A Smart Healthcare Framework for Accurate Detection of Schizophrenia using Multi-Channel EEG

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***Abstract*—In recent years, advanced computing techniques have been investigated and employed for the computerized detection of brain disorders like schizophrenia. Schizophrenia is a neurological condition leading to hallucinations and disorganized speech in patients. Emerging deep-learning approaches can augment the computer-based diagnosis of this brain disorder by measuring and analyzing the Electroencephalography (EEG) signals. This paper proposes a novel concept of easy-to-wear cap, namely SczCap, integrating hardware and software for acquiring EEG signals from the scalp for accurate schizophrenia detection. In this research, A seven-layer model comprising of convolution neural network (CNN) and temporal convolution network (TCN) is designed and tested using raw EEG data (approach 1) and manually extracted features (approach 2). Three pre-trained models, VGG 16, AlexNet, and ResNet 50, along with the proposed model, have also been implemented in this work. A dataset consisting of EEG signals of 14 healthy and 14 schizophrenic patients is used in this work for the implementations. The performance of the proposed CNN-TCN model (approach 1 & 2) is also presented using non-subject-wise and subject-wise experiments. It is found that the proposed CNN-TCN model using approach 1 outperformed all other implemented models with 99.57% accuracy, 99.51% sensitivity, 99.64% specificity, and 99.63% precision in non-subject-wise experiments. The experimental results also exhibit the superiority of this model over other schizophrenia models in the state of art literature.**

***Index Terms*—A Wearable device, CNN, EEG Measurement, TCN, Schizophrenia Disorder, Smart Healthcare.**

I. INTRODUCTION

SCHIZOPHRENIA is a pathological condition of the brain accompanied by cognitive disorders like persistent delusions and hallucinations. With 1 in 300 persons affected worldwide, this illness leads to discrimination, the social boycott of the patients, and educational, financial, and personal damages in their life. Diagnosing psychiatric disorders was conventionally conducted using face-to-face interactions with patients, their behavioral indications, and typical observable symptoms [1]. To analyze the biological markers causing the abnormal brain functioning in a person who has schizophrenia, researchers worldwide are working on different techniques [2].

EEG offers cost-effective technology for non-invasive acquire neural data of continual brain activities [3]. The test involves carefully placed electrodes on the scalp of the patient under diagnosis to record and measure the ongoing electrical activity of numerous neurons inside the human brain. These brain activities are represented in the form of graphs and chart for further analysis. The information acquired by EEG signals provides a reliable tool for the diagnosis of various neurological abnormalities occurring in brain activities due to conditions like epilepsy [4], Autism [5], schizophrenia [6], [7], Depression [8] etc. The advancements in non-linear computation theories helped augment the analysis and understanding of complex, non-linear EEG signal data. The EEG from healthy and schizophrenia subjects is shown in Figure 1. The irregularities and choppy activities are more prominent in the EEG of schizophrenia subjects. The indications deciphered from temporal EEG signals can provide rich data for traditional techniques deployed for feature extraction [9]. At present, EEG is a preferred tool due to its capacity to record data during a specific time interval. Detailed analysis of EEG recordings is time-consuming and may result in inaccurate results even when interpreted by proficient neurophysiologists. Accurate diagnosis demands efficient visual inspection of recorded patterns. Recent advances in high-performing data processing techniques like machine learning can address the concerns of decoding the massive amount of data acquired by healthcare systems [10]–[12]. To further enhance the usability of such diagnoses, the timely detection of neurological diseases can be a milestone in augmenting the medical industry with intelligent systems. A wearable device for real-time EEG data capture and processing is crucial for a health practitioner's fast detection and early treatment.

The proposed device, SczCap, aims to detect schizophrenia disease from EEG signals gathered from a person's head. Signals acquired by the electrodes are processed by the edge

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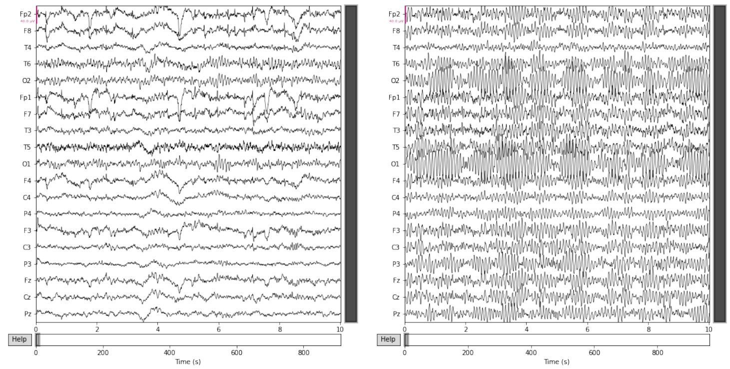


(a) Normal Subjects (b) Schizophrenia Subjects

Fig. 1: EEG from normal and schizophrenia subjects.

processing unit (EPU), and generated results are sent for server storage on the cloud. This is a novel model for integrating hardware and software in a single device to imploring the advantages of cloud computing in the medical field. The CNN-TCN model can use the acquired EEG signals for training and classification if the person has schizophrenia. Figure 2 gives a conceptual diagram for SczCap. The chart shows that the edge processing unit implements the deep learning model for automatic schizophrenia detection. This comprises the device's main module, which indicates schizophrenia detection with green and schizophrenia absence with a red indicator. Electrodes placed over the entire unit collect data, and processed data can be sent for cloud storage.

