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EEG-BASED SCHIZOPHRENIA DETECTION USING ADEEP LEARNING WITH CNN-TCN MODEL

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Abstract

Schizophrenia is a complex, chronic mental health disorder characterized by an array of symptoms, including delusions, hallucinations, disorganized speech or behavior, and impaired cognitive ability. Schizophrenia is a debilitating mental illness which involves three groups of symptoms, i.e., positive, negative and cognitive, and has major public health implications. According to various sources, it affects up to 1% of the population. The Patho mechanism of schizophrenia is not fully understood and current antipsychotics are characterized by severe limitations. Firstly, these treatments are efficient for about half of patients only. Secondly, they ameliorate mainly positive symptoms (e.g., hallucinations and thought disorders which are the core of the disease) but negative (e.g., flat affect and social withdrawal) and cognitive (e.g., learning and attention disorders) symptoms remain untreated. Thirdly, they involve severe neurological and metabolic side effects and may lead to sexual dysfunction or agranulocytosis (clozapine). The purpose of the study is to identify a common person who are affected by Schizophrenia. Our presentation will also cover the role of psychotherapy, specifically cognitive- behavioral therapy for psychosis, and the benefits of family therapy and support groups. It will create impact on social skills training, focusing on communication, social interaction, problem-solving, and decision-making skills. This application is very user-friendly, efficient and it has got many unique features. Tenants can register using their phone number, store information about their identity and upload the dataset of EEG data it will train the dataset and produce the accurate result of whether the person is affected the disease. Proposed system aims to shed light on the comprehensive and multi-faceted approach required to manage schizophrenia effectively and improve the quality of life for those affected by this complex disorder.

Keywords: Schizophrenia, Web Application, Early Intervention and Prevention, CNNs for Schizophrenia Detection, TCNs for Schizophrenia Analysis, Deep learning.

1. INTRODUCTION

Schizophrenia is the major mental illness of our time. It was first described by Kraepelin (1896) as "dementia praecox" and later given the name "schizophrenia" by Bleuler in 1911. It is a condition characterized by disturbances of thought, perception and a blunting of affect. These disturbances "involve the most basic functions that give the normal person a feeling of individuality, uniqueness, and self-direction" (WHO 1992). In 1959 a German Psychiatrist identified what he considered to be first rank symptoms of schizophrenia (Schneider 1959). Schneider grouped the collection of symptoms into three main categories, namely, auditory hallucinations, passivity experience and delusional thinking. Schizophrenia sufferers experience hallucinatory "voices" which may either provide a running commentary on one's movements or instruct the person to carry out certain tasks. [1]. Some sufferers experience voices which are derogatory or insulting. Passivity feelings refer to those feelings, thoughts or behaviors which the individual experiences as being under the influence of a third party. Delusional thinking arises from perceptions which may be distorted. Delusional thinking is often insight less and unamenable to reason. Although these symptoms are no longer used as the sole diagnostic aid Schneider's categorization of the symptoms gives a glimpse of the level of disturbance those with schizophrenia experience Schizophrenia however is also associated with a wide range of other symptoms including social withdrawal, incongruent affect and thought disturbances, which contribute to the devastating effects this illness can have on the person. The cost of schizophrenia in both human terms and in its cost to the nation is immense. As well as the symptoms described above loss of social contacts and career prospects often go hand-in-hand with the illness schizophrenia, working towards a more objective and accurate diagnosis of schizophrenia. Ford et al. presented a study to classify schizophrenic patients using EEG through N100, in which brain waves are given auditory stimulation and then stimulation is decreased after 100 ms [2].

2. LITERATURE SURVEY

There has been a substantial amount of introduced studies that analyze the relationship between EEG and patients have hearing impairment due to auditory cortex dysfunction, it has been demonstrated that N100, a large, negative evoked potential that is elicited by auditory stimulus, differs in schizophrenic patients compared to the general population. In addition, Kim et al and Thilakavathi et al. Analyzed the pattern of EEG or compared EEG numerical values to validate the correlation between schizophrenia and EEG. Ruxandra et al. [3] trained on a deep learning model without transforming time series data. This study suggests the importance and limitations of learning time series data in deep learning methods.

In Zhang et al., data analyzed in Ford et al was classified through machine learning technology. The Random Forest was used to differentiate EEGs of schizophrenic patients from the general public, and the highest classification accuracy was 81.1%. In addition to schizophrenia, the utilization of EEG was also recommended as methods for diagnosing mental disorders such as epilepsy and depression. Archarya et al. proposed a system for automatically diagnosing epilepsy by learning EEG data in the CNN model without any other conversion of EEG. The accuracy of differentiating between epilepsy patients and healthy subjects was 88.67%. Naira et al. used a new EEG methodology to improve classification accuracy of schizophrenic patients and healthy subjects.

