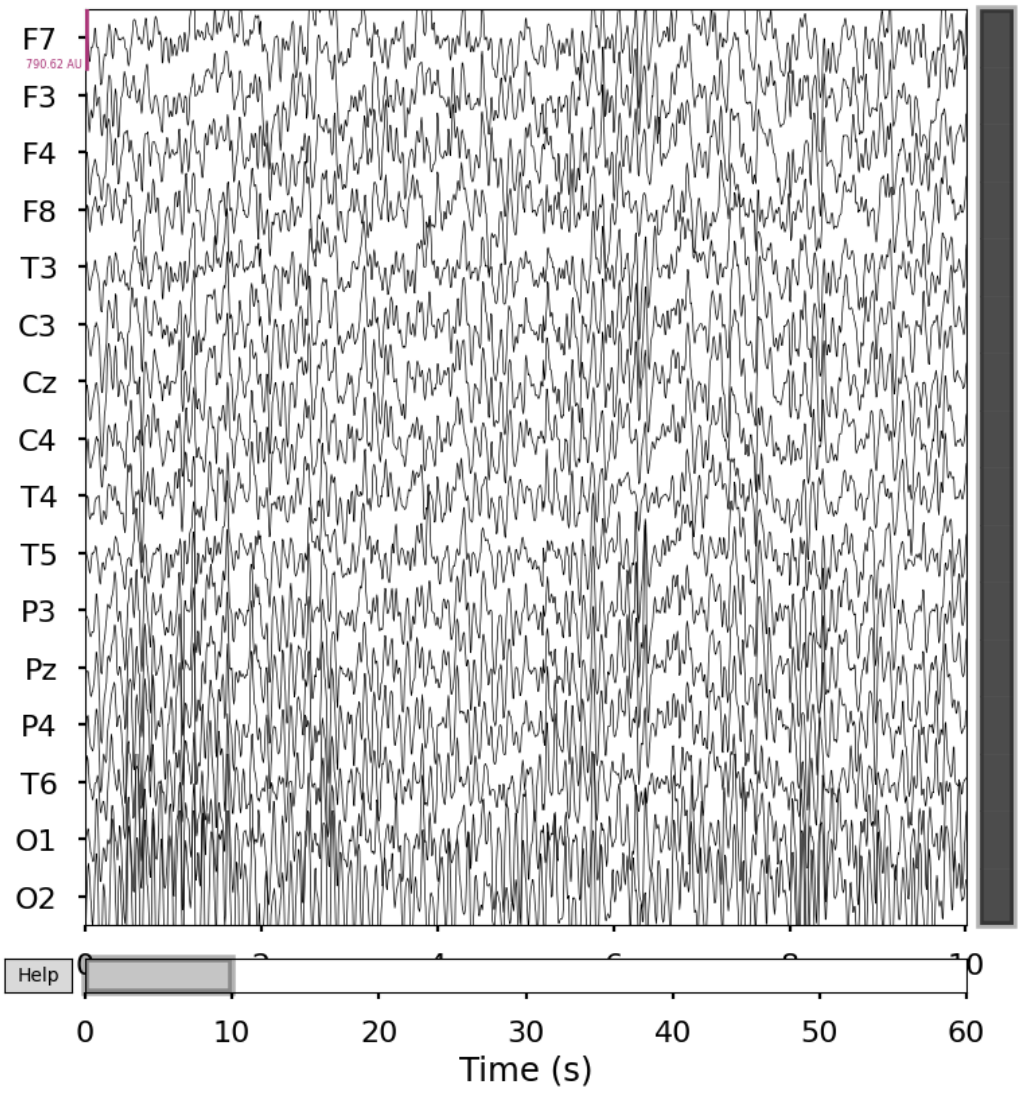


Figure 4.3: Raw EEG data from Dataset II

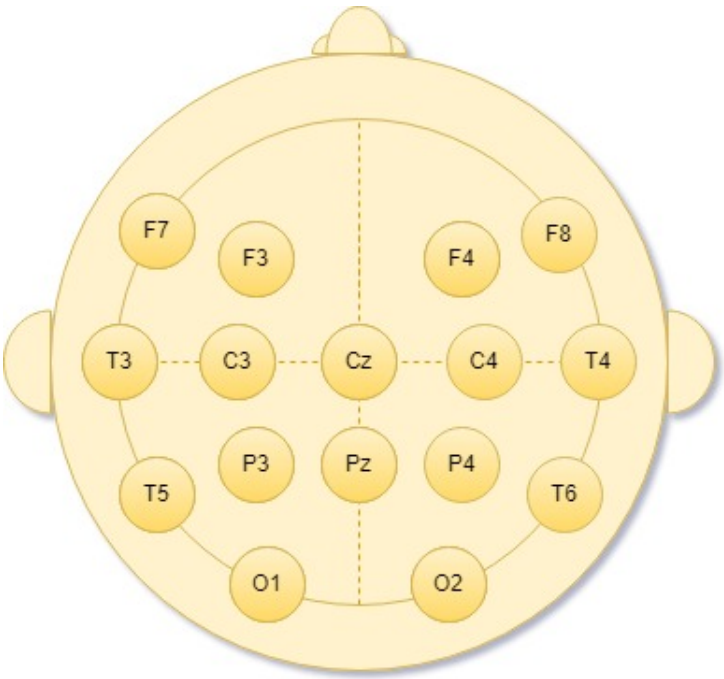


Figure 4.4: Electrode