# Automated Novel Heterogeneous Meditation Tradition Classification via Optimized Chi-Squared 1DCNN Method

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## Abstract

The realm of human-computer interaction delves deep into understanding how individuals acquire knowledge and integrate technology into their everyday lives. Among the various methods for measuring brain signals, electroencephalography (EEG) stands out for its non-invasive, portable, affordable, and highly time-sensitive capabilities. Some researchers have revealed a consistent correlation between meditation practices and changes in the EEG frequency range, observed across a wide array of meditation techniques. Furthermore, the availability of EEG datasets has facilitated research in this field. This study explores the effectiveness of the One-Dimensional Convolutional Neural Network (CNN-1D) based novel classification method, which impressively achieved an 62% training accuracy, showcasing the robustness of these models in meditation classification tasks. The proposed methodology unveiling a novel method to differentiate neural oscillations in 4 types of meditators and control. This approach analyzes an EEG dataset of highly experienced meditators practicing Vipassana (VIP), Isha Shoonya (SYN), Himalayan Yoga (HYT), and untrained control subjects (CTR) by employing chi-square, CNN, hyperparameter models for data analysis, The outcomes indicate that different meditation types exhibit distinct cognitive features, enabling effective differentiation and classification.

**Keywords:** EEG, 1DCNN, Meditation Tradition, Chi-Square dimension reduction.

## Introduction

Recent research has shown a growing interest in utilizing peripheral physiological signals, such as electroencephalogram (EEG), to recognize and understand human emotions (Akshay K et al., 2022). Through scalp-mounted electrodes, the non-invasive EEG technique records the brain's electrical system. This data is then categorized into different frequency ranges, offering valuable insights into various cognitive processes, including meditation (Gevins et al., 1975). One of the significant applications of EEG data is in the classification of different meditation types, where machine learning algorithms and signal processing methods have proven to be effective in achieving accurate results (Braboszcz et al., 2017).

This article presents a novel feature-based approach to differentiate meditation types using a Convolutional neural network in one dimension (1D-CNN). The EEG dataset undergoes simplified signal pre-processing, and a combination of neural network architectures and feature reduction techniques is applied to enhance accuracy. The chosen 1D-CNN architecture demonstrates its effectiveness in the task of meditation type recognition. A comparison of accuracy and loss values is performed based on different frequency and time domain (Avvaru & Parhi, 2023) feature sets.

The paper is set up as follows: next section provides an overview of related research and approaches in the domain of meditation and EEG signal analysis. After next section describes the supplies and techniques used in the experimental design. After next section presents the results obtained from the feature-based 1D-CNN classification and provides insightful discussions. Finally, last Section concludes the paper by addressing its limitations and suggesting potential directions for future research.

Furthermore, this article delves into the broader application of EEG signals in studying cognitive processes and human-computer interaction. The EEG recordings enable the measurement of cognitive load, assessment of user experience, and exploration of the interaction between individuals and technology. The integration of neuroethology and brain-computer interfaces has enabled real-time monitoring of meditation practices and facilitated collaborations among researchers from diverse fields.

Notably, certain meditation practices like Vipassana, Isha Shoonya, and Himalayan Yoga, have been extensively studied using EEG datasets (Braboszcz et al., 2017). These

investigations have shed light on changes in gamma activity and global coherence observed among expert meditators. This work aims to identify neural representations of meditation across different meditation styles, providing a comprehensive analysis in this domain.

The article also addresses the challenges associated with the preprocessing of EEG data, as the limited number of examples available for training in EEG datasets poses a significant obstacle. As deep learning methods continue to show promise in decoding brain signals, sophisticated algorithms are needed for denoising, decoding, and deriving meaningful insights from the data.

In conclusion, this article enhances the study of meditation type recognition by introducing a novel feature-based approach utilizing a 1D-CNN model. By analyzing EEG signals, researchers gain valuable insights into cognitive processes and deepen the understanding of meditation practices, opening doors for various potential applications and future research endeavors.

## Literature Review

**Available Meditation Datasets**

Chi et al (Lai et al., 2018) has presented various method for EEG recording setup. In their study, the authors (Tee et al., 2020) conducted EEG data collection from 10 participants undergoing three distinct meditation states: resting state, focused attention meditation, and open monitoring meditation. They extracted 10-sec of data (after the start of meditation approximately at the 9-minute mark) and 9-sec of transition data (marking the end of the meditation, around the 11-min mark) from each data sequence.

The author (Dong et al., 2021) does not provide information on the specific dataset used in the study. However, it does mention that the study recruited 14 participants to perform an auditory oddball task while their EEG was being recorded. Machine learning models were trained to categorize attentional states based on the N1 and P3 ERP components using preprocessed EEG data.

The study (Singh et al., 2022) used the dataset compiled by Braboszcz et al. (Braboszcz et al., 2017), which contains EEG exercise of meditation practitioners for 3 different meditation traditions (HYT, SNY, VIP and CTR). The information was gathered in Rishikesh, India at the Meditation Research Institute.