This publication presented a method of calculating Pearson Correlation in EEG data, converting into a matrix representing the relationship between EEG channels, and then learning in a CNN model. Previous studies using Support Vector Machine (SVM) and Random Forest obtained 81.07% and 84.5% accuracy, respectively and deep learning models that learned by converting EEG data into Pearson Correlation matrix demonstrated an improved classification accuracy of 90%. Alhagry et al. conducted an experiment to discern human emotions using EEG. Emotions were classified by learning raw EEG data in LSTM model, which is used for time series data learning, and the maximum accuracy of emotion classification obtained was 87.99%.

There are various studies that convert EEG into images to learn from artificial intelligence. WeiKoh et al. used EEG data to limit new methods of diagnosing patients with schizophrenia. In this study, EEG is transformed into a spectrogram and then trained with KNN, one of the machine learning models. Sobahi et al. [4] converted the EEG into an image form using a local binary pattern. Then, using the transformed image, the CNN is trained. In this research, Recurrence Plot (RP) and Gramian Angular Field (GAF) were used as methods of converting time series data into images [10,22].

The two methods calculated numerical conversion information of time series data using nonlinear analysis and represented the data as a square image. RP and GAF are techniques to which algorithms to analyze patterns of time series data are applied [21-25]. Therefore, specific changes in EEG data can be efficiently checked, and the overall flow is expressed in one image, which is effective for CNNs where receptive fields are important. In addition, RP and GAF change the patient's EEG into an image for each channel, so it has the advantage of accurately learning a deep learning model with more data.

Previous studies have explored various traditional machine learning techniques such as support vector machines (SVM), random forests, and logistic regression for schizophrenia prediction using neuroimaging data. While these methods have shown promising results, they often struggle with capturing complex spatial and temporal patterns inherent in neuroimaging data. There is a growing body of research utilizing deep learning techniques for schizophrenia prediction. Convolutional Neural Networks (CNNs) have been employed to extract meaningful features from structural and functional brain images. However, these approaches often overlook the temporal dynamics present in longitudinal neuroimaging data. which are crucial for understanding the progression of schizophrenia. TCNs have emerged as a powerful tool for modeling sequential data due to their ability to capture long-range dependencies and temporal patterns. Several studies have demonstrated the effectiveness of TCNs in various tasks such as time series forecasting and natural language processing. However, their application to neuroimaging data for schizophrenia prediction remains relatively unexplored. Pre-trained CNNs developed on vast image datasets can be repurposed for EEG analysis in schizophrenia.[5]. By finetuning these models on labeled schizophrenia EEG data, researchers can achieve good classification accuracy even with limited datasets, improving efficiency. Spatial pyramid pooling network, or SPP-Net, is 24-102 times faster than the R-CNN approach.

3. MATERIALS AND METHODS

3.1 DATA

Data used in this experiment was measured data presented by the National Institute of Mental Health (NIMH; R01MH058262), and was provided at https://www.kaggle.com/broach/button-tone-sz (accessed on 17 July 2022), in which data was measured in 49 schizophrenic patients and 32 healthy patients, generating a total of 81 EEGs. The composition of the research data is as follows.[6]. Data of 81 subjects used in the experiment were measured to study the difference in EEG between schizophrenic patients and healthy subjects. N100 refers to a negative deflection in EEG brain waves after 100 ms when auditory stimulation is given. Schizophrenia patients have problems with N100 because they have hearing impairment due to a dysfunction in the auditory cortex. Thus, a study was conducted to verify the difference in N100 between schizophrenic and healthy patients using EEG data of 81 subjects.

EEG was measured 100 times each under the following three conditions.

(1) Subject pressed a button to generate the tone.

(2) Subject pressed a button without generating the tone.

(3) Subject passively listened to the same tone.[7].

EEG was measured in a total of 70 channels by measuring 64-channel scalp EEG and 6 channels around the eyes and nose. In this study that compared the N100 differences between schizophrenic patients and healthy subjects, among the 70 analyzed channels, 9 electrode sites (Fz, FCz, Cz, FC3, C3, CP3, FC4, C4, CP4) had distinct N100 differences. [38].

Figure 1 shows the N100 difference between schizophrenic patients and healthy subjects in the Fz channel. As a result of the analysis, in the case of the healthy subjects, N100 was more suppressed in Condition 1 than in Condition 2, but in the case of schizophrenic patients, it was demonstrated that there was no difference between Conditions 1 and 2. In this experiment, the average of 100 values measured under each condition was used, and the measured data was edited from 1.5 s before hearing the tone to 1.5 s after hearing the tone to use 3 full seconds of EEG data. This experiment proceeded in classifying EEG of schizophrenic patients and healthy subjects using 9 out of 70 channels, similar to that in previous studies.