Placement for EEG Dataset II

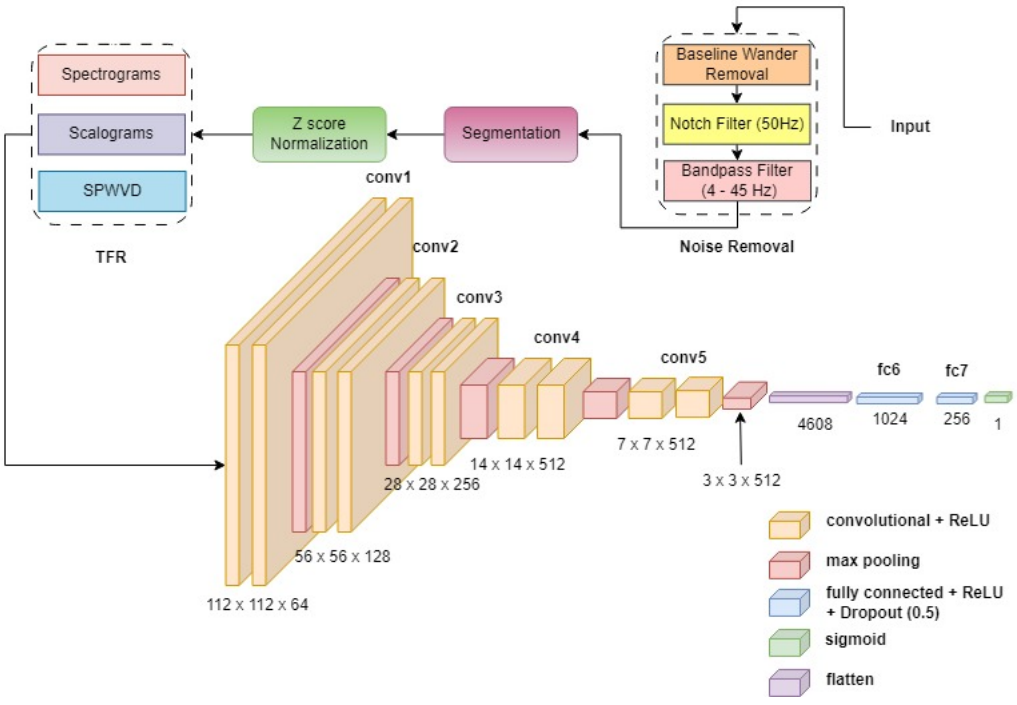
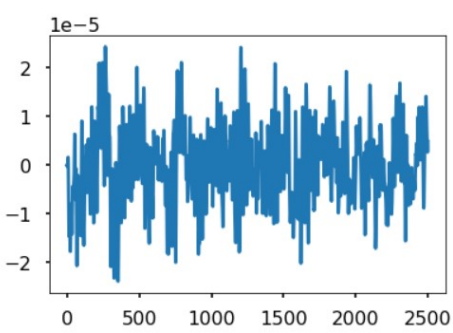
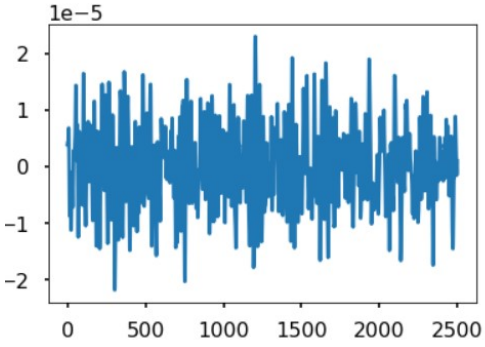