In the study (Pandey & Prasad Miyapuram, 2020), the EEG dataset referenced as was acquired from a publicly available repository. To ensure accurate analysis, it is preprocessed using MATLAB and EEGLAB software. The data was set at 256 Hz, and we segmented it into 20-second epochs. These epochs covered a time range from -20 seconds to -0.05 seconds

before the initiation of the question Q1. In total, our dataset comprised 943 epochs, with 540 epochs from expert meditators and 443 epochs from non-expert meditators. Each epoch was characterized by 64 channels and 4992-time points.

## Meditation Type Analysis

The study (Braboszcz et al., 2017) looks into how various meditation practices affect electroencephalographic (EEG) activity. The findings demonstrated that compared to control subjects, all meditators had increased parieto-occipital 60-110 Hz gamma amplitudes. Overall, the study adds to the expanding body of knowledge about how meditation affects brain activity.

The study (Ahani et al., 2014) is a thorough analysis of the machine learning techniques used to interpret EEG readings during yoga and meditation. The paper uses EEG bands to explain Employing Zen, CHAN, mindfulness, TM, Rajayoga, Kundalini, Yoga, and other forms of meditation, one can achieve various mental states. It has been documented how to classify using neural networks, convolutional neural networks, fuzzy logic, KNN, SVM, and Random Forest, we can model mental states. Overall, the paper provides a comprehensive overview of the interpretation methods of EEG signals during yoga and meditation practices and highlights the potential of machine learning strategies in this field.

The paper (Tee et al., 2020) presents a method for classifying different meditation states using EEG signals and DWT. The results showed wherein the SVM classifier could accurately classify the different meditation states with an average accuracy of 91.67%.

In the study (Dong et al., 2021) used two approaches to classification: person-dependent models and person-independent models. Person-dependent models classify attentional states within a subject, while person-independent models attempt to generalize the model across subjects. To categorize attentional states based on the EEG data, the study used a variety of machine learning approaches, including linear discriminant analysis, support vector machines, and random forests. The findings revealed that the machine learning models based on the EEG data, were effective in identifying mind-wandering.

The study (Singh et al., 2022) employed EEG data from 10 non-expert control volunteers who had never meditated before and 20 expert meditators from the Vipassana, Isha Shoonya traditions and Himalayan Yoga. 13 distinct machine learning models were utilized in the study for both within- and between-subject analyses. The regions of change following mindfulness sessions were also identified using the SHAP explainable machine learning model.

The study (Pandey & Prasad Miyapuram, 2020) featured 24 Himalayan Yoga practitioners of meditation, divided into two groups according to their level of expertise and

daily practice. In the feature engineering stage, wavelet decomposition and feature extraction were performed using five wavelet families. The extracted features were then used to train 12 different machine learning classifiers. The best performing classifier was the Multi-Layer Perceptron and QDA.

In all the previous study, all has attempted for classification between control and meditation but very less author (Singh et al., 2022) has classified between different meditation types has got very low accuracy. Proposed methodology has classified 4 different meditation type and outperform all the previous work done till date.

**Feature Engineering**

In the study (Kora et al., 2021) the theta, delta, beta, gamma and alpha waves are the EEG's output or information. Various author used different type of feature (Moctezuma & Molinas, 2020) (Ghaemi et al., 2017) like EMD, DWT (Tee et al., 2020), time, frequency, time-frequency domain. The paper discusses (Braboszcz et al., 2017) EEG data and uses spectral power analysis to investigate the effects of different meditation practices on brainwave activity. The feature types used in the study(Kora et al., 2021) include spectral power, phase analysis, statistical features, power spectral density, wavelet coefficients, fuzzy C-means, and independent component analysis(Stancin et al., 2021). The feature type used in the paper (Tee et al., 2020) is not explicitly mentioned. However, the authors state that they extracted features from the EEG signals using DWT and a binomial logical regression classifier was used to analyses the feature data. The feature type used in the study (Pandey & Prasad Miyapuram, 2020) was a combination of relative entropy and power, extracted from the EEG signals using wavelet decomposition. The paper (Y. Chen et al., 2021) uses the STFT method to extract from the normalized EEG signals features of five frequency bands' spectral power. The feature used in the study (Mai et al., 2023) is the relative power spectral density (PSD), from FFT. The feature types used in the paper (Adeli & Ghosh-Dastidar, 2010) are the correlation dimension (CD) and the largest Lyapunov exponent. In the paper author (B. Chen et al., 2023)  demonstrated the utility of the feature extraction model using a nonnegative Tucker decomposition. The study (Hsu & Cheng, 2023) suggests using the Wavelet-based Temporal-Spectral-attention (WTS) module will offer more effective discriminative characteristics.