There are various studies that convert EEG into images to learn from artificial intelligence. WeiKoh et al. [8] used EEG data to limit new methods of diagnosing patients with schizophrenia. In this study, EEG is transformed into a spectrogram and then trained with KNN, one of the machine learning models. Sobahi et al. converted the EEG into an image form using a local binary pattern. Then, using the transformed image, the CNN is trained. In this experiment, the average of 100 values measured under each condition was used, and the measured data was edited from 1.5 s before hearing the tone to 1.5 s after hearing the tone to use 3 full seconds of EEG data.

This experiment proceeded in classifying EEG of schizophrenic patients and healthy subjects using 9 out of 70 channels, similar to that in previous studies. The N100 is a specific component of the brain's electrical activity measured by EEG (electroencephalogram). The N100 is a negative peak in the EEG waveform occurring around 100 milliseconds after a sound stimulus. It reflects sensory processing in the auditory cortex. Some studies report reduced N100 amplitude in schizophrenic patients compared to healthy individuals.[9] This might indicate weaker initial processing of auditory stimuli.

3.2 IMAGE CONVERSION OF EEG DATA

Unlike previous studies that learn EEG in table form or in EEG graphs, the newly proposed schizophrenia diagnosis method in this study required a process of converting EEG data into images. Possible methods of converting time series data into images included Recurrence Plot (RP), Gramian Angular Field (GAF), and Markov Transition Field (MTF). The aforementioned methods represent the amount of change in time series data values as a matrix and are expressed as an image. Looking into the characteristics of each method, RP displays the amount of change in the data value in a two-dimensional space, expressing the distance between each point as a matrix, and GAF as the inner matrix of the data values. MTF uses the Markov Transition Matrix to express the probability that the data value will change to the next value in chronological order and converts it into an image.[10]. After comparing classification accuracies of the three image conversion methods, RP and GAF, which have high classification accuracy, were applied to the learning process for this experiment. Figure 2 portrays the overall process of the experiment, and EEGs of schizophrenic patients and of healthy subjects were classified after converting EEG data into images using the previously mentioned two methods and trained in deep learning.

3.3 DEVICE ARCHITECTURE

System architecture refers to the design and organization of the various components of a computer system or software application, including hardware, software, networks, and data storage. The architecture of a system can has a significant impact on its performance, scalability, security, and maintainability. Fig 3.1 defines proposed work of the system. In this architecture, we can collect the datasets from CHB-MIT database. Then read the EEG datasets and perform preprocessing steps to eliminate the irrelevant and missing data removal. Train the model using CNN algorithm and visualize the performance of the system. In the testing phase, user login to the system and extract the attributes. Finally provide the disease details with precautious.

3.4 USE CASES

Use case diagrams are usually referred to as behavior diagrams used to describe a set of actions (use cases) that some system or systems (subject) should or can perform in collaboration with one or more external users of the system (actors). Each use case should provide some observable and valuable result to the actors or other stakeholders of the system.[11] Thus, the representation and quality of data is first and foremost before running any analysis. Often, data preprocessing is the most important phase of a machine learning project, especially in computational biology. In the pre-processing stage, continuous EEG recordings are firstly segmented without overlapping by a sliding time window. Then wavelet transform is performed on the EEG data to provide the signals form of dataset.

3.5 RECURRENCE PLOT

This step corresponds to (A) of Figure 2 and describes the process of converting the EEG into an image using RP. In order to visualize the movement of time, RPs represent data values in two-dimensional spatial trajectories and then convert them into images by representing the Euclidean distance between spatial trajectories [12]. Therefore, they can be useful in converting time series data, such as EEGs, into images.

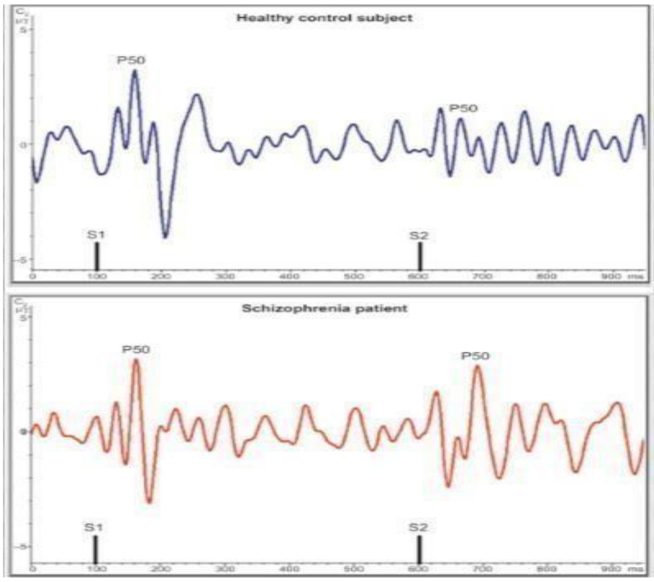

Figure 1. Differences in N100 EEG between schizophrenic patients and healthy

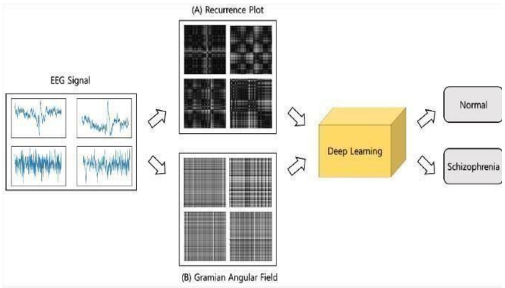

Figure 2. Image conversion and deep learning process of EEG data.