The rest of this paper is organized in the following manner:

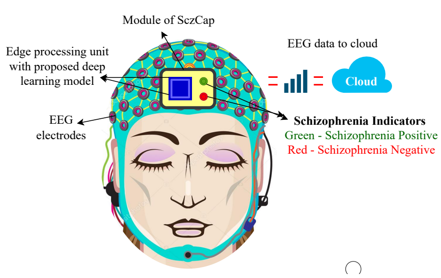


Fig. 2: Conceptual diagram of SczCap.

Section II presents the background and contribution. The methodology, along with the datasets, is explained in Section III. The implementation is elaborated on in section IV. Section V covers the results, and discussions are carried out in Section VI. Finally, the conclusion is presented in section VII.

II. State of the Art

A. Literature based on consumer electronics in schizophrenia detection

Smart healthcare systems have received widespread attention with the advancement of the Internet of Medical Things (IoMT). IoMT aims to interconnect medical devices and instruments for real-time patient data collection [13]. Improvement in communication technologies increased sensing devices, and efforts to provide swift medical services helped conceive the idea of smart healthcare systems. In a study, the psychomotor activity of 55 patients was measured for 24 hours, and it was discovered that, in those with Schizophrenia, differences in physical activity accurately distinguished between the first psychotic episode and subsequent outbreaks, with lower activity indicating more significant deterioration [14]. A wearable mHealth was used on 30 schizophrenia and 25 normal subjects to record their regular daily activity and movements [15].

The gadget collected data on mobility, electrodermal activity (EDA), and heart rate variability (HRV). In individuals with Schizophrenia, the relationship between physiological measurements, functioning, symptoms, and medication levels was evaluated. A study demonstrated how commercially accessible wrist-wearables and smartphones could be used to passively collect digital data and find out how useful they are in predicting health outcomes in schizophrenia patients. They used Fitbit Charge 3 or 4 wristbands and a smartphone and in-house built app: HOPES (Health Outcomes through Positive Engagement and Self Empowerment) to collect data for further analysis using machine learning algorithms [16]. A method to gather behavioral representation from mobile sensing data using clustering models, which could be helpful for relapse prediction, was presented in. [17]. A bidirectional LSTM layer-based model for detecting people with Schizophrenia by visualization of distinguishing traits was developed in [18]. The model collected EEG data from a wearable wristband and separated the healthy and unhealthy people with 86.60% accuracy.

B. Literature based on EEG-based schizophrenia detection

Much research has been suggested for listing the methods employed for acquiring the EEG data and further filtering the stored data for noise removal [19]–[21]. As observed in literature survey, various techniques have been proposed and implemented for schizophrenia diagnosis procedure. Table I summarizes different approaches and models for accurate schizophrenia detection and prediction.

A visually evoked potential method to categorize a schizophrenic patient was investigated in [22]. Mean, kurtosis, and skewness from SNR units were recorded for 95s, and K-Nearest Neighbor attained the highest accuracy of 91.3% when compared to other applied classifiers. The healthy person's EEG signal was differentiated from a person suffering from schizophrenia in [23], and this information was utilized for training a linear classifier which results in agreeable accuracy and specificity. A regression analysis model was demonstrated in [24] that processed segmented data over five frequency spectrum bands with an accuracy of 87%. EEG signals obtained from children of growing age from 9 to 12 years were analyzed in [25] for abnormal brain activity. A hybrid convolution network R-CNN (Recurrent convolution neural network) 2D-LSTM CNN delivered the highest accuracy of 72.54% with raw EEG data. Time-frequency combination plots were proposed in [26] to segregate EEG signals to plot 2D graphs using wavelet transform, SPWV distribution, and Fourier transform to achieve high accuracy of 93.36% using a four-layered CNN model. An automatic diagnosis method to extract non-linear features for selected classifiers was demonstrated in [27] with the highest accuracy of 92.19% with SVM-RBF (Support Vector Machine-Radial basis) Function. A method involving Time- frequency domain-based EEG signal data with complex interconnected 1D features network was proposed in [28], which attained 93.06% accuracy with CNN. Fifteen features extracted from two-dimensional data on a Cartesian plane using K-Nearest Neighbor classifier excelled in performance with 94.80% accuracy in [6]. Results were validated using the 10-fold cross-validating methodology. A CNN-LSTM-based model was also present in [29], which reported an accuracy of 99.9%.