**Classification's Methodologies**

This section is going to discuss about classification techniques for EEG signal analysis of meditation data. Segregating signals into various classes is referred to as classification (Kora et al., 2021). KNN, SVM (Alotaiby et al., 2015), RF, Fuzzy logic, and CNN are some of the common techniques used to classify EEG signals. The article (Moctezuma & Molinas, 2020) presents a novel approach to the non-dominated-sorting genetic algorithm is used to select EEG channels for seizure classification for epileptics. The proposed method is tested on EEG

data from 24 patients and achieves an average classification accuracy of 94.5% using only 5 EEG channels. The paper (Ghaemi et al., 2017)discusses the use of methods for machine learning in brain-computer interface systems using feature reduction using principal component analysis (PCA) and channel selection using various algorithms such as independent component analysis (ICA) (Delorme et al., 2007), genetic algorithms, and binary particle swarm optimization. The paper (Y. Chen et al., 2021) proposes a method for emotion recognition using physiological signals, which is evaluated on the DEAP dataset. The paper (Mattioli et al., 2021) presents a deep learning approach for classifying motor imagery (MI) tasks using electroencephalogram (EEG) recordings. The study (Mai et al., 2023) aimed to propose an end-to-end system for real-time emotion recognition utilizing a machine learning model and an on-chip device based on ear EEG. The authors used the DEAP dataset, preprocessed the EEG signals directly on the embedded device, extracted features using the relative power spectral density, and three common machine learning models were trained: support vector machine (SVM), multilayer perceptron and one-dimensional convolutional neural network (Samizade & Abad, 2018). The paper (Wang et al., 2023) presents a novel weighted multi-branch structure for subject-specific motor imagery EEG classification. On a variety of EEG datasets, such as BCICIV-2a, High-Gamma, BCICIV-2b, Upper Limb Movement, and P300, the proposed technique is compared with ten models, including ConvNet, ResNet, EEG TCNet, FBCNet, Deep EEGNet, and Shallow ConvNet. The paper (Adeli & Ghosh-Dastidar, 2010) explains a wavelet-chaos approach to EEG and EEG subband analysis to find seizures and epilepsy. Wavelet analysis, initial chaos analysis, and final chaos analysis make up the three stages of the process. The author (Wang et al., 2023) has employed multi-class common spatial patterns and empirical mode decomposition based KNN classification for motor imagery task. Various author used different technique like 1D-CNN and RNN (Zamani & Wulansari, 2021), 2D-CNN (Farokhah et al., 2023). The paper (Braboszcz et al., 2017) does not discuss any classification models or algorithms. Instead, it focuses on analyzing the differences in spectral power between different meditation practices and a control group.

The study (Ahani et al., 2014) used SVM (Support Vector Machine) classification, a supervised binary classification model. The authors (Tee et al., 2020)used method based on the features retrieved from the EEG data using DWT, an SVM classifier will classify the various stages of meditation. The study (Dong et al., 2021) used machine learning models to classify attentional states based on EEG data. Two approaches to classification were used: person-dependent models and person-independent models. The study (Pandey & Prasad Miyapuram, 2020) used several machine learning classifiers for classification tasks, including K-Nearest Neighbors (KNN), Logistic Regression with L1 regularizer, Polynomial-SVM, and Gaussian-NB (Prasetya Wibawa et al., 2021). The Deep Learning-LSTM structures were used in study (Houran et al., n.d.). Various author used various technique for classification like FastNet (Xiao et al., 2023), HcLSH activation function based deep learning model (Abdel-Nabi et al., 2023), Hjorth parameters feature selection and classification (Majid Mehmood et

al., 2017) but no one has implemented chi-squared based hyperparameter tuned 1dcnn method for meditation type classification.

