

Discrete mathematical modelling for enhancing mental illness detection

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Abstract

In this paper a machine learning approach is used for diagnosis of mental illness such as Schizophrenia (SCZ) using Electroencephalogram (EEG) signals. EEG signals helps identification of normal and abnormal brain signals. In this approach, the methodology is divided in three major steps: data collection and pre-processing, feature extraction, and classification. The main focus of the work is feature extraction. For this multi-channel pattern correlation and feature merging (MCPCFM) is proposed that identifies and combines the linear and non-linear features using CNN model. Then data augmentation is also applied to handle data imbalance issue for training random forest classifier. This framework aims to efficiently represent EEG signals and reduce feature dimensionality issue to improve mental illness classification performance. The result analysis shows 90% of accuracy for detection. As compared to state-of-art models the proposed model outperforms best.

Subject Classification: Primary 424C0, Secondary 94A12.

Keywords: Mental health, Schizophrenia detection, EEG, Feature engineering, CNN model.

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1. Introduction

Mental health disorders affect a large proportion of the global population and includes emotional, cognitive, and behavioural challenges. These include anxiety, mood disorders, schizophrenia, eating disorders, and addictive behaviours. According to a 2017 survey, over 792 million people globally, or more than 10% of the population, suffer from mental illnesses [1]. Anxiety and depression are among the most common mental diseases worldwide, with biological causes connected to disturbances in neurotransmitter function. People with depression often demonstrate symptoms of anxiety, resulting in a co-event of both diseases. “Mixed anxiety and depressive disorder” refer to those who demonstrate both anxiety and depression symptoms without reaching full criteria for diagnosis, but these symptoms have a major impact on their daily function [2]. Despite the progress of anti-risk medications, the degree of recovery has not improved significantly [3]. Structured neuroimaging techniques, such as structural magnetic resonance imaging (smri), are used in the early stages of the diagnosis of mental disorders. Increasing availability of medical data combined with progress in processing capacity has inspired researchers to use machine learning (ML) and Deep Learning (DL) technologies to improve the flexibility of diagnostic systems [4].

2. Literature Review

Mental disorders have a considerable impact on social and economic standing, which is a key concern in the healthcare sector. Advances in artificial intelligence (AI) have enhanced non-invasive diagnostic approaches [5]. Recent research has highlighted these achievements. Siuly et al. [6] employed empirical mode decomposition (EMD) to analyse EEG data for schizophrenia (SZ) diagnosis, reaching a 93.21% accuracy using intrinsic mode functions (IMFs) and a bagged tree ensemble classifier. Shalbaf, Bagherzadeh, and Maghsoudi [7] used deep convolutional neural networks (CNNs) and support vector machine (SVM) classifiers to translate EEG signals into images using continuous wavelet transforms. ResNet-18 coupled with SVM demonstrated great diagnostic metrics. Khare, Bajaj, and Acharya [8] successfully identified SZs using time-frequency analysis approaches and a bespoke CNN. Furthermore, Khare and Bajaj [9] used robust variational mode decomposition (RVMD) and an optimised extreme learning machine (OELM) classifier to optimise parameters using whale techniques. Seal et al. [10] created “DeprNet” to

differentiate between EEG data from depressed and normal patients, attaining 99.37% accuracy with an AUC of 0.999 in record-wise data and 91.4% with an AUC of 0.956 in subject-wise data using the Patient Health Questionnaire. Sharma, Parashar, and Joshi [11] used CNNs and Long Short-Term Memory (LSTM) architectures for sequential EEG signal learning. Sakalle et al. [12] proposed a modified LSTM (MLSTM)-based model for assessing COVID-19’s influence on mental health. Melamine pattern recognition and discrete wavelet transform (DWT) were coupled for MDD detection by Aydemir et al. [13], who used SVM and k-nearest neighbour (kNN) classifiers. Loh et al. [14] employed spectrogram pictures from Short-Time Fourier Transform (STFT) and CNN to detect mental illnesses using EEG data. Park et al. [15] used an elastic net model to classify mental illnesses based on power spectrum density and functional connectivity. Tasci et al. [16] used quantum local binary pattern (QLBP) functions to extract EEG features for bipolar disorder, schizophrenia, and intellectual disability diagnosis.