TABLE I: Existing techniques and models for schizophrenia detection using EEG signals.

Author/Year	Method Used	Accuracy (%)
Johannesen et al. [24]/2016	SVM	87.00
Alimardani et. al. [22]/2018	KNN	91.30
Jahmunah et.al. [27]/2019	SVMRBF	92.19
Pang et al. [28]/2019	MDC-CNN	93.06
Devia et al. [23]/2019	LDA	80.00
Ahmed-Aristizaba et al. [25]/2020	2D-CNN-LSTM	72.54
Khare et al. [26]/2021	SPWVD-CNN	93.36
Akbari et al. [6]/2021	KNN	94.80
Sharma et al. [29]/2022	CNN-LSTM	99.9

C. Novel Contribution of proposed work

1) The problem addressed in the paper: This paper aims to address the issues of robustness and portability for accurate schizophrenia detection in remote applications. Is it possible to design a wearable device for schizophrenia detection, and if the answer is yes, which data processing technique should be selected with good performance using edge computing principles?

2) The challenges encountered in solving the problems: The main hindrance in addressing the above research issues is validating the designed model using an actual patient data set. Due to the medical fraternity's privacy issues and ethical regulations, acquiring data sets directly from patients is challenging. This leaves us with the only option of using publicly available data sets. Another challenge is to decide which technique will be suitable for these problems from Machine learning or Deep learning.

3) The proposed solution to the problem: This work proposes a novel concept of an easy-to-wear schizophrenia detection cap that can process EEG signals remotely and accurately. The proposed CNN-TCN model is used to process the EEG signals from electrodes placed in the lid using a processing unit inside the cap. Two different approaches are implemented using raw EEG data and manually extracted features.

4) The Novelty in the paper: This is good work for implementing schizophrenia detection applications in smart healthcare.

- A new concept of the portable and wearable cap for schizophrenia detection is proposed for smart healthcare.
- A new hybrid seven-layered CNN-TCN model is implemented and proposed for schizophrenia detection, wherein TCN shows superior performance for temporal sequencing compared to other recurrent networks implemented in literature.
- The proposed CNN-TCN model also showed good performance when implemented using five electrodes only instead of 19 electrodes. This supports the feasibility of proposed SczCap for real-time implementation.
- The proposed CNN-TCN model is highly robust, accurate, and reliable in detecting schizophrenia disorder.
- The proposed model's complexity is less compared to other implemented machine learning and deep learning models.

III. The proposed framework for automatic schizophrenia detection

This section explains the proposed framework for schizophrenia detection, proposed Hybrid CNN-TCN network, dataset and its pre-processing, and experimental setup used for experimental analysis. To reduce data latency and transmission time from source to the processing unit, a concept of wearable cap is proposed, comprising electrodes for data acquisition and a processing unit for feature extraction, classification, and schizophrenia detection. This work proposes a concept of an easy-to-wear schizophrenia detection cap (SczCap) for registering real-time EEG signals using the proposed CNN-TCN model. Figure 3 shows detailed proposed architecture depicting all the processing units and blocks. Being portable, the planted EEG electrodes on SczCap assist health practitioners in collecting a person's data and persistent storage on the cloud for later reference. EEG signal is first sent to the edge processing unit (EPU), which prepares interpretable results for the IoMT framework. EPU filters the artifacts from raw received data using the windowing and normalization process. The proposed CNN-TCN model is applied to this data for schizophrenia detection. The generated results can be notified to doctors and patients along with persistent cloud storage.

A. Proposed Hybrid CNN-TCN Network

Temporal Convolution Networks (TCN) aim for simpler and automatic modeling predictions along with long-term memory.

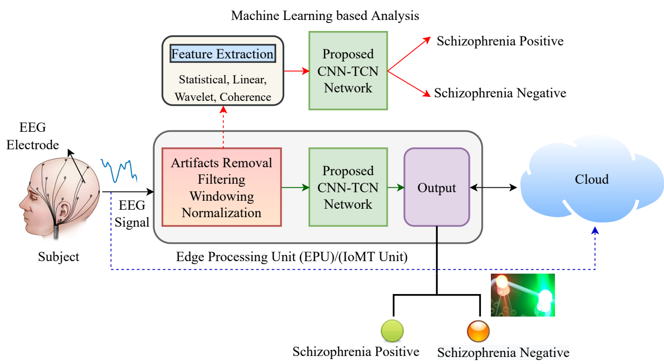


Fig. 3: Proposed architecture for SczCap-based schizophrenia detection.