Figure 4.5: Block Diagram of proposed model

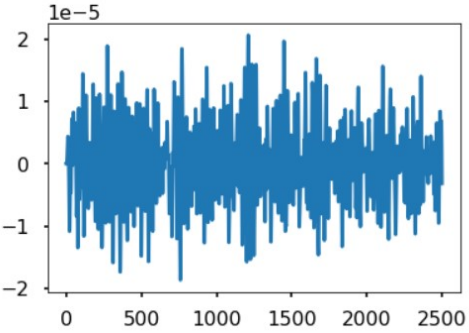


(a) Signal before Baseline Correction

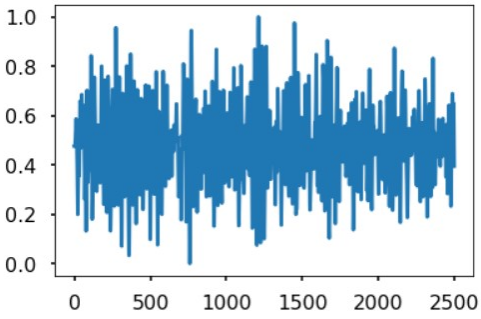


(b) Signal after Baseline Correction

Figure 4.6: Baseline Correction



(a) Signal before Normalization



(b) Signal after Normalization

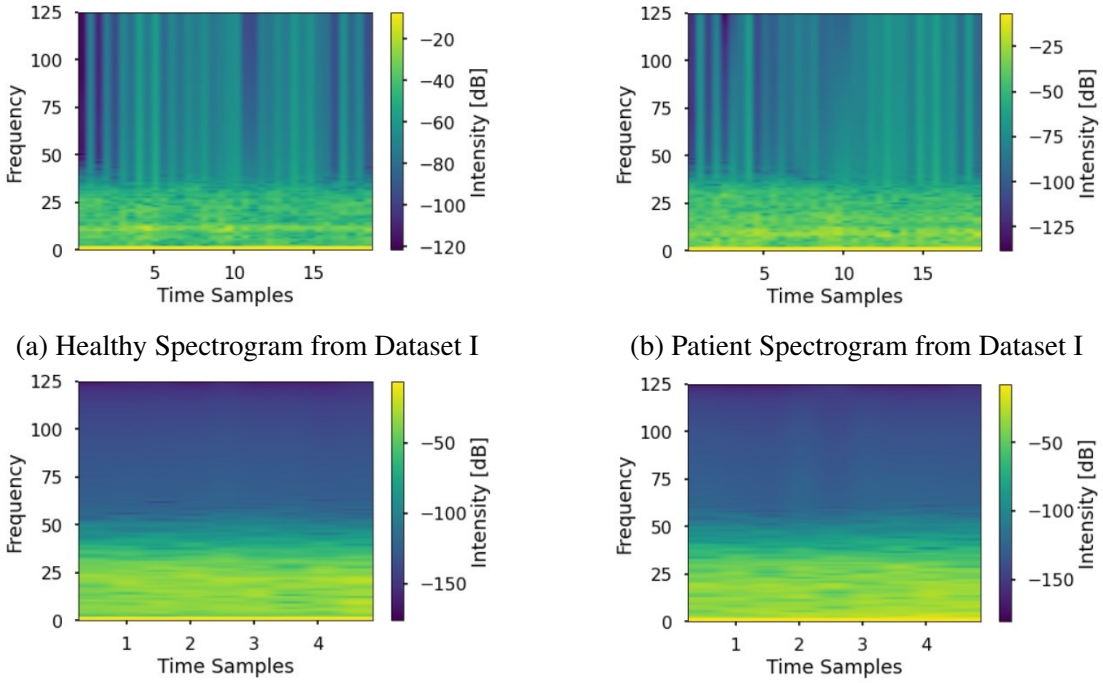
Figure 4.7: Normalization

4.2.1 Spectrogram

A spectrogram displays the "loudness" or signal intensity over time at different frequencies in a given waveform. One may see the amount of energy present and how it changes over time. After that, a picture of the spectrograms is plotted. The STFT algorithm's output, the normalised, squared magnitude of the STFT coefficients, is known as a spectrogram. Thus, spectrograms are used to display STFTs.

$$STFT(x_n, h, k) = \sum_{n=0}^{N-1} x_{n+h} w_n e^{-i2\pi \frac{kn}{N}} \tag{4.1}$$

With time on the x-axis, frequency on the y-axis, and a colour scale representing the signal intensity at certain times and frequencies, the spectrogram picture displays the spectrogram.



(a) Healthy Spectrogram from Dataset I

(b) Patient Spectrogram from Dataset I

(c) Healthy Spectrogram from Dataset II

(d) Patient Spectrogram from Dataset II

Figure 4.8: Spectrograms

4.2.2 Scalogram

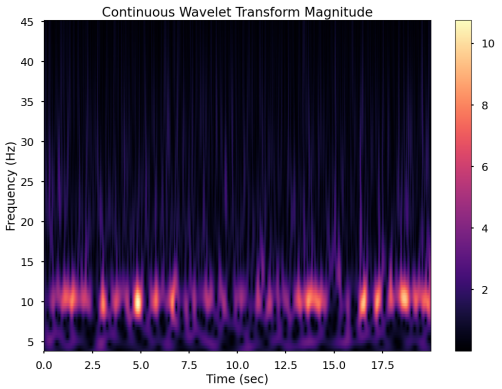
The continuous wavelet transform coefficients of a signal are expressed as an absolute value called a scalogram. A scalogram is an image of the original signal after a Continuous Wavelet Transformation (CWT) has been applied. The "mother wavelet" is a set of values produced by the CWT that represent the correlation between a radar signal and an example wave at various frequencies.

$$CWT(a, kT_s) = T_s a^{-1/2} \sum_n s(nT_s)\psi^*[\frac{(n-k)T_s}{a}] \tag{4.2}$$

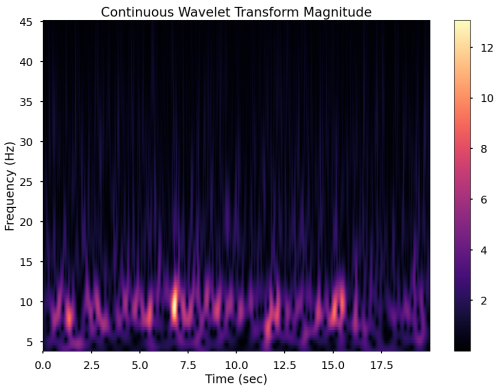
The scalogram image shows a scalogram with frequency and time on the y-axis and a colour scale showing the signal intensity at each frequency and period.

4.2.3 Smoothed Pseudo Wigner-Ville Distribution

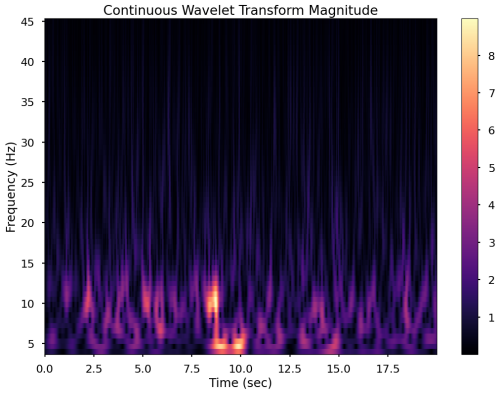
By modifying the rapid Fourier transform technique, pseudo-Wigner-Ville distribution perfectly depicts a nonstationary signal in the time-frequency domain. Interference terms in the Wigner-Ville distribution frequently make it more challenging to compre-