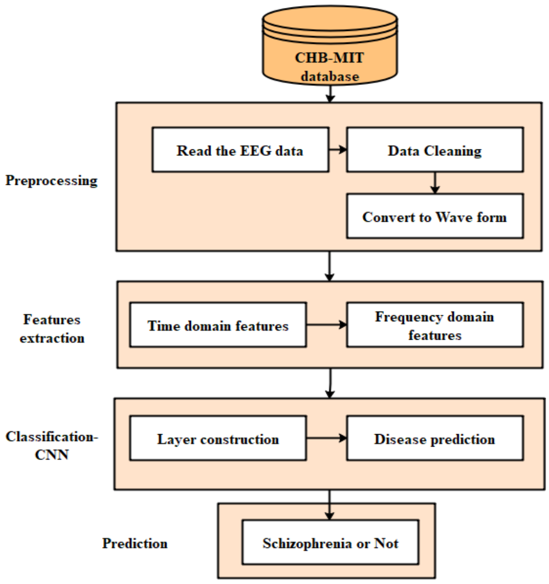

Figure 3. System Architecture

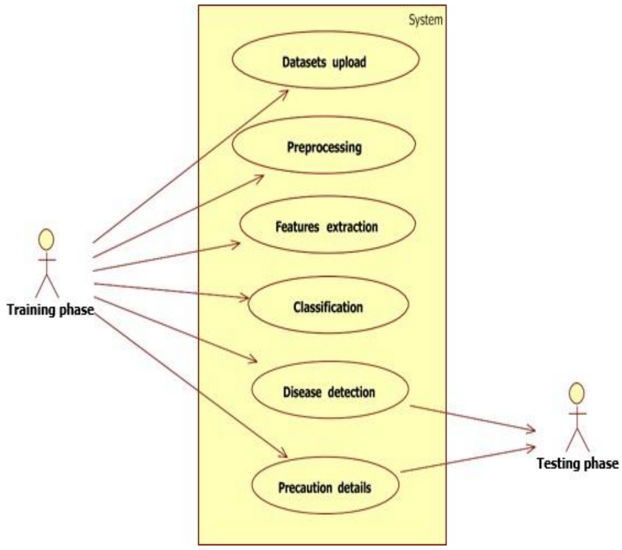

Figure 4. Use Case Diagram

$$R_{i,j} := H(\varepsilon_i - \|\vec{x_i} - \vec{x_j}\|),\ i,j = 1,\ldots,N \quad (1)$$

Equation (1) of the Recurrence Plot represented the value of the Euclidean distance matrix. $\|\vec{x_i} - \vec{x_j}\|$ meant the distance between trajectories in a two-dimensional spatial trajectory, and ε_i means a threshold. $H(x)$ was the output of a Heaviside Function equal to 1 if x value was greater than or equal to 0 or 0 if x value was less than or equal to 0. [40]. If the distance between the trajectories in a two-dimensional spatial trajectory was farther than the threshold, it was represented by a value of 0, and if it was closer than the threshold, it was represented by a value of 1. In the RP, 1 was marked in black and 0 was marked in white to represent an image. Thus, when the EEGs of schizophrenic patients and of healthy subjects were expressed as RPs, the results of the conversion were square images with values of 0 and 1.

3.6 GRAMIAN ANGULAR FIELD

The step corresponding to (B) in Figure 2 is the process of converting the EEG into an image using GAF. GAF is an introduced method in order to visualize the movement of time, similar to the RP [13]. If RP is a method of calculating the Euclidean distance between spatial trajectories as a matrix and expressing it as an image, GAF uses polar coordinates to represent the temporal correlation between each time point.

Gramian Angular Field (GAF) x ¯ = x i − m a x (x) + (x i min (x)) m a x (x) − m i n (x) .

The Gramian Angular Field (GAF) is a technique for analyzing time series data. It goes beyond just looking at individual data points, instead focusing on how those points relate to each other over time. GAF works by transforming the data into a visual representation that highlights these correlations. This is achieved by converting the data to polar coordinates and then calculating a Gramian matrix. From this matrix, two key components are derived: the Gramian Angular Summation Field (GASF) and the Gramian Angular Difference Field (GADF). These components highlight similar and contrasting patterns within the data, respectively. This visual representation helps researchers identify relationships that might be missed in the raw data, making GAF a valuable tool for analyzing complex time series across various fields.