3. Methodology

This section provides an approach to detect mental illnesses using EEG data and deep learning algorithms. The framework is separated in three steps: EEG data is collected, cleaned and pre-developed in step 1; Linear and non-linear functions are extracted using a CNN model and

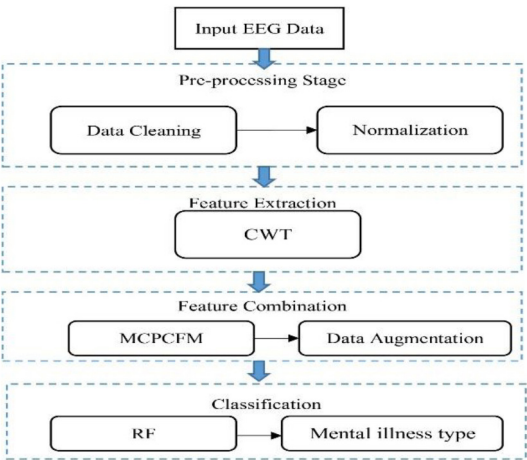


Figure 1
Proposed Framework

MCPCFM technology for data text in phase 2; And recognition and classification are done using an outfit randomly classify in step 3. The goal is to represent EEG data effectively by reducing dimensions and improving classification accuracy. Figure 1 shows the general structure of the proposed model.

Each steps are described individually as mentioned:

Stage 1: Data Collection and Pre-processing

The dataset used in this study is derived from a basic sensory function, designed to check nerve treatment differences with schizophrenia and without individuals. This includes Electroneg (EEG) registration from a total of 81 participants, including schizophrenia (SCZ) and 32 demographic Health (HC) persons [17][18]. The participant pool is primarily male, with the average age of subjects around 39 years[19].

EEG data was collected using the Biosemia Activetwo system, a high-resolution neurofiziological recording platform. The signs were tested at a speed of 1024 Hz, ensuring proper temporary resolution that was appropriate for analyzing fast sensory and cognitive processes. A standard 64 channel electrode cap was used, where the electrode was strategically distributed over the shell according to the international 10-20 system to capture wide brain activity. During the experiment, participants engaged in a task involving three different buttons reaction conditions, designed to assess sensory-motor-motor integration and cognitive reaction mechanisms.

Data Normalization: Data is normalized because the EEG data set is collected from different channels and therefore to scale connection. In this work, z-score-normalization is used where the values of a characteristic A are generalized according to their and standard deviations. Mathematically it is represented as:

$$\hat{a} = \frac{a - \mu(A)}{\sigma(A)} \quad (1)$$

Stage 2: Feature Extraction

In order to remove meaningful EEG signals, the constant wave change (CWT) that is represented as $W_{(\varnothing, \delta)}$ is used as mother's waves using Moolat Waverlet. This approach provides a detailed time ethical representation of the indication, which is able to detect transient fluctuations and localized spectral variations.

$$W_{(\varnothing, \delta)}[z(t)] = \int_{-\infty}^{\infty} \hat{z}(f) \widehat{\psi}^*(\varnothing f) e^{j2\pi f \delta} df \quad (2)$$

Continuous Wavelet Transformation (CWT) is used on one-dimensional signal $Z(T)$ and is controlled by main parameters such as translation parameters, scale parameters and mother Wavelet ϕ , usually selected as the Peacock Wavelet in this study. The change decomposes the signal in different parameters and time inputs allows for a broad time ethics analysis. The energy of the converted signal is calculated using the Wavelet Energy formula, which determines the distribution of time and scale power, provides insight into localized frequency components and their temporary development is:

$$Energy_{(\varnothing, \delta)} = \sum_{\varnothing} \sum_{\delta} W(\varnothing, \delta)^2 \quad (3)$$

Stage 3: Linear and Non-Linear Feature Combination

In this stage feature combination is performed. Before feature combination, multi-channel pattern correlation and feature merging (MCPCFM) algorithm is applied. The MCPCFM is a modification of binary pattern feature correlation. In MCPCFM, the center values of all feature sets are selected. These center values change from one feature set to another. The steps of MCPCFM are evaluated in two steps. In the very first step different feature sets are extracted and in second step the MCPCFM is applied to for center based binary pattern evaluation [19].