However, CNN excels in accurate feature extraction but fails to address the time lags, and delays resulting in temporal incoherence. The information transfer in TCN is causal, ensuring zero data leakage from the previous to subsequent layer [30]. Fully-connected network (FCN) in 1D ensures that the length of the output sequence generated is the same as that of the input in this technique. The causal convolution model is applied in TCN, which predicts the output at any time interval t_o, which corresponds to the input sequence at the same time t_o in current and previous layers only. These two features of TCN ensure its superior performance for temporal sequencing when compared to recurrent models for sequence modeling. Also, dilated convolution in TCN helps expand the receptive field exponentially and gather multi-scale contextual information without dramatically increasing computing costs and running time in comparison to RNNs as LSTM or GRU. This also addresses the linear field size issue of conventional convolution networks. The dilated convolution layer employs a size ‘k filter on all the elements in the input sequence with the dilation factor d_o. The value of d is exponentially increased by two as we proceed to the next layer. The output sequences after dilation at each state are combined with a variable range filter. The dilation factor decides the step value to be skipped in the input values sequence and hence applies a filter to a substantial area. For an input data sequence ‘g’ and filter ‘f,’ convolution operation with dilation is given as:

$$F(s) = (g *_{do} f)(s) = \sum_{i=0}^{m-1} f(i).g_{s-d\times i} \tag{1}$$

k is the filter size
$d_o = 2^L$ for a L level network
$*d_o$ is used for convolution with dilation
For the TCN model, two convolution layers are implemented with the dilation method [31], which further relays data to a rectified linear activation function unit (ReLU) as shown in Figure 4. Spatial dropout will perform an adaptive regularization for a given model [32], thereby reducing the burden of excess weights for generalization. Two holds to enhance the receptive field’s capacity due to the presence of two convolution layers.

1) Schizophrenia detection using approach 1 (raw data) and approach 2 (extracted features): We have used two approaches, approach 1 and approach 2. In approach 1, raw EEG data is used with the CNN-TCN model, while approach 2 uses extracted features. Various studies have been reported using efficient human brain interfacing methods for extracted features in CNN [33]. The extracted features from the proposed model are shown in Table II. EEG signals are divided into five frequency bands: Delta, Alpha, Beta, Theta, and Gamma. Total of four feature sets: Statistical features, Linear features, Wavelet features, and Coherence features, are categorized for respective EEG segments. For linear parameters, Power Spectral Density is recorded. For statistical analysis, 14 features are extracted, as listed in the table. For feature extraction, wavelet transform decomposes signals into five selected frequency bands. Finally, coherence from eight channel pairs is computed. Support vector machine (SVM), K-nearest neighbor (KNN), and XGBoost classifiers are used at the end to classify these features.

TABLE II: Feature sets.

Category	Features
Statistical	Mobility, Complexity, Mean, Absolute mean, Standard deviation, Absolute standard deviation, variance, range, maximum, median, minimum, root mean square, skewness and kurtosis
Linear	Power Spectral Density from each EEG band
Wavelet Feature	Wavelet transform by decomposing signals into five frequency bands and energy calculation
Coherence	From 8 EEG channel pairs

CNN-TCN model implemented here comprises seven layers whose filter dimensions, layer size, and stride are listed in Figure 4. Initially, the extracted features are fed to the first convolution layer with 32 kernels of size [1x15] and stride 2. It is followed by another convolution layer with kernel 16 of size [1x10] and stride=1. It is further cascaded to a TCN block as demonstrated by Bai et al. [34] having 32 filters of size [1x5] and a dilation factor of (1,2,4). Here, a ReLU activation function is implemented after each convolution layer. ReLU function is applied after the first dense layer of 64 units to replace the negative values in input with zeros. A dropout layer with a 20% probability is added after the first dense layer. Finally, the output is classified using the softmax layer, followed by another dense layer of 32 units.

B. Dataset Used

For this work, publically available EEG data of 14 schizophrenic patients undergoing treatment at the Institute of Psychiatry and Neurology in Warsaw, Poland, is used along with EEG data of 14 healthy people [35]. Both the datasets comprised seven males and seven females with average male and female ages of 27.9 ± 3.3 and 28.3 ± 4.1 years, respectively, for schizophrenic patients and 26.8 ± 2.9 and 28.7 ± 3.4 years for healthy people. Data was collected for fifteen minutes using the international 10-20 standard for EEG at a 250 Hz sampling frequency rate. O1, O2, T3, T4, T5, T6, C3, Cz, C4, P3, Pz, P4, Fp1, Fp2, F7, F3, Fz, F4, and