GAF was also visualized as an image by converting time series data values into matrices, similar to RP, and GAF expressed EEGs of schizophrenic patients and of healthy patients by using inner product values of data to convert into square images. RP and GAF are methods to represent images using changes in time series data. The EEG data used in the experiment is data measuring the difference in EEG change between schizophrenia and normal.

3.7 FEATURES EXTRACTION

In this module, we can extract the time and frequency domain features from preprocessed data. It includes “mean”, variance", "kurtosis", "skewness” and other features for future classification. Mean: It is the average of an N sample EEG signal; it can be defined [14].

$$\mu = \frac{1}{N} \sum_{i=1}^{N} Y_i$$

Standard deviation: The dispersion of data from it’s a mean value of a signal is a standard deviation.[15].

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (Y_i - \mu)^2}$$

Kurtosis: It is a one of the statistical moments, it gives the time series data peaked nature. Kurtosis can be derived as

$$k = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{y_{i-\mu}}{\sigma}\right)^4$$

Skewness: It measures the symmetry shape of the distribution of a signal, it can be derived as [16]

$$skewness = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{y_{i-\mu}}{\sigma}\right)^3$$

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4 THE PROPOSED FRAMEWORK FOR SCHIZOPHRENIA DETECTION

4.1 SIGN UP PAGE

Figure 5 shows the registration part. In the registration part, there are 7 columns (Name, Age, Email, Mobile, Address, Username, Password). Here, the phone number and email must be unique. For registration user have to fill up this page, first of all user give the register ID, then write the full name, username, here email have to be verified email then contact number, password and confirm password. From this page user can reset their information also.[17].

4.2 LOGIN PAGE

A login page acts as the gateway to a secure online platform. It typically consists of a form where users enter their credentials, including username or email address and password. The login page verifies these credentials against a database to grant access to the user's account. Some login pages may offer additional features like password recovery or two-factor authentication for enhanced security. User can enter their separate username and password to login to the website. If user forget their username and password, they can reset using forget password and Sign in again to the website.[18]

4.3 UPLOAD EEG DTA SET

Some websites might offer a basic upload functionality where you can directly browse your local files and select the EEG

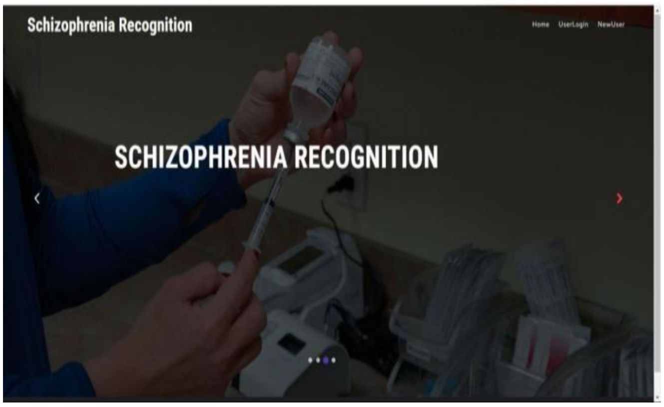

Figure 5. Index page

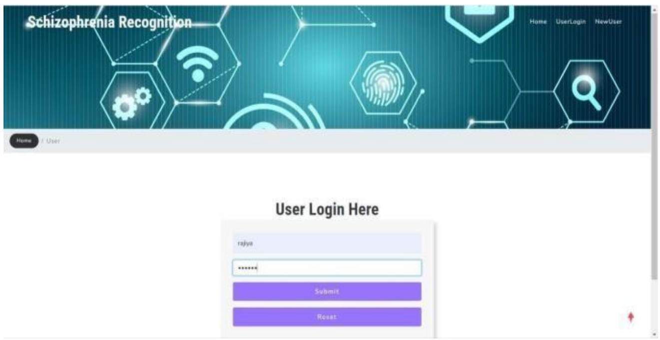

Figure 6. User Login

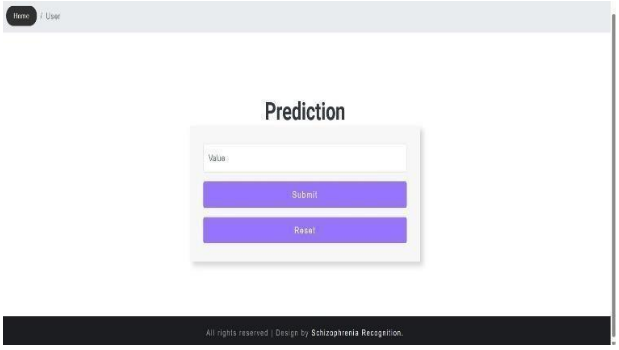

Figure 7. Prediction Page

dataset for upload. These inputs field typically behaves similarly to uploading any other file type [19]. Once you select the file, clicking an "Upload" button initiates the transfer process. For a more user- friendly experience, some websites might provide a drag-and- drop upload zone. In this case, you would navigate to the folder containing your EEG dataset on your computer and simply drag the file onto the designated area on the website. This eliminates the need to manually browse and select the file.