In this work, each feature set extracted out of multiple channels are taken. Local patterns were analyzed by finding correlation among other features in a local feature set. In specific, all features, whose co-relation is positive is selected (represented as 1) for further evaluation and those whose correlation is negative are rejected (represented as 0) out for further evaluation. These correlations are represented as binary string of 1s and 0s. Afterwards, the binary patterns are converted into decimal value and it is represented as weight [20]. This procedure is mathematically represented as:

$$MCPCFM = \sum_{n=1}^N W_n * MCPC_{local_n} \quad (4)$$

Where, $i = 1, 2, \dots$ No. of Feature Sets and

Where, W_n = Weight for each feature set

The local MCPC were collected from multiple features collected from multiple EEG channels and termed as 'MCPC Local Set'. The candidate feature sets of each MCPC Local Set are selected and combined to form a covariance matrix which represents the optimal feature set that will further reduce the complexity of entire calculation for classification.

Stage 4: Feature Classification

In this stage, the combined features, selected in above section, are fed into random forest classification model for disease type classification. In this stage other machine learning algorithms are also implemented to compare the performance according to evaluation methods.

4. Result Analysis

This section emphasizes the results achieved from the application and evaluation of the proposed function to detect mental illness with a specific attention to schizophrenia (SZ). All experiments were performed using the Python programming environment within the Google Colab platform, giving access to the "Tesla P100 PCIE GPU" to enable high performance, rapid calculations and efficient model training. The primary purpose of this study was to assess the effectiveness of the model proposed in accurately identifying individuals diagnosed with schizophrenia.

This matrix allows for a good understanding of the model's ability to distinguish between patients with schizophrenia and healthy controls, and emphasizes the accuracy of both detection and strengthening predictions.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (6)$$

$$Precision = \frac{(TP)}{(TP + FP)} \quad (7)$$

$$Recall = \frac{(TP)}{(TP + FN)} \quad (8)$$

$$F1_score = \frac{(2 * Precision * Recall)}{(Precision + Recall)} \quad (9)$$

The accuracy of the proposed model is approx. 90%. The model achieved precision of 91%. The recall of the system is also 91% and f1-score was also observed to be 91%.

Following observations are noted:

- Precision: This measures the accuracy of the positive predictions. The model has a precision of 91% for both healthy individuals and those with SZ. This means that when the model predicts an individual as either healthy or having SZ.
- Recall: For healthy individuals, the recall is 92%, meaning it correctly identifies 92% of all actual healthy individuals. For SZ individuals, the recall is 91%, indicating it correctly identifies 91% of all actual SZ cases.
- F1-Score: An F1-score of 91 for both. This suggests a balanced performance between precision and recall, indicating good overall accuracy.

The DGCNN model was presented in 20 with accuracy of 80%. Whereas SVM was used in 21 and achieved an accuracy of 89%. The proposed model achieved an accuracy of 90% which shows best result.

5. Conclusion

The proposed EEG-based framework for mental illness recognition demonstrates significant potential, achieving around 90% accuracy with a precision and recall of 91%. The methodology efficiently handles EEG data through meticulous pre-processing, feature extraction using both wavelet transforms and the MCPCFM algorithm, and robust classification using a random forest classifier. Results indicate a balanced and effective approach to identifying mental illness, particularly schizophrenia, in patients.

References

- [1] Saloni Dattani, Hannah Ritchie, and Max Roser. "Mental Health." Published online at *OurWorldInData.org*. Retrieved from: <https://ourworldindata.org/mental-health> (2021).
- [2] Yuyang Fan, Rui Yu, Jie Li, Jing Zhu, and Xiang Li. "EEG-based mild depression recognition using multi-kernel convolutional and spatial-temporal feature." *2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, IEEE (2020).