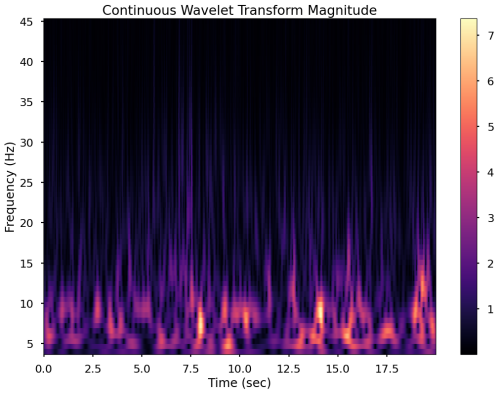
(a) Healthy Scalogram from Dataset I



(b) Patient Scalogram from Dataset I



(c) Healthy Scalogram from Dataset II



(d) Patient Scalogram from Dataset II

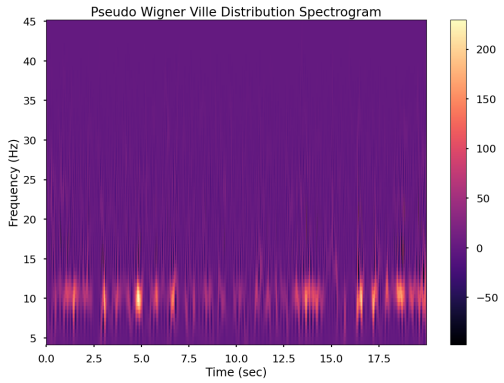
Figure 4.9: Scalograms

hend. One may use lowpass windows to filter the definition and refine the distribution. Independent windows are used to smooth the pseudo-Wigner-Ville distribution in time and frequency.

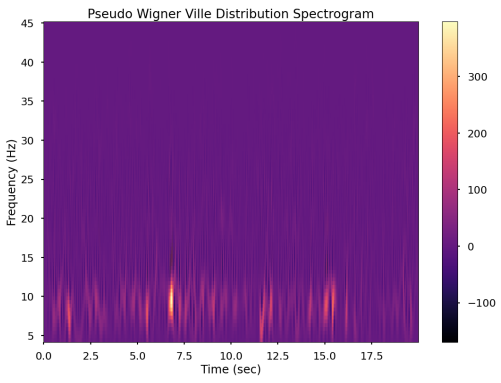
$$SPWVD_x^{g,H}(t,f) = \int_{-\infty}^{\infty} g(t)H(f)x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})e^{-j2\pi ft}d\tau \tag{4.3}$$

With time on the x-axis, frequency on the y-axis, and a colour scale representing the signal intensity at certain times and frequencies, the SPWVD graphic represents the SPWVD.

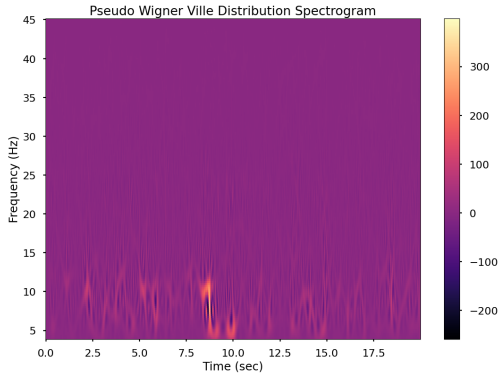
These TFR images are then resized into (112, 112, 3) dimensions and fed into the CNN model.



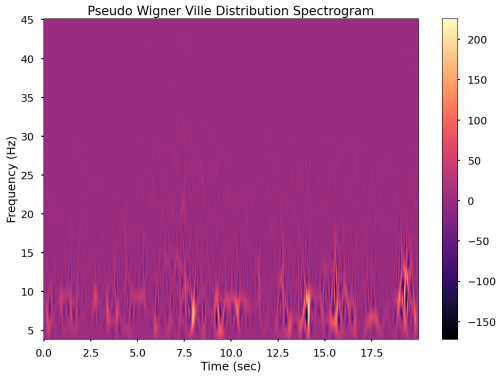
(a) Healthy SPWVD from Dataset I



(b) Patient SPWVD from Dataset I



(c) Healthy SPWVD from Dataset II



(d) Patient SPWVD from Dataset II

Figure 4.10: SPWVDs

4.3 CNN Model Architecture

In this experiment, a 19-layered Convolutional Neural Network is used. The Network has been derived from the VGG16 network while trying to reduce overfitting in the model training.

The input shape is (112, 112, 3), which is the image size of the spectrogram images. These images go through 5 convolutional blocks consisting of 2 convolutional layers with padding as 'same' and kernel size (3, 3). A max-pooling layer followed these Convolutional layers in the block with (2, 2) pooling size. The five convolutional blocks have 64, 128, 256, 512 and 512 filters, respectively. The feature vector obtained is then flattened and passed through 2 FC (Fully Connected) layers with 1024 and 256 units, respectively, with ReLU activation function. Dropout layers with 50% probability follow both the FC layers. The output layer is a classification layer with 1 neuron, with the sigmoid activation function.

The model is compiled with optimizer AdamW (Loshchilov et al.[23]) having a learning rate of 0.0001, and has been run for 5 epochs with 128 batch size. Table

Layer	Type	Number	Size	Stride	Activation	Dropout
1	Input	-	112 x 112	-	-	-
2	Conv	64	112 x 112	1	ReLU	-
3	Conv	64	112 x 112	1	ReLU	-
4	Max Pool	-	56 x 56	2	-	-
5	Conv	128	56 x 56	1	ReLU	-
6	Conv	128	56 x 56	1	ReLU	-
7	Max Pool	-	28 x 28	2	-	-
8	Conv	256	28 x 28	1	ReLU	-
9	Conv	256	28 x 28	1	ReLU	-
10	Max Pool	-	14 x 14	2	-	-
11	Conv	512	14 x 14	1	ReLU	-
12	Conv	512	14 x 14	1	ReLU	-
13	Max Pool	-	7 x 7	2	-	-
14	Conv	512	7 x 7	1	ReLU	-
15	Conv	512	7 x 7	1	ReLU	-
16	Max Pool	-	3 x 3	2	-	-
17	Flatten	-	4608	-	-	-
18	Fully Connected	1024	-	-	ReLU	0.5
19	Fully Connected	256	-	-	ReLU	0.5
20	Output	1	-	-	Sigmoid	-