4.4 PREDICTION PAGE

The prediction page utilizes deep learning to analyze your EEG dataset for potential signs of schizophrenia. Deep learning algorithms like CNNs extract features from a visual representation of your EEG data, while TCNs focus on the sequential nature of brain activity. This CNN-TCN combination analyzes your EEG and classifies it based on patterns learned from a large existing dataset. However, remember this is a screening tool, not a diagnosis. Consult a medical professional for any concerns.[20]

5. RESULTS

Unlike the existing method of classifying schizophrenic patients by learning deep learning without converting EEG data, this study differentiated schizophrenic patients by learning deep learning after converting time series data EEG into images. A total of 81 EEG data were used in the experiment, in which the data were converted into images using RP and GAF and then learned in the deep learning model

The measured timeframe of EEG data was 3 s and had 3072 values per channel. Each channel was converted into a single image, and 3072 values passed through RP and GAF to result in a 3072 × 3072 size image. Since the input size of the model in this experiment was 224 × 224, the 3072 × 3072 size image was adjusted to 224 × 224 to learn in the deep learning model. In training, 2187 EEG images of 81 patients were used in 9 channels and 3 conditions were converted to RP and GAF. RP and GAF are methods for converting time series data into images by calculating the change. Therefore, if RP and GAF are used, the difference in the EEG change between schizophrenia and normal can be expressed as an image. The transformed EEG image is trained on the aforementioned VGG Net-based deep learning model. This model trained the difference between schizophrenia and normal EEG and makes classification possible. Deep learning model trained 200 epochs using binary cross entropy as loss function and Adam as optimizer. Then, the data converted for the experiment is validated by dividing it into train data and test data for each patient using 10-fold cross validation.

Classification accuracy was determined through learning on CNN with EEG data that was converted into images using Recurrence Plot and Gramian Angular Field. Figure 4 shows the learning curve of the model in which the RP was learned. The maximum accuracy and loss obtained as a result of learning were 0.945, 0.209, respectively [23]. Figure 4 shows the learning curve of the model in which GAF was trained. The maximum accuracy and loss obtained as a result of learning were 0.963, 0.184, respectively.

For result analysis, classification accuracy obtained by learning EEG Graph and classification accuracy from previous studies that differentiated schizophrenic patients using the same data were used in this experiment.[54]. Previous studies classified schizophrenic patients using Random Forest but used the same channels as those used in this experiment Confusion matrices of the approaches using RP and GAF, presented in Table 1 and Table 2 were used to determine model performance. For the RP approach, sensitivity and specificity were 90.9% and 88.6%, respectively. For the GAF approach, sensitivity was 93.9% and specificity was 92.1%. The subject-wise testing of the implemented models is also done along with the non-subject-wise testing. In subject-wise testing, 28 participants are divided into ten groups. Out of these ten groups, eight groups hold EEG data of three subjects each, and rest two groups hold EEG data of 2-2 participants each. Here, the 10-fold cross-validation process is used to train and test the proposed and all other implemented model. This labeled data is

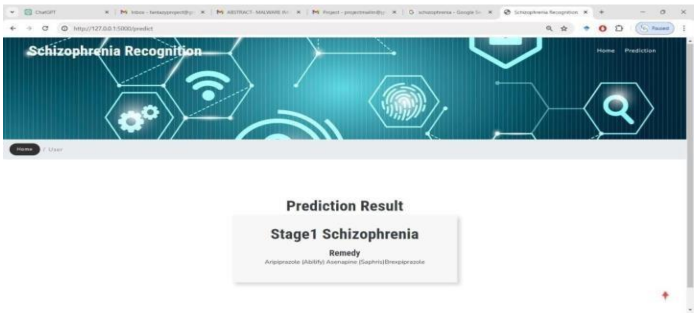

Figure 8**.** Prediction Result.