## Methodology

### Block Diagram of the Suggested Technique

The data preparation phase and the neural network phase make up the two key procedures that make up the framework for this study, as depicted in Figure 1. The following section will provide an explanation of each step in-depth.
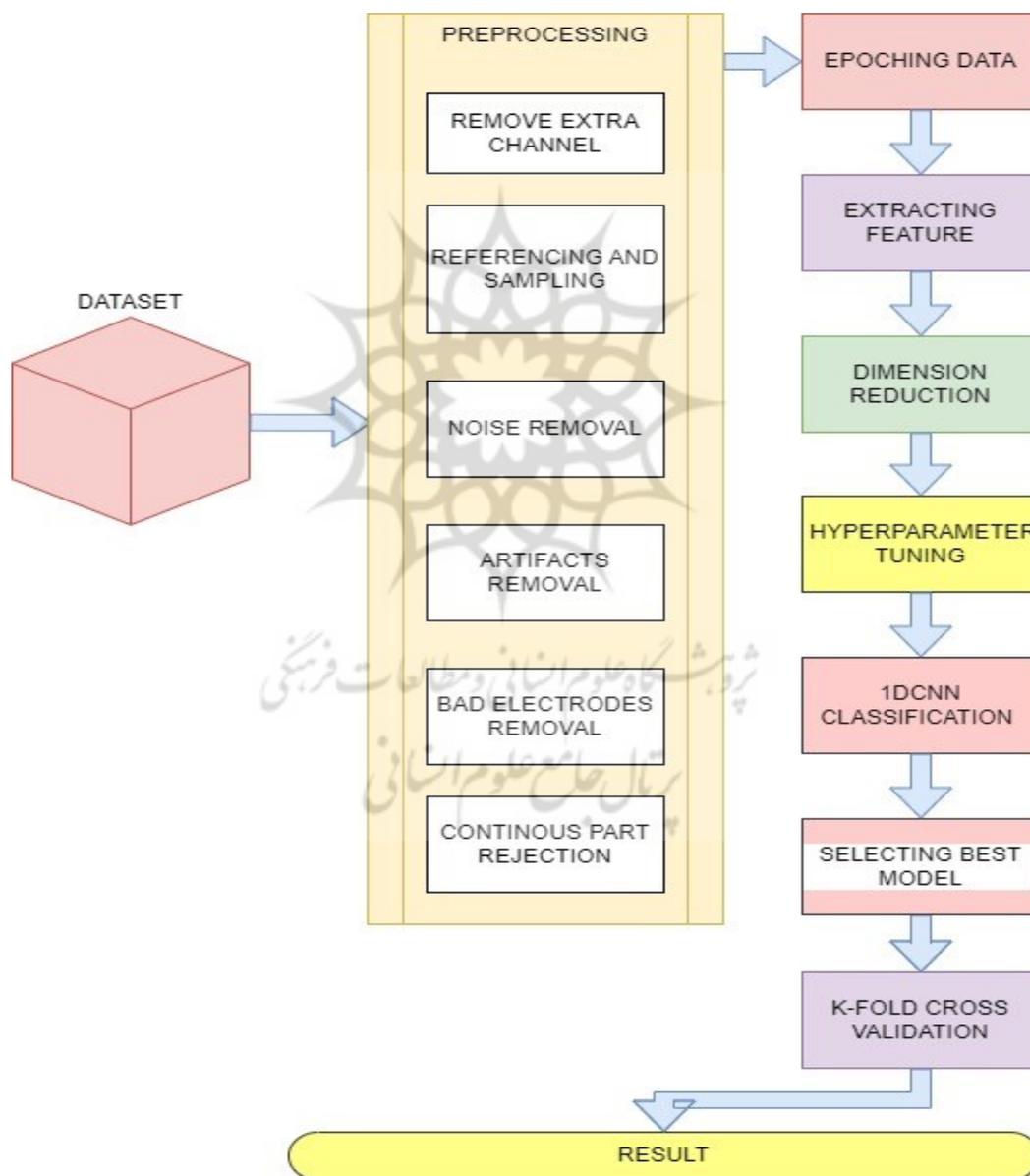


**Figure 1. Block diagram of proposed method**

**Datasets and Label Classification**

The proposed methodology uses The Braboszcz et al. (Braboszcz et al., 2017) dataset contains EEG activity of meditation practitioners across Vipassana (VIP), Himalayan Yoga (HYT), Isha Shoonya (SNY), and a control (CTR) group during meditation and instructed daydreaming block. Collected at the Meditation Research Institute India, the EEG data has 64 channels, and each meditation technique group has 16 subjects, making it 64 subjects overall, sampled at 256Hz. The researchers conduct a 4-class classification to identify participant groups. Dataset structure detail is shown in Table 1.

**Table 1. Raw Dataset Shape**

| Array Name | Array Shape | Array Content |
|---|---|---|
| Data | 98, 64, 6400 | subject, channel, data |
| label | 98 | Label (htr, ctr, vip, sny) |

**Data Pre-Processing**

We initiated the data preprocessing by the down sampling to 256 Hz and a band-pass filter with a frequency bandwidth of 4-45 Hz was used to filter the data. Data were averaged to the common reference after EOG artefacts were also eliminated. Applying an IIR high-pass filter with a cutoff frequency set at 1 Hz. The filter was designed with a transition bandwidth of 0.3 Hz to effectively remove low-frequency noise from the EEG signals. To assess the impact of the high-pass filter, we generated a frequency response plot as shown in figure 2, ensuring that the filter's characteristics aligned with our data processing requirements.
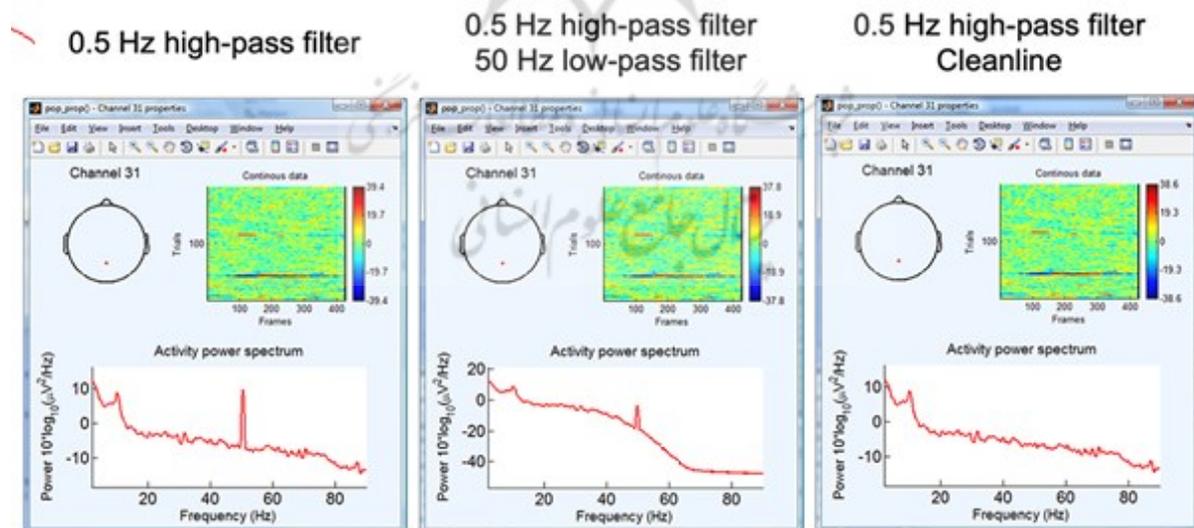