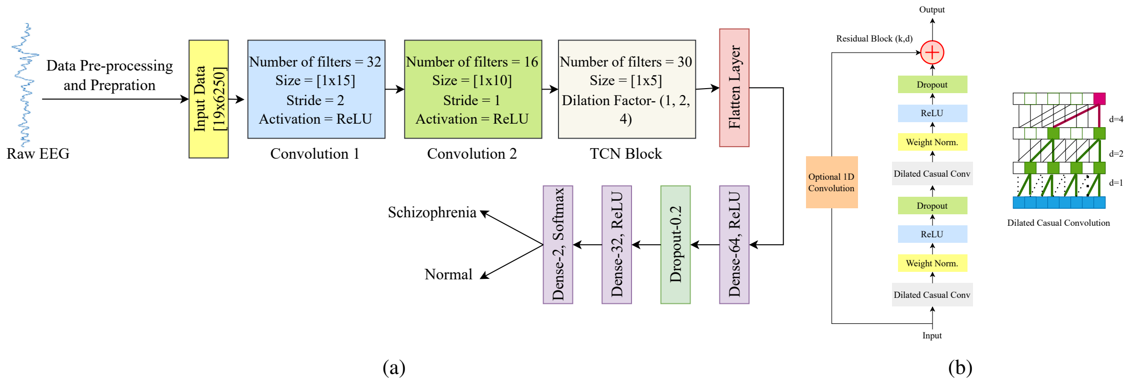


Fig. 4: (a) Proposed CNN-TCN model structure, (b) TCN with dilated causal convolution.

F8 EEG electrodes were connected to the patients lying in a resting state with the eyes-closed position. First, a 50Hz notch filter was used for pre-processing of these EEG data to eliminate power line noises, and independent component analysis was done for denoising after performing whitening with PCA. Then, EEG data from these electrodes was filtered by a Butterworth filter of 0.2-45 Hz. The signals were then segmented into small segments which might be considered stationary. Each segment was normalized with a Z-score before being sent to a one-dimensional deep convolution network for training and testing. Each segment had a 25s (19x6250 sampling points) window length.

EEG datasets often exhibit class imbalance, where certain classes or conditions may have a significantly larger number of instances than others, which can lead to undesirable outcomes. Resampling techniques, ensemble methods, cost sensitive learning, effective feature selection and engineering, and selection of sensitive evaluation metrics are some methods that can be helpful in dealing with issue of imbalanced EEG datasets. Granular computing and random forest algorithm are indeed valuable methods for addressing imbalanced datasets and refining data analysis. Granular computing finds the right balance between capturing important patterns in the minority class and avoiding overfitting. Similarly, the ensemble nature of Random Forests allows them to capture the complexities and interactions in the data, making them well-suited for imbalanced datasets. The order acceptance decision problem and process control often involve dealing with imbalanced datasets, and these techniques can help improve decision-making and control processes [36]. At last, the choice of techniques depends on the specific dataset, the research question, and the available resources.

IV. Experimental Results

The CNN-TCN model proposed in this work is trained and tested using two approaches: feeding direct EEG data and extracting features from EEG data. The overall performance of the models is evaluated in terms of four performance matrices: Accuracy, Sensitivity, Specificity, and Precision.

A. Parameter Settings

All the experiments and implementations are done on a workstation with a 2.30GHz processor with 12GB RAM. Python 3.8.1 language is used for the model designing. After extensive experimental analysis, the selection of all the parameters, i.e., the number of layers, filter size, and the number of filters, is done. Table III presents the performance comparison of the proposed CNN-TCN (approach1) model with a variable number of convolution layers and TCN blocks. This table shows that the proposed CNN-TCN model using raw data is giving the best performance with two convolution layers and one TCN block in terms of accuracy and time taken. The backpropagation algorithm is used to tune the network weights efficiently, and performance improvement is ensured by batch normalization. The dropout layer is used for regularisation and avoiding overfitting. To avoid the overfitting of the proposed model, a model checkpoint is also used with early stopping and eight epochs on validation loss.

TABLE III: Performance of proposed CNN-TCN model (approach 1) with a variable number of convolutional layers and TCN block.

Convolution Layer	TCN Block	Accuracy	Average Training Time (sec)	Testing Time (sec) for one sample
1	0	0.426	582	0.0041
2	0	0.712	649	0.0098
3	0	0.95	817	0.035
4	0	0.972	987	0.089
1	1	0.789	661	0.0094
2	1	0.995	824	0.042

TABLE IV: Parameter settings for the proposed model.