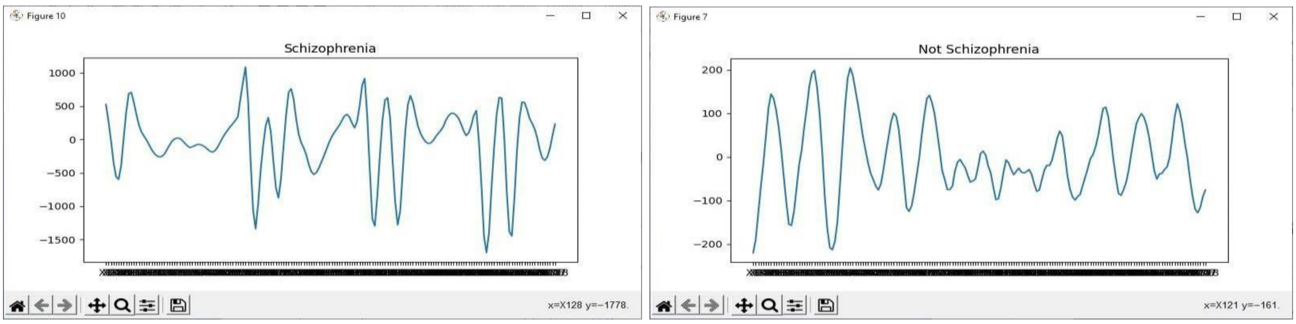

Figure 9. Learning curve of Recurrence Plot and Gramian Angular Field Schizophrenic

fragmented into ten equal segments with similar class label selections throughout the segment. Out of ten segments, nine records train the model, and data in the tenth segment will test the model repeatedly ten times. The training and validation accuracy curve of the proposed CNN-TCN Model (using approach 1) for subject-wise and non-subject wise data is shown in Figure 9.

As a result of data analysis, the method of converting the time series data, EEG, into an image and learning in deep learning indicated an improvement in classification accuracy compared to prior methods and proposed methods in previous studies. In this study, EEG data was converted into images using RP and GAF, and based on the analysis results, it can be demonstrated that the approach using GAF is more effective and accurate in classifying EEGs in schizophrenic patients and healthy subjects.

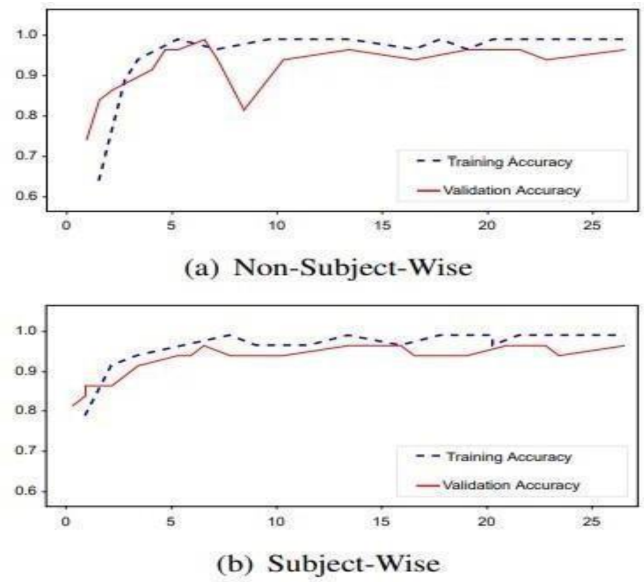

Figure 10. Training and Validation accuracy of proposed CNN-TCN model for non-subject wise and subject-wise data

REFERENCES

1. World Health Organization. Schizophrenia. Available online:https://www.who.int/en/newsroom/fact- sheets/detail/schizophrenia (accessed on 17 July 2022).
2. Laursen, T.M.; Nordentoft, M.; Mortense, P.B. Excess early mortality in schizophrenia. Annu. Rev. Clin. Psychol. 2014, 10, 425–448. [Google Scholar] [CrossRef]
3. American Psychiatric Association. Diagnostic and Statistical Manual of Mental Disorders, Dsm-5; American Psychiatric Association: Washington, DC, USA, 2014;pp. 107–110. [Google Scholar]
4. Oh, S.L.; Hagiwara, Y.; Raghavendra, U.; Yuvaraj, R.; Arunkumar, N.; Murugappan, M.; Acharya, U. A deep learning approach for Parkinson’s disease diagnosis from EEG signals. Neural Comput. Appl. 2020, 32, 10927–10933. [Google Scholar] [CrossRef]
5. Acharya, U.R.; Sudarshan, V.K.; Adeli, H.; Santhosh, J.; Koh, J.E.W.; Puthankatti, S.D.; Adeli, A. A Novel Depression Diagnosis Index Using Nonlinear Features in EEG Signals. Eur. Neurol. 2015, 74, 79–83. [Google Scholar] [CrossRef] [PubMed].
6. Aharon, Z.D.; Fogelson, N.; Peled, A.; Intrator, N. Schizophrenia Detection and Classification by Advanced Analysis of EEG Recordings Using a Single Electrode Approach. PLoS ONE 2015, 10, e0123033. [Google Scholar]
7. Heo, J.; Chung, K. EEG Recording Method for Quantitative Analysis. Korean J. Clin. Lab. Sci. 2019, 51, 397–405. [Google Scholar] [CrossRef] [Green Version]