**Figure 2. Filtering for noise removal**

To further enhance data quality, we performed bandpass filtering. This step successfully eliminated 50-Hz line noise, commonly known as notch filtering. We carefully configured

parameters such as Bandwidth, ChanCompIndices, LineFrequencies, and others to achieve optimal results.

In order to address non-stereotyped artifacts, we employed the pop_continuousartdet (EEG) in ERPlab. Additionally, we ran the function twice, using distinct freqlimit and threshold values for artifact rejection as shown in figure 3.
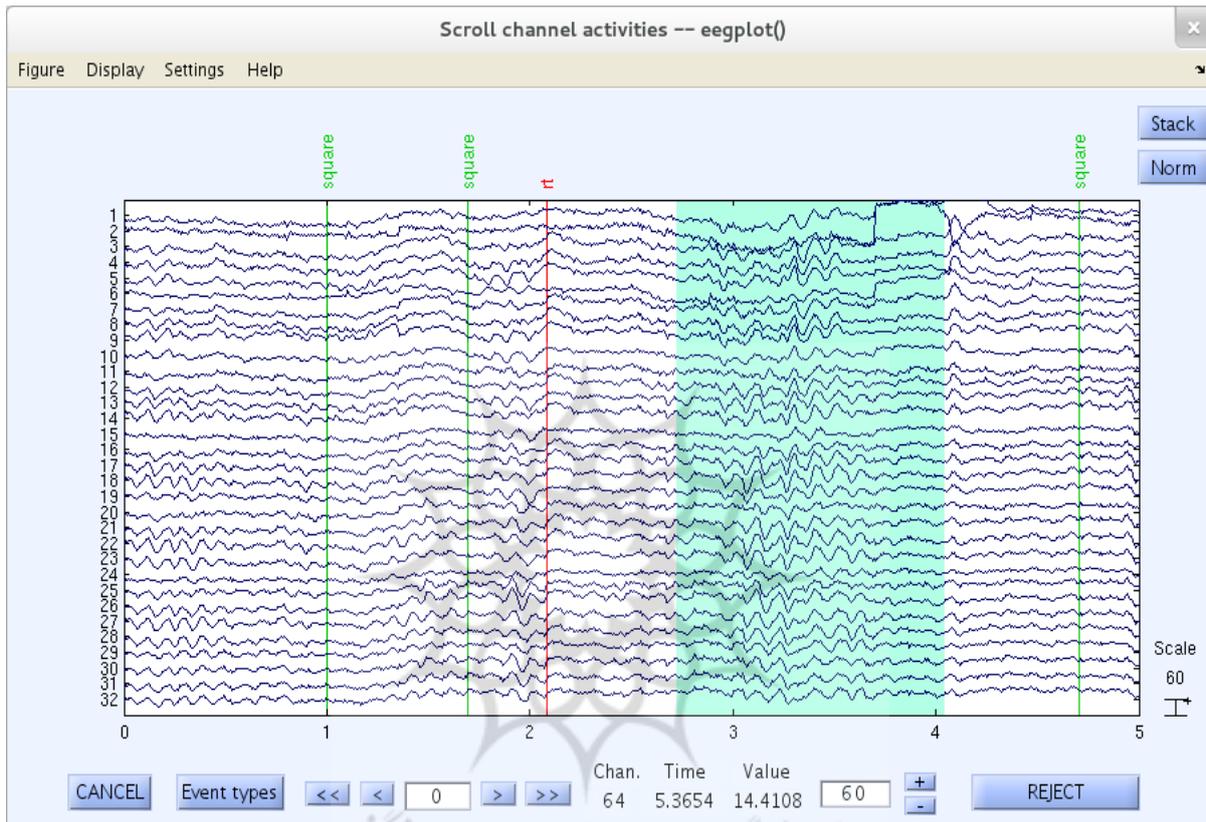


**Figure 3. bad segment removal**

For precise artifact identification, we conducted manual inspection and selectively removed bad electrodes from the EEG data. On average, each subject had around 5 electrodes removed, with the number of rejected electrodes ranging from 0 to 18 per subject.