Parameter	Value
Batch Size	64
Loss	Categorical cross entropy
Optimizer	Adam
Output Metric	Accuracy, specification, sensitivity, precision
Learning rate	0.0001
Epochs	30

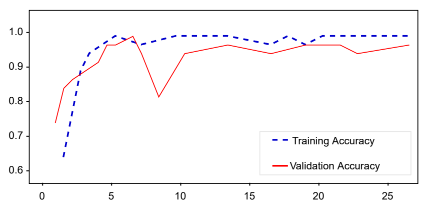
Table IV gives setting information of parameters used in conventional machine learning methods and the proposed models. The value and type of each parameter has been selected after extensive literature review and experimental

TABLE V: Comparison of results using approach 2 (feature-based data). **(Best results are highlighted)**.

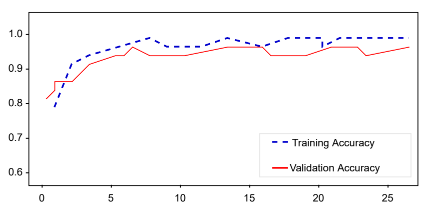
Author/Year	Method used	Number of participants	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
2019 [27], Non Subject-Wise	RBF-SVM	14 Normal, 14 Schizophrenia	92.91	93.45	92.24	93.60
2020 [37], Non Subject-Wise	ResNet-18-SVM	14 Normal, 14 Schizophrenia	98.60	99.65	96.92	-
2021 [38], Non Subject-Wise	MIF-SVM	14 Normal, 14 Schizophrenia	98.90	99.00	98.80	98.40
2022-Present Work, Non Subject-Wise	features-SVM	14 Normal, 14 Schizophrenia	94.23	96.62	92.66	91.98
2022-Present Work, Non Subject-Wise	features-KNN	14 Normal, 14 Schizophrenia	89.09	90.21	88.56	89.98
2022-Present Work, Non Subject-Wise	features-XGBoost	14 Normal, 14 Schizophrenia	93.49	94.10	92.33	92.19
Proposed Work+Subject-Wise	Features-CNN-TCN	14 Normal, 14 Schizophrenia	95.89	96.45	95.36	95.41
Proposed Work+Non Subject-Wise	**Features-CNN-TCN**	**14 Normal, 14 Schizophrenia**	**98.89**	**99.62**	**98.16**	**98.18**

TABLE VI: Comparison of results using approach 1 (raw data). **(Best results are highlighted)**.

Author/Year	Method used	Number of participants	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
2019 [39], Non Subject-Wise	CNN	14 Normal, 14 Schizophrenia	98.07	97.32	98.17	98.45
2019 [39], Subject-Wise	CNN	14 Normal, 14 Schizophrenia	81.26	75.42	87.59	87.59
2020 [40], Non Subject-Wise	CNN	14 Normal, 14 Schizophrenia	98.56	98.88	99.05	98.87
2021 [41], Non Subject-Wise	L2-CNN-LSTM	14 Normal, 14 Schizophrenia	99.25	98.86	99.73	98.33
2021 [42], Non Subject-Wise	LSTM	14 Normal, 14 Schizophrenia	99.00	98.57	-	97.80
2022 [29], Non Subject-Wise	CNN-LSTM	14 Normal, 14 Schizophrenia	99.90	100	99.80	99.8
2022 [29], Subject-Wise	CNN-LSTM	14 Normal, 14 Schizophrenia	90.11	88.46	91.66	92.03
2022-Present Work, Non Subject-Wise	VGG 16	14 Normal, 14 Schizophrenia	93.30	93.19	93.11	93.11
2022-Present Work, Non Subject-Wise	AlexNet	14 Normal, 14 Schizophrenia	88.09	87.50	89.59	88.99
2022-Present Work, Non Subject-Wise	ResNet 50	14 Normal, 14 Schizophrenia	94.63	93.80	94.44	93.76
Proposed Work+Subject-Wise	CNN-TCN	14 Normal, 14 Schizophrenia	96.45	97.66	95.23	95.34
Proposed Work+Non Subject-Wise	**CNN-TCN**	**14 Normal, 14 Schizophrenia**	**99.57**	**99.51**	**99.64**	**99.63**



(a) Non-Subject-Wise



(b) Subject-Wise

Fig. 5: Training and Validation accuracy of proposed CNN-TCN (approach 1) model for non-subject-wise and subject-wise data.

TABLE VII: Gaussian noise effect on performance parameters.

SNR	Accuracy(%)	Sensitivity(%)	Specificity(%)	Precision(%)
10	99.01	99.12	99.35	99.01
20	98.92	98.98	99.08	98.81
30	98.73	98.53	98.9	98.23
40	98.59	98.17	98.40	98.03
0	99.57	99.51	99.64	99.63

analysis. 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 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 [43]. The training and validation accuracy curve of the proposed CNN-TCN Model (using approach 1) for subject-wise and non-subjet-wise data is shown in Figure 5.