8. Hatami, N.; Gavet, Y.; Debayle, J. Classification of Time- Series Images Using Deep Convolutional Neural Networks. Comput. Vis. Pattern Recognit. 2017. [CrossRef] [Green Version]
9. Wang, Z.; Oates, T. Imaging Time-Series to Improve Classification and Imputation. In Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, Buenos Aires, Argentina, 25–31 July 2015; pp. 3939–3945. [Google Scholar]
10. J. K. Wing, "The management of schizophrenia in the community," in Research in the Schizophrenic Disorders. Springer, 1985, pp. 113–154.
11. R. P. Shukla, C. Rapier, M. Glassman, F. Liu, D. L. Kelly, and H. Ben-Yoav, "An integrated electrochemical microsystem for real-time treatment monitoring of clozapine in microliter volume samples from schizophrenia patients" Electrochemistry Communications, vol. 120, p.106850, 2020
12. S. Kumar, T. Tsunoda, and A. Sharma, "SPECTRA: a tool for enhanced brain wave signal recognition," BMC bioinformatics, vol. 22, no. 6, pp.1–20, 2021.
13. M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. P. Zaveri, "eSeiz: An edge-device for accurate seizure detection for smart healthcare," IEEE Transactions on Consumer Electronics, vol. 65, no. 3, pp. 379–387,2019.
14. P. Lekshmylal, A. Radhakrishnan, and G. Shiny, "Analysis of autism spectrum disorder using EEG waveforms through signal processing techniques," in proc. of IEEE Recent Advances in Intelligent Computational Systems (RAICS), 2020, pp. 23–27.
15. H. Akbari, S. Ghofrani, P. Zakalvand, and M. T. Sadiq, "Schizophrenia recognition based on the phase space dynamic of EEG signals and graphical features," Biomedical Signal Processing and Control, vol. 69.
16. G. Sharma and A. M. Joshi, "Novel EEG based schizophrenia detection with iomt framework for smart healthcare," arXiv preprintarXiv:2111.11298, 2021.
17. WeiKoh, J.E.; Rajinikanth, V.; Vicnesh, J.; Pham, T.H.; Oh, S.L.; Yeong, C.H.; Sankaranarayanan, M.; Kamath, A.; Bairy, G.M.; Barua, P.D.; et al. Application of local configuration pattern for automated detection of schizophrenia with electroencephalogram signals. Expert Syst. 2022, e12957. [Google Scholar] [CrossRef]
18. Sobahi, N.; Ari, B.; Cakar, H.; Alcin, O.F.; Sengur, A. New Signal to Image Mapping Procedure and Convolutional Neural Networks for Efficient Schizophrenia Detection in EEG Recordings. IEEE Sens. J. 2022, 22, 7913– 7919.[Google Scholar] [CrossRef]
19. Eckmann, J.P.; Kamphorst, S.O.; Ruelle, D. Recurrence Plots of Dynamical Systems. Europhys. Lett. 1987, 4, 973–977. [Google Scholar] [CrossRef] [Green Version]
20. Hornero, R.; Abasolo, D.; Jimeno, N.; Sanchez, C.I.; Poza, J.; Aboy, M. Variability, regularity, and complexity of time series generated by schizophrenic patients and control subjects. IEEE Trans. Biomed. Eng. 2006, 53, 210–218. [Google Scholar] [CrossRef]
21. Schirrmeister, R.T.; Springenberg, J.T.; Fiederer, L.D.J.; Glasstetter, M.; Eggensperger, K.; Tangermann, M.; Hutter, F.; Burgard, W.; Ball, T. Deep learning with convolutional neural networks for EEG decoding and visualization. Hum. Brain Mapp. 2017, 38, 5391–5420. [Google Scholar] [CrossRef] [Green Version]
22. Chandran, A.N.; Sreekumar, K.; Subha, D.P. EEG- Based Automated Detection of Schizophrenia Using Long Short-Term Memory (LSTM) Network. In Advances in Machine

Learning and Computational Intelligence; Springer: Singapore, 2020; pp. 229–236. [Google Scholar]
23. Lecun, Y.; Boser, B.; Denker, J.S.; Henderson, D.; Howard, R.E.; Hubbard, W.; Jackel, L.D. Backpropagation applied to handwritten zip code recognition. Neural Comput. 1989, 1, 541–551. [Google Scholar] [CrossRef]
24. Sak, H.; Senior, A.; Beaufays, F. Long Short-Term Memory Recurrent Neural Network Architectures for Large Scale Acoustic Modeling. Neural and Evolutionary Computing. arXiv 2014, arXiv:1402.1128. [Google Scholar]
25. Simonyan, K.; Zisserman, A. Very Deep Convolutional Networks for Large-Scale Image Recognition. Computer Vision and Pattern Recognition. arXiv 2015, arXiv:1409.1556. [Google Scholar].