Components classification was carried out using ICLabel(figure 4), where components related to eye and muscle artifacts were flagged with a confidence range of 0.9 to 1. These flagged components were subsequently rejected from the data.
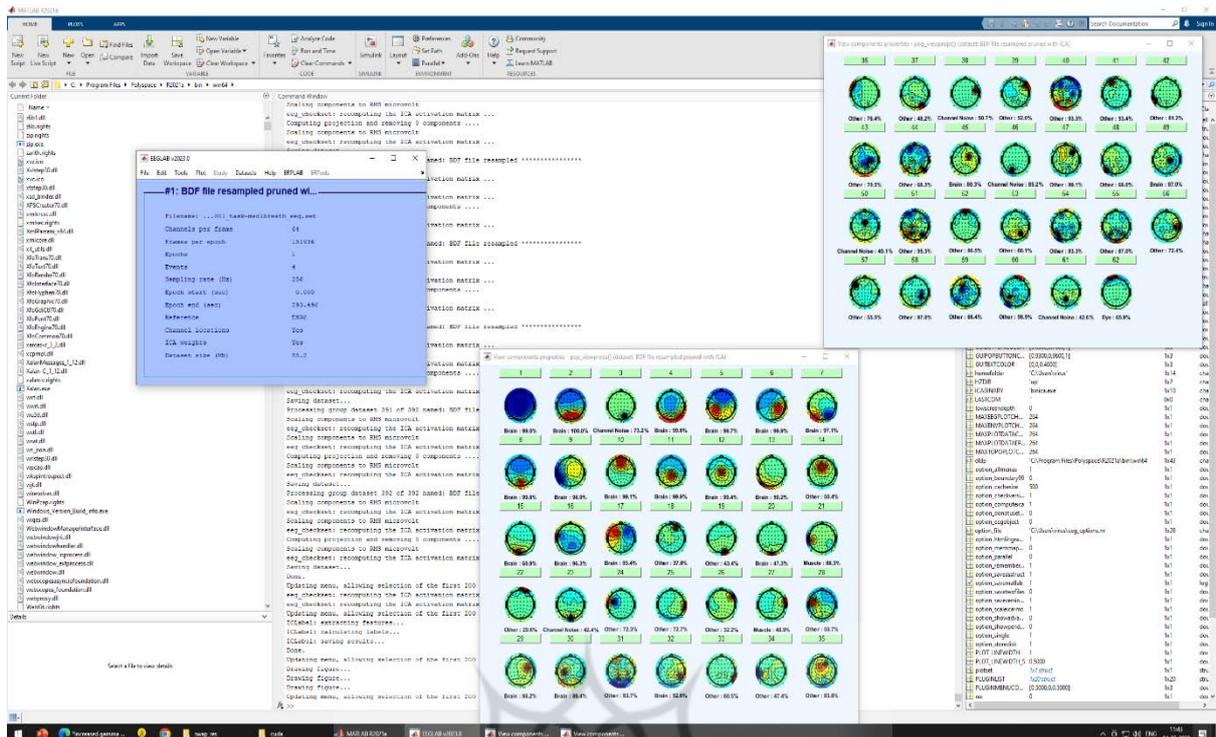
**Figure 4. Artefact removal**

By meticulously following these highly specific EEG data preprocessing steps, we ascertained the production of top-quality data, devoid of artifacts, and primed for accurate analysis and interpretation.