- [3] Kritiprasanna Das and Ram Bilas Pachori. "Schizophrenia detection technique using multivariate iterative filtering and multichannel EEG signals." *Biomedical Signal Processing and Control*, vol. 67, Article 102525 (2021).
- [4] Ashima Tyagi, Vibhav Prakash Singh, and Manoj Madhava Gore. "Towards artificial intelligence in mental health: A comprehensive survey on the detection of schizophrenia." *Multimedia Tools and Applications*, vol. 82, no. 13, pp. 20343–20405 (2023).
- [5] Syed Yasin, S. A. Hussain, S. Aslan, I. Raza, M. Muzammel, and A. Othmani. "EEG based Major Depressive Disorder and Bipolar Disorder detection using Neural Networks: A review." *Computer Methods and Programs in Biomedicine*, vol. 202, Article 106007 (2021).
- [6] Syed Siuly, Smith K. Khare, Varun Bajaj, Hui Wang, and Yi Zhang. "A computerized method for automatic detection of schizophrenia using EEG signals." *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 11, pp. 2390–2400 (2020).
- [7] Ahmad Shalbaf, Sara Bagherzadeh, and Arash 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).
- [8] Smith K. Khare, Varun Bajaj, and U. Rajendra Acharya. "SPWVD-CNN for automated detection of schizophrenia patients using EEG signals." *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–9 (2021).
- [9] Smith K. Khare and Varun Bajaj. "A hybrid decision support system for automatic detection of schizophrenia using EEG signals." *Computers in Biology and Medicine*, vol. 141, Article 105028 (2022).
- [10] Ankur Seal, Rakesh Bajpai, Jaideep Agnihotri, Ahmed Yazidi, Enrique Herrera-Viedma, and Ondrej Krejcar. "DeprNet: A deep convolution neural network framework for detecting depression using EEG." *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–13 (2021).
- [11] Geetanjali Sharma, Abhishek Parashar, and Amit M. Joshi. "DepHNN: A novel hybrid neural network for electroencephalogram (EEG)-based screening of depression." *Biomedical Signal Processing and Control*, vol. 66, Article 102393 (2021).
- [12] Aditi Sakalle. "A modified LSTM framework for analyzing COVID-19 effect on emotion and mental health during pandemic using EEG signals." *Journal of Healthcare Engineering* (2022).

- [13] E. Aydemir, T. Tuncer, S. Dogan, R. Gururajan, and U. Rajendra Acharya. "Automated major depressive disorder detection using melamine pattern with EEG signals." *Applied Intelligence*, vol. 51, no. 9, pp. 6449–6466 (2021).
- [14] H. W. Loh, C. P. Ooi, E. Aydemir, T. Tuncer, S. Dogan, and U. Rajendra Acharya. "Decision support system for major depression detection using spectrogram and convolution neural network with EEG signals." *Expert Systems*, vol. 39, no. 3, e12773 (2022).
- [15] Sang Min Park, Byoung Oh Jeong, Do Yoon Oh, Chang Hyun Choi, Hyun Young Jung, Jin Young Lee, and Jin Seok Choi. "Identification of major psychiatric disorders from resting-state electroencephalography using a machine learning approach." *Frontiers in Psychiatry*, vol. 12, Article 707581 (2021).
- [16] Gokhan Tasci, M. Volkan Gun, Tugce Keles, Burcu Tasci, Pranesh D. Barua, Ilke Tasci, and U. Rajendra Acharya. "QLBP: Dynamic patterns-based feature extraction functions for automatic detection of mental health and cognitive conditions using EEG signals." *Chaos, Solitons & Fractals*, vol. 172, Article 113472 (2023).
- [17] Dataset, Available at: <https://www.kaggle.com/datasets/broach/button-tone-sz>.
- [18] Keshav Upreti, Shih-Lin Peng, Prashant R. Kshirsagar, Pradeep Chakrabarti, Hamad A. Al-Alshaikh, Ajay Kumar Sharma, and Ramesh C. Poonia. "A multi-model unified disease diagnosis framework for cyber healthcare using IoMT-cloud computing networks." *Journal of Discrete Mathematical Sciences and Cryptography*, vol. 26, no. 6, pp. 1819–1834 (2023).
- [19] Keshav Upreti, Sandeep Arora, Ajay Kumar Sharma, Anil Kumar Pandey, K. K. Sharma, and Mudit Dayal. "Wave height forecasting over ocean of things based on machine learning techniques: An application for ocean renewable energy generation." *IEEE Journal of Oceanic Engineering*, vol. 49, no. 2, pp. 430–445 (2023).
- [20] Ashish B. Kanwade, M. P. Sardey, S. A. Panwar, M. P. Gajare, M. N. Chaudhari, and Keshav Upreti. "Combined weighted feature extraction and deep learning approach for chronic obstructive pulmonary disease classification using electromyography." *International Journal of Information Technology*, vol. 16, no. 3, 2024, pp. 1485–1494 (2024).