Table 4.1: Configuratioin of proposed model

4.2 below shows the experimental values for epoch and batch size and the optimizer, learning rate, and loss function. The weight updation process using AdamW looks like this

$$W(t) = W(t-1) - \alpha \frac{\beta_1 m_{t-1} + (1-\beta_1)(\nabla f_t + w x_{t-1})}{\sqrt{v_t} + \epsilon} \tag{4.4}$$

Parameter	Details
TFR image size	112 x 112 x 3
Learning rate	0.0001
Epochs	50
Optimizer	AdamW
Batch size	128
Loss function	Binary Cross Entropy

Table 4.2: Training parameters for proposed model

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Performance Metrics

The most popular performance measures in schizophrenia classification tasks were utilised to evaluate the proposed framework's classification performance, such as accuracy (ac), specificity (sp), sensitivity (sn) or recall (rc), precision, and F1-score. These metrics' formulae are mentioned below.

$$ac = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{5.1}$$

$$sn/rc = \frac{T_p}{T_p + F_n} \tag{5.2}$$

$$sp = \frac{T_n}{T_n + F_p} \tag{5.3}$$

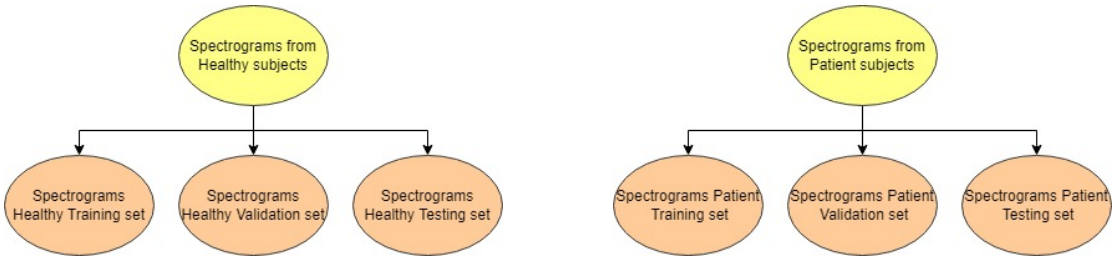
$$pr = \frac{T_p}{T_p + F_p} \tag{5.4}$$

$$F1 - score = \frac{2 \times pr \times rc}{pr + rc} \tag{5.5}$$

These metrics can be calculated using the confusion matrix produced during model testing using test data. Where the classification's true positive, true negative, false positive, and false negative values are denoted by T_p, T_n, F_p, and F_n, respectively.

5.2 Performance Evaluation

TFR images of sizes (112, 112, 3) are created separately for both healthy and patient subjects. Then, training, validation, and testing sets are created from the healthy and patient sets of TFR pictures. The division ratios were 60%, 20% and 20%. Then, the healthy and patient parts are concatenated for the training, validation and testing sets. These combined training, validation and testing sets are then fed to the model.



(a) Healthy Spectrogram data being divided into Training, Validation and Testing sets

(b) Patient Spectrogram data being divided into Training, Validation and Testing sets

Figure 5.1: Training, Validation and Testing dataset

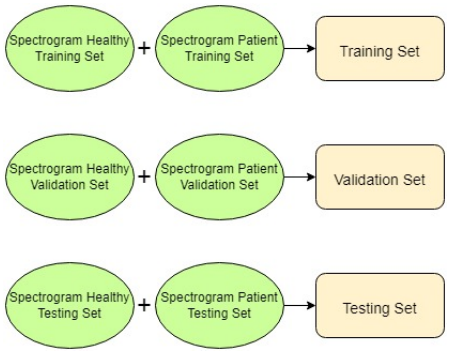


Figure 5.2: Healthy and Patient training, validation and testing sets being concatenated

Additionally, the model has undergone 5-fold cross-validation training and testing. The folds created were stratified, meaning the percentage of healthy and Sz patients in the training, validation and testing sets were the same for all the 5 folds. The accuracy recorded on all 5 folds was averaged to get the results.

TFR	Accuracy	Precision	Recall	Specificity	F1 Score
Spectrogram	**95.40%**	**95.53%**	**94.46%**	**96.20%**	**94.99%**
Scalogram	88.72%	88.32%	87.15%	90.08%	87.73%
SPWVD	79.05%	77.16%	77.70%	79.37%	80.20%

Table 5.1: TFR Comparison on Dataset I

TFR	Accuracy	Precision	Recall	Specificity	F1 Score
Spectrogram	**96.53%**	**97.42%**	**96.06%**	**97.06%**	**96.74%**
Scalogram	92.68%	93.22%	93.15%	92.15%	93.18%
SPWVD	89.43%	88.81%	90.69%	87.98%	89.74%

Table 5.2: TFR Comparison on Dataset II

5.3 Performance Comparison

5.3.1 Comparison between TFRs

For Dataset I, Table 5.1 shows the 5-fold validation process results. The Spectrogram gives much better results than the other considered TFRs. Something similar can be seen in Dataset II, where Spectrogram results are better than the other TFRs. The TSNE plots at the end of the Convolutional layers for each TFR used are as follows.