**Epoching**

In the process of epoching (figure 5), particular time frames are taken out of the continuous EEG input. The first step in completing this operation is to extract each signal's 25-second wavelengths with a 0–second overlap. As a result, it will provide us with 6400 data points for each epoch, which corresponds to 25 seconds of the signal, and 2107 signals for each channel.
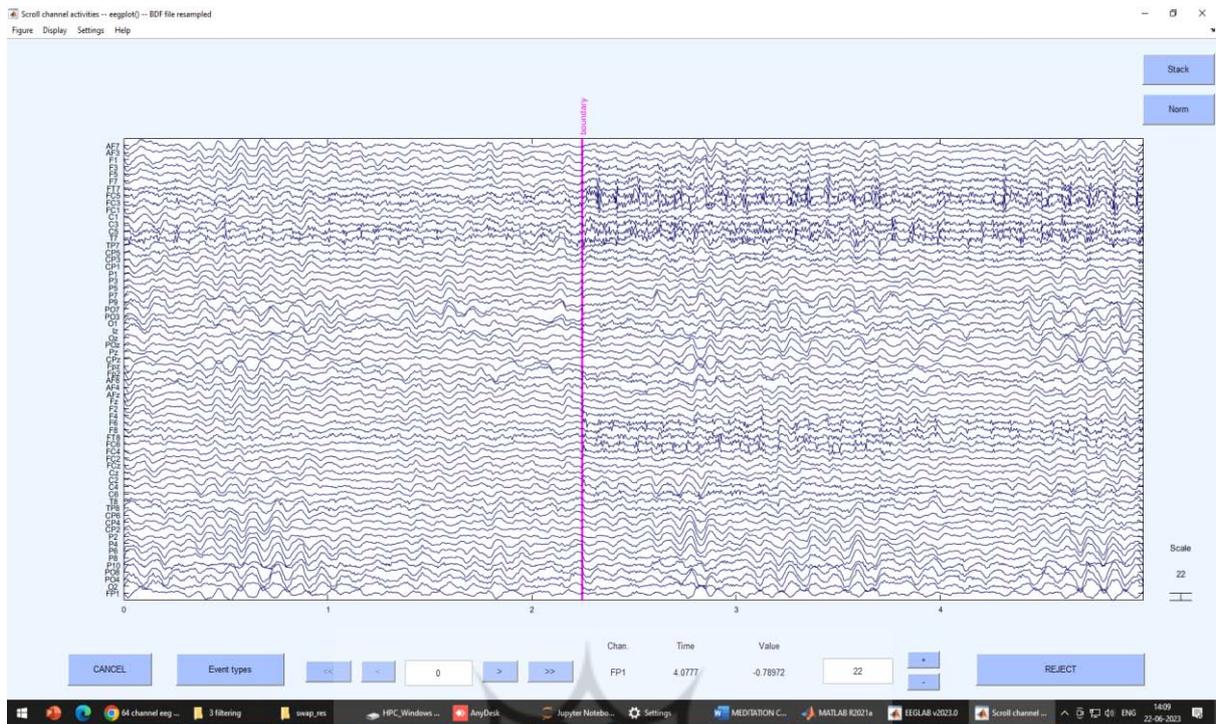
**Figure 5.Epoching**

## Feature Reduction

In this experiment statistical following statistical feature were calculated for each 64 channels of 98 subject: Which result 20X64 number of features. To remove redundancy of information and reduce complexity and calculation cost, we Chi-Square Test for Feature reduction technique (Parui et al., 2022) choose the appropriate number of features that have the highest Chi-square values.

## Data Shape

The dataset from 98 participants was first preprocessed, and then the preprocessed dataset underwent additional preprocessing steps and label classification. Then, using an 80:20:20 ratio, we partitioned the dataset into train, validation, and test data at arbitrary. Table 2 displays the data shape for our investigation.

**Table 2. Data Shape**

| Array Name | Array Shape | Array Content |
| --- | --- | --- |
| Data | 2107, 64, 6400 | Epoch, channel, data |
| label | 2107,4 | Label(htr, ctr, vip, sny) |

## Neural Network Architecture

The one-dimensional convolutional neural network will be used in the proposed method. The next section will provide a quick summary of each architecture. All signals used in this investigation are one-dimensional. An extremely effective technique for use with time-series

data, such as EEG signals, is the one-dimensional convolutional neural network (1D-CNN). This model is able to extract and discriminate a number of EEG data elements that are important for classification tasks.

Model: "sequential"
_____

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv1d (Conv1D) | (None, 48, 160) | 640 |
| Activation (Activation) | (None, 48, 160) | 0 |
| max_pooling1d (MaxPooling1D) | (None, 24, 160) | 0 |
| Flatten (Flatten) | (None, 3840) | 0 |
| Dense (Dense) | (None, 4) | 15364 |

Total params: 16,004
Trainable params: 16,004
Non-trainable params: 0
_____

## Classifiers and Hyper parameter Tuning

The 64-channel EEG time series is averaged to create the input space. The proposed study uses resampling to estimate the performance of models. In order to choose the appropriate parameters, it uses 5-fold cross validation. To tune the hyper parameters, it use Bayesian search. The Bayesian search approach performs a thorough examination of the hyper parameters over a predetermined range of values. Hyper parameters need to be properly tweaked in order to produce effective results. The optimizer used is Adam, and the batch size for our architectures has been determined to be 256. Following is the search space for hyper parameter:

Default search space size: 5
n_hidden (Int)
{'default': 2, 'conditions': [], 'min_value': 0, 'max_value': 8, 'step': 1, 'sampling': 'linear'}
n_neurons (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 256, 'step': 1, 'sampling': 'linear'}
learning_rate (Float)
{'default': 0.0001, 'conditions': [], 'min_value': 0.0001, 'max_value': 0.01, 'step': None, 'sampling': 'log}
Optimizer (Choice)
{'default': 'sgd', 'conditions': [], 'values': ['sgd', 'adam'], 'ordered': False}
input_units (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 256, 'step': 32, 'sampling': 'linear'}

## Results

**Experimental Setup**

The suggested methodology generated a series of time splits by dividing the EEG data for each subject into 25-second chunks (6400 time steps in each chunk) with overlaps of 0 seconds. The features are then created by averaging the timestamp inputs for each 64 channels. Then, several 1DCNN with different parameter are fed these characteristics. This meditation experiment was conducted cross-subject: In the train-Val-test set, this technique chooses 98 participants, and each participant's time chunks are employed in the appropriate data fold. Five train-Val-test samples are created, and we do k-5 fold cross validation on them. In each run, the validation fold is utilized for hyper parameter tuning, and the test folds are used to show the findings (confusion matrix, epoch vise accuracy graph). Tensor flow, Keras, Python, EEGLAB, and MATLAB are used to implement each experiment. Windows 10 is run on a workstation with an AMD Ryzen Thread ripper 3960X 24-Core Processor running at 3.80 GHz with 48.0 GB of RAM.