B. *Accuracy assessment of the model*

For the raw data (approach 1) and extracted features (approach 2), the comparison of performance parameters of the proposed model is listed in Table V and table VI concerning conventional and implemented models. The performance of raw data based CNN-TCN model is compared with CNN [39], [40], LTSM [41], [42] and, CNN-LSTM [29], [41] models proposed in the literature and three pre-trained models: VGG 16, AlexNet and ResNet 50. The performance of extracted features based CNN-TCN model is compared with K-nearest neighbor [44], Support-Vector machine (SVM) [45] and, XGBoost based models along with other models proposed in the literature. As evident from the results shown in the

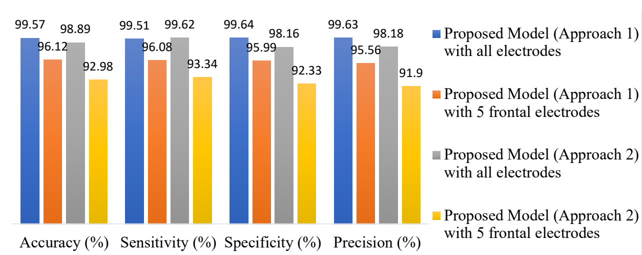


Fig. 6: Performance comparison of proposed model using all electrodes and five electrodes only.

Figure 7, the performance of the proposed feature-based CNN-TCN model with 98.89% accuracy, 99.62% sensitivity, 98.16% specificity and, 98.18% precision supersedes the conventional KNN, SVM and, XGBoost classifier based models. Although

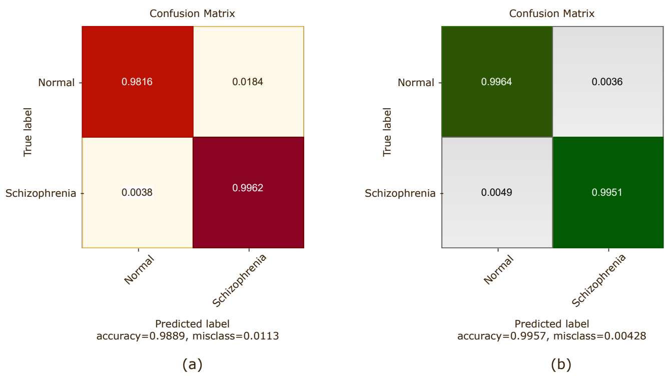


Fig. 7: Confusion matrix of proposed model using (a) approach 2 & (b) approach 1.

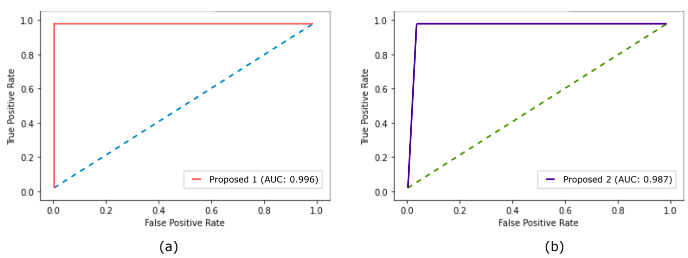


Fig. 8: ROC curve obtained from proposed model using (a) approach 2 & (b) approach 1.

SVM shows improved accuracy of 94.23% as compared to KNN and XGBoost, it is still comparatively much lower than the proposed model. The accuracy of 98.90% is reported in [38] using multivariate iterative filtering (MIF)-SVM method that is comparable to the accuracy proposed in this work. The MIF decomposes EEG based on mean frequency and then non-linear features are extracted from each frequency component. This gives a good accuracy but significantly increases the complexity. This also increases the overall time to run the model in comparison to model with simple features. For raw data input, an appreciable and highest accuracy of 99.57% is reported along with 99.51% sensitivity, 99.64% specificity, and 99.63% precision compared to implemented pre-trained models and other models proposed in the literature. The classification performance of the proposed model using approach 1 and approach 2 is also shown in Figure 8 using ROC curves. Although the results presented by [29] are slightly close to the proposed CNN-TCN model, the proposed model is showing much better overall performance in terms of complexity, training, and testing time as given in the Tables below. It is because of the parallelized convolution in TCN, unlike LSTM or GRU. It proves the superiority of the proposed CNN-TCN model for accurately diagnosing a person who has Schizophrenia when processed with raw EEG data.
As reported in [29], the EEG signals from the frontal part of the brain can give comparable results instead of using all electrodes. So, an experiment is also conducted in this work to detect Schizophrenia using only five electrodes from the frontal part of the brain. Results for the same are given in Figure 6.

TABLE VIII: Complexity comparison of proposed CNN-TCN (approach 1) model with other implemented models.