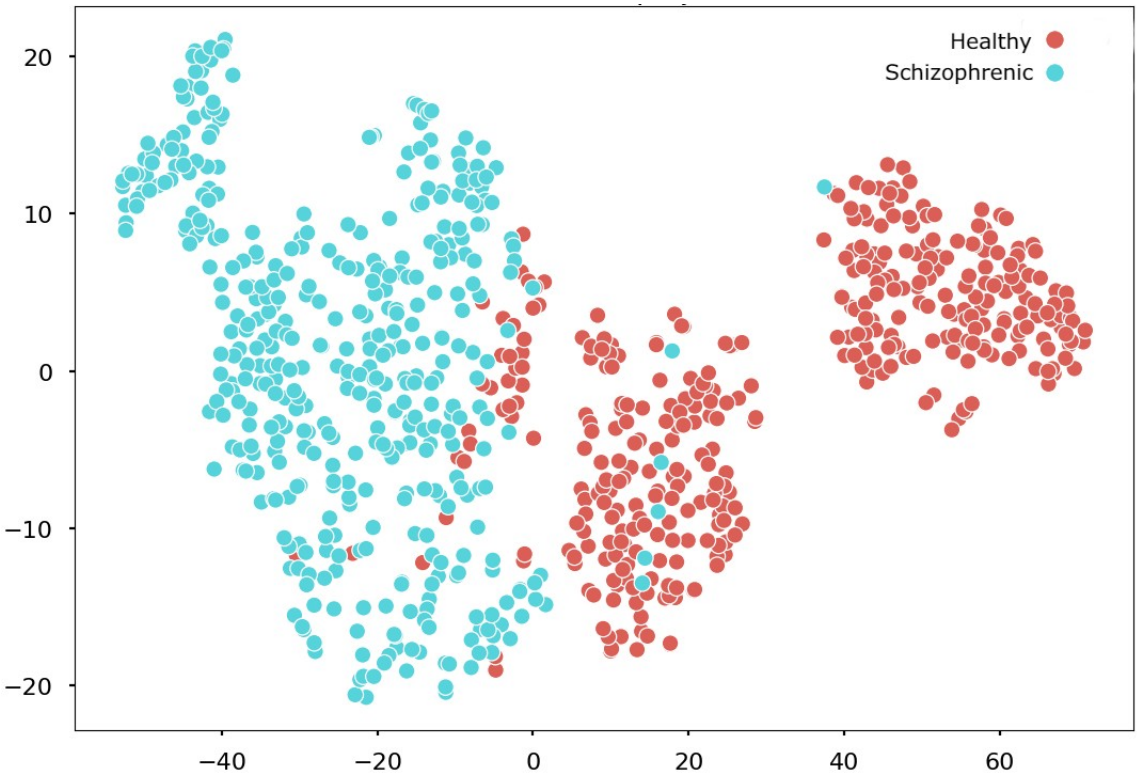


Figure 5.3: TSNE plot for Spectrogram

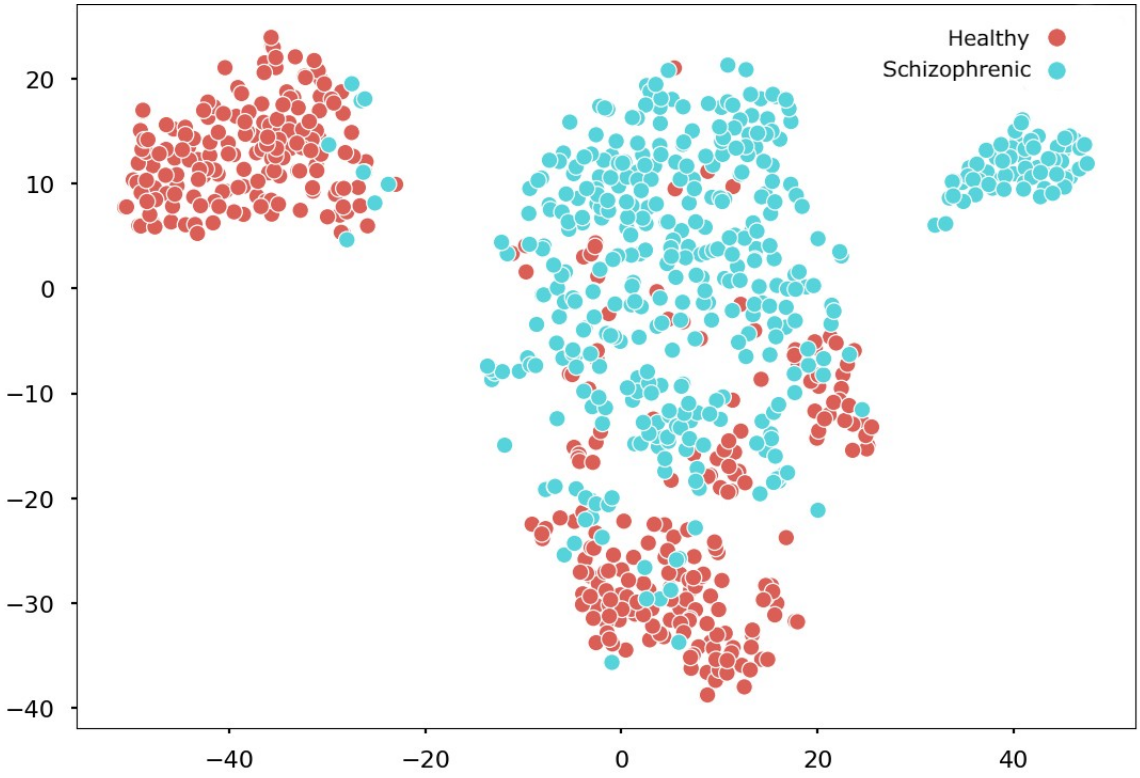


Figure 5.4: TSNE plot for Scalogram

5.3.2 Comparison against other works

The results found using the proposed method fare well amongst other methods and is shown to be capable of giving good results.

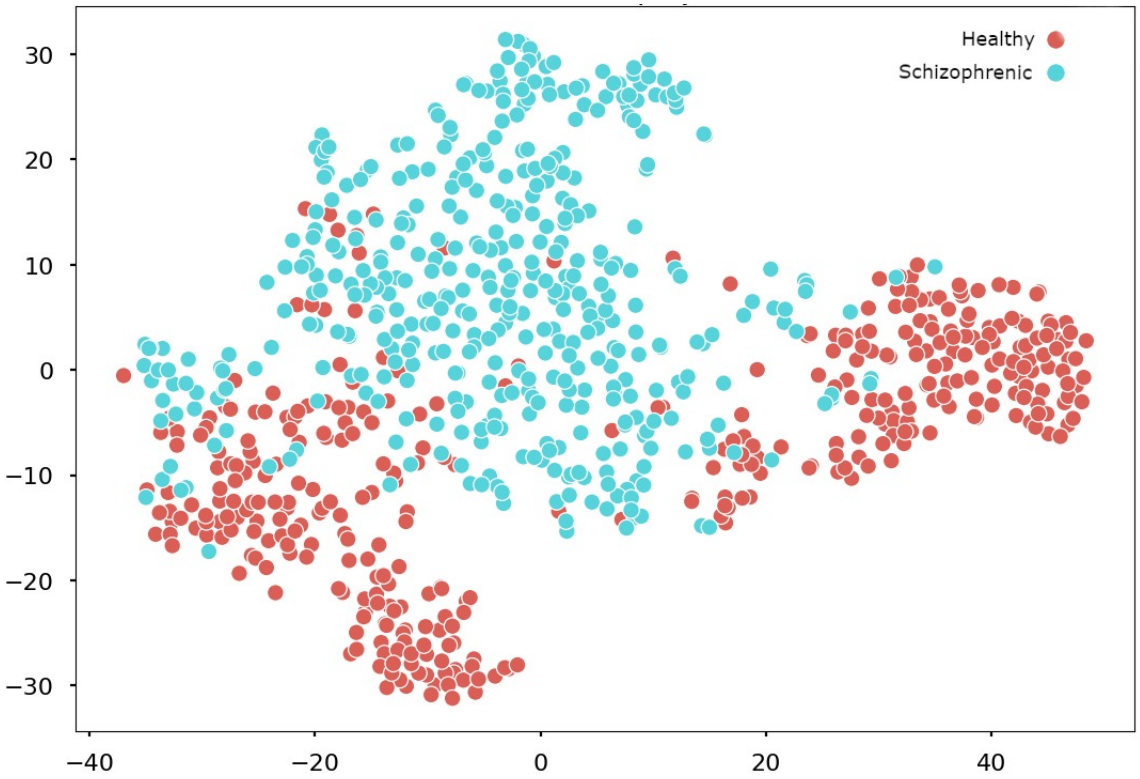


Figure 5.5: TSNE plot for SPWVD

Author	Dataset	Preprocessing	Input	Classifier	Accuracy
Kim et al.[1]	Personal	Yes	Spectral Power	ANNOVA	62.2%
Laksono et al.[2]	Button-Tone-Sz	No	Raw EEG	SVM	79.2%
				CNN	76%
Oh et al.[24]	RepOD	Yes	Normalized EEG	CNN	81.26%
Wu et al.[3]	RepOD	No	Raw EEG	RAE	81.81%
Johannesen et al.[4]	Personal	Yes	SWMT	SVM	87%
Naira et al.[5]	MHRC	No	PCC	CNN	90%
Phang et al.[6]	MHRC	No	VAR, PDC, CN	CNN	91.69%
Khare et al.[7]	Button-Tone-Sz	No	SPWVD	CNN	93.36%
Lillo et al.[8]	RepOD	Yes	Random Walk	CNN	93%
Aslan et al.[9]	RepOD	No	Spectrogram	VGG16	95%
	MHRC				97%
Kumar et al.[10]	RepOD	No	HLV, SLBP	Adaboost	99.15%
	MHRC				92.85%
Ko et al.[11]	Button-Tone-Sz	No	GAF image	VGGNet	93.2%
Dvey-Aharon et al.[12]	Personal	Yes	TFFO	RT ANOVA	93.9%
Sun et al.[14]	Personal	No	Fuzzy Entropy	CNN	99.22%
Supakar et al.[15]	MHRC	Yes	RP	RNN-LSTM	98%
Shalbaf et al.[16]	RepOD	No	CWT	ResNet-18-SVM	98.60%
Göker et al.[17]	RepOD	Yes	Multitaper method	1D-CNN	98.76%
Shoebi et al.[18]	RepOD	No	Normalized EEG	CNN-LSTM	99.25%
Aslan et al.[19]	RepOD	No	Scalogram	VGG16	99.8%
	MHRC				99.5%
Bagherzadeh et al.[20]	RepOD	Yes	TE Connectivity	EfficientNetB0-LSTM	99.9%
Şeker et al.[21]	MHRC	Yes	SPWVD	ViT	100%
Sairamya et al.[22]	MHRC	No	RLNDiP	ANN	100%
Proposed Model	**MHRC**	**Yes**	**TFR images**	**CNN**	**96.53%**
	RepOD				**95.40%**

Table 5.3: TFR Comparison with other works

CHAPTER 6

Conclusion

In this research, we looked into the possibilities of CNN with several TFRs. Utilizing this framework, we have achieved an accuracy of 96.30% and 95.40% in classifying Sz subjects from healthy ones in two datasets respectively. We hope our approach will enable us to construct an on-device system capable of diagnosing Sz from EEG signals.

REFERENCES

[1] J. W. Kim, Y. S. Lee, D. H. Han, K. J. Min, J. Lee, and K. Lee, "Diagnostic utility of quantitative eeg in un-medicated schizophrenia," *Neuroscience letters*, vol. 589, pp. 126–131, 2015.