Models	**Convolution Layer**	**Fully Connected Layer**	**Learnable Parameters**	**Filter Size**	**Training Time (sec)**
VGG16	13	3	138M	3	17,849
AlexNet	5	3	62M	3, 5, 11	11,336
ResNet50	50	1	25M	1, 3, 7	8,970
CNN	4	3	0.65M	15, 10, 10	987
CNN-LSTM [29]	2+1(LSTM)	3	0.88M	15, 10, 32	1289
Proposed CNN-TCN	2+1(TCN)	3	0.48M	15, 10, 5	824

C. Robustness assessment of the model

The model is tested for robustness for performance comparison using approach 1 and approach 2 for schizophrenia detection with the addition of Gaussian noise at multiple levels. Several parameters regulate the proposed CNN-TCN structure. The best model parameters are achieved through trial and error for the highest performance. Furthermore, to increase the reliability of the proposed system, Gaussian noise is added to the signals at different levels of SNRs (Signal to noise ratio) 10, 20, 30, 40, and results for the same are reported in Table VII. As evident from the table, only minor changes are visible in output results with a gradual increase in noise levels. It establishes the robustness of the proposed model for schizophrenia detection.

D. Complexity assessment of the model

The number of learnable parameters of that network or the time taken measures the complexity of any neural network. Table VIII presents the complexity comparison of the proposed CNN-TCN and other implemented models in terms of learnable parameters and average training time in ten folds. It shows that the proposed CNN-TCN model is less complex than the other compared models as it only has 0.48M Learnable parameters and 824 seconds of average training time over ten folds. The training of the LSTM network is relatively slow compared to TCN because of non-parallelized computation, which further increases the computation complexity. TCN networks also capture much less complex temporal information by utilizing a backpropagation path.

V. Discussion

This work presents the first-ever concept of a portable and wearable device, SczCap, for schizophrenia detection using EEG signals in smart healthcare applications. The EEG signals are electrical activities of the brain which are very informative, and with recent advancements, the availability and measurement of these signals have become much easier. As the main idea of this paper is to propose a concept of wearable device for schizophrenia detection, the issues related to complexities, robustness, and portability while maintaining high accuracy are addressed in this work. The conventional machine learning methods such as SVM, KNN, and XGBoost utilizing different time and frequency features did not perform so well in differentiating normal and schizophrenia patients and made the whole system more complex. There are two approaches implemented in this work, In approach 2, primary features are extracted manually and secondary features using CNN. This reduces the feature spectrum and overall performance also get effected. In approach 1 using raw data, the features are extracted from the complete dataset using CNN only and these features are then fed into TCN, this increases the performance as all the important features are explored. The CNN-TCN model using raw data reported high accuracy, sensitivity, specificity, and precision compared to other implemented and proposed models in the literature. For all the implementations and experiments, a publicaly available EEG dataset [35] is used and a concept of wearable SczCap is proposed in smart healthcare. The proposed CNN-TCN model used in the SczCap concept uses seven layers and took 824 seconds of training time, which is relatively less than other implemented models. An experiment using different SNRs was also conducted for the proposed model using raw EEG and reported high robustness against noise.

The proposed model is designed after experimenting with several parametric settings for accuracy and time taken. The proposed model is also implemented using five electrodes only instead of 19 electrodes and reported good accuracy of 96.12% using approach 1 and 92.98% using approach 2. This supports the portability, reliability, and feasibility of SczCap in remote applications. Three pre-trained networks, VGG 16, Alexnet, and ResNet 50, were also implemented on the exact data for better and more fruitful comparisons and reported the accuracy of 93.30%, 88.09%, and 94.63%, respectively. The model was trained using both non-subject-wise and subject-wise split data using both approaches and reported good results, which support the model's generalization. The results reported in this work are optimistic, and the real-time implementation of SczCap can benefit humankind in the future.

VI. Conclusion and Future work

In this work, we investigated the performance of a seven-layered CNN-TCN model to accurately detect the presence of schizophrenia disorder in a person using a device named SczCap, a schizophrenia detection cap. The CNN model with excellent feature extraction capability is augmented with a TCN block for enhanced machine-learning modeling. Although the data set is small, the results are validated by a 10-fold validation process to establish the authenticity of the results. The exceptional accuracy of 98.89% and 95.89% for non-subject-wise and subject-wise data using extracted features-based approach and 99.57% and 96.45% for non-subject-wise and subject-wise using raw data indicated the usability of this model for schizophrenia detection.

A negligible effect of gaussian noise on this model proves it a viable candidate for helping professional health practitioners in early detection. Another remarkable feature is the ability of the model to give highly accurate and reliable results even with raw EEG data and removes the overhead of extracting features for schizophrenia detection. Data security features are not explored in this work and can be considered for future endeavors. To further increase the useability of the proposed model for smart healthcare applications, advanced data security protocols can be implemented.

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