[2] I. K. Laksono and E. M. Imah, "Schizophrenia detection based on electroencephalogram using support vector machine," in *2021 International Conference on ICT for Smart Society (ICISS)*. IEEE, 2021, pp. 1–6.

[3] Y. Wu, M. Xia, X. Wang, and Y. Zhang, "Schizophrenia detection based on eeg using recurrent auto-encoder framework," in *Neural Information Processing: 29th International Conference, ICONIP 2022, Virtual Event, November 22–26, 2022, Proceedings, Part II*. Springer, 2023, pp. 62–73.

[4] J. K. Johannesen, J. Bi, R. Jiang, J. G. Kenney, and C.-M. A. Chen, "Machine learning identification of eeg features predicting working memory performance in schizophrenia and healthy adults," *Neuropsychiatric electrophysiology*, vol. 2, pp. 1–21, 2016.

[5] C. A. T. Naira, C. Jos *et al.*, "Classification of people who suffer schizophrenia and healthy people by eeg signals using deep learning," *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 10, 2019.

[6] C.-R. Phang, F. Noman, H. Hussain, C.-M. Ting, and H. Ombao, "A multi-domain connectome convolutional neural network for identifying schizophrenia from eeg connectivity patterns," *IEEE journal of biomedical and health informatics*, vol. 24, no. 5, pp. 1333–1343, 2019.

[7] S. K. Khare, V. Bajaj, and U. R. Acharya, "Spwvd-cnn for automated detection of schizophrenia patients using eeg signals," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–9, 2021.

[8] E. Lillo, M. Mora, and B. Lucero, "Automated diagnosis of schizophrenia using eeg microstates and deep convolutional neural network," *Expert Systems with Applications*, vol. 209, p. 118236, 2022.

[9] Z. Aslan and M. Akin, "Automatic detection of schizophrenia by applying deep learning over spectrogram images of eeg signals." *Traitement du Signal*, vol. 37, no. 2, 2020.

[10] T. S. Kumar, K. N. Rajesh, S. Maheswari, V. Kanhangad, and U. R. Acharya, "Automated schizophrenia detection using local descriptors with eeg signals," *Engineering Applications of Artificial Intelligence*, vol. 117, p. 105602, 2023.

[11] D.-W. Ko and J.-J. Yang, "Eeg-based schizophrenia diagnosis through time series image conversion and deep learning," *Electronics*, vol. 11, no. 14, p. 2265, 2022.

[12] Z. Dvey-Aharon, N. Fogelson, A. Peled, and N. Intrator, "Schizophrenia detection and classification by advanced analysis of eeg recordings using a single electrode approach," *PloS one*, vol. 10, no. 4, p. e0123033, 2015.

[13] L. Santos-Mayo, L. M. San-José-Revuelta, and J. I. Arribas, "A computer-aided diagnosis system with eeg based on the p3b wave during an auditory odd-ball task in schizophrenia," *IEEE transactions on biomedical engineering*, vol. 64, no. 2, pp. 395–407, 2016.

[14] J. Sun, R. Cao, M. Zhou, W. Hussain, B. Wang, J. Xue, and J. Xiang, "A hybrid deep neural network for classification of schizophrenia using eeg data," *Scientific Reports*, vol. 11, no. 1, pp. 1–16, 2021.

[15] R. Supakar, P. Satvaya, and P. Chakrabarti, "A deep learning based model using rnn-lstm for the detection of schizophrenia from eeg data," *Computers in Biology and Medicine*, vol. 151, p. 106225, 2022.

[16] A. Shalbaf, S. Bagherzadeh, and A. Maghsoudi, "Transfer learning with deep convolutional neural network for automated detection of schizophrenia from eeg signals," *Physical and Engineering Sciences in Medicine*, vol. 43, pp. 1229–1239, 2020.

[17] H. Göker, "1d-convolutional neural network approach and feature extraction methods for automatic detection of schizophrenia," *Signal, Image and Video Processing*, pp. 1–10, 2023.

[18] A. Shoeibi, D. Sadeghi, P. Moridian, N. Ghassemi, J. Heras, R. Alizadehsani, A. Khadem, Y. Kong, S. Nahavandi, Y.-D. Zhang *et al.*, "Automatic diagnosis of schizophrenia in eeg signals using cnn-lstm models," *Frontiers in neuroinformatics*, p. 58, 2021.

[19] Z. Aslan and M. Akin, "A deep learning approach in automated detection of schizophrenia using scalogram images of eeg signals," *Physical and Engineering Sciences in Medicine*, vol. 45, no. 1, pp. 83–96, 2022.

[20] S. Bagherzadeh, M. S. Shahabi, and A. Shalbaf, "Detection of schizophrenia using hybrid of deep learning and brain effective connectivity image from electroencephalogram signal," *Computers in Biology and Medicine*, vol. 146, p. 105570, 2022.

[21] M. Şeker and M. S. Özerdem, "Eeg based schizophrenia detection using spwvd-vit model," *European Journal of Technique (EJT)*, vol. 12, no. 2, pp. 137–144.

[22] N. Sairamya, M. Subathra, and S. T. George, "Automatic identification of schizophrenia using eeg signals based on discrete wavelet transform and rlndip technique with ann," *Expert Systems with Applications*, vol. 192, p. 116230, 2022.

[23] I. Loshchilov and F. Hutter, "Decoupled weight decay regularization," *arXiv preprint arXiv:1711.05101*, 2017.

[24] S. L. Oh, J. Vicnesh, E. J. Ciaccio, R. Yuvaraj, and U. R. Acharya, "Deep convolutional neural network model for automated diagnosis of schizophrenia using eeg signals," *Applied Sciences*, vol. 9, no. 14, p. 2870, 2019.