**Result and comparison**

The findings from proposed experiments is reported in this section. First, we will go into detail about how various experiments utilized in this study performed in terms of model accuracy. The results of this experiment's current work are compared to those of earlier work in the section that follows. Later, a thorough explanation of the experiment's general findings and analyses will be provided. Finally, we spoke about the method's shortcomings.

The goal of the experiment is to assess the effectiveness of the 1D-CNN model for the classification problem of the meditation type utilizing a variety of variables and hyperparameters. Following are some results with various no of feature after dimension reduction and best tuned hyperparameter. Some result out of rigorous parameter evaluation experiment is:

**Experiment no 1:**

No of feature after dimension reduction: 50

```
Search space summary
Default search space size: 5
n_hidden (Int)
{'default': 2, 'conditions': [], 'min_value': 0, 'max_value': 8, 'step': 1, 'sampling': 'linear'}
n_neurons (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 256, 'step': 1, 'sampling': 'linear'}
learning_rate (Float)
{'default': 0.0001, 'conditions': [], 'min_value': 0.0001, 'max_value': 0.01, 'step': None, 'sampling': 'log'}
optimizer (Choice)
{'default': 'sgd', 'conditions': [], 'values': ['sgd', 'adam'], 'ordered': False}
input_units (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 256, 'step': 32, 'sampling': 'linear'}
```

**Figure 6. search space summery**

| conv1d_input | input: | [(None, 50, 1)] |
|---|---|---|
| InputLayer | output: | [(None, 50, 1)] |

| conv1d | input: | (None, 50, 1) |
|---|---|---|
| Conv1D | output: | (None, 48, 160) |

| activation | input: | (None, 48, 160) |
|---|---|---|
| Activation | output: | (None, 48, 160) |

| max_pooling1d | input: | (None, 48, 160) |
|---|---|---|
| MaxPooling1D | output: | (None, 24, 160) |

| flatten | input: | (None, 24, 160) |
|---|---|---|
| Flatten | output: | (None, 3840) |

| dense | input: | (None, 3840) |
|---|---|---|
| Dense | output: | (None, 4) |
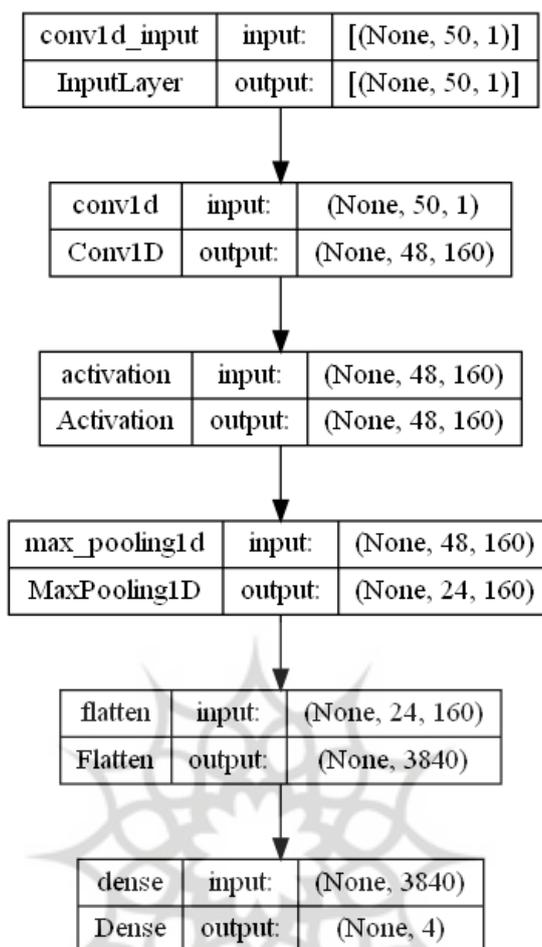
**Figure 7. Best model after hyperparameter tuning**

```
Model: "sequential"
_____
Layer (type)                 Output Shape              Param #
=================================================================
conv1d (Conv1D)              (None, 48, 160)           640

activation (Activation)      (None, 48, 160)           0

max_pooling1d (MaxPooling1D  (None, 24, 160)           0
)

flatten (Flatten)            (None, 3840)              0

dense (Dense)                (None, 4)                 15364

=================================================================
Total params: 16,004
Trainable params: 16,004
Non-trainable params: 0
_____
```

**Figure 8. best model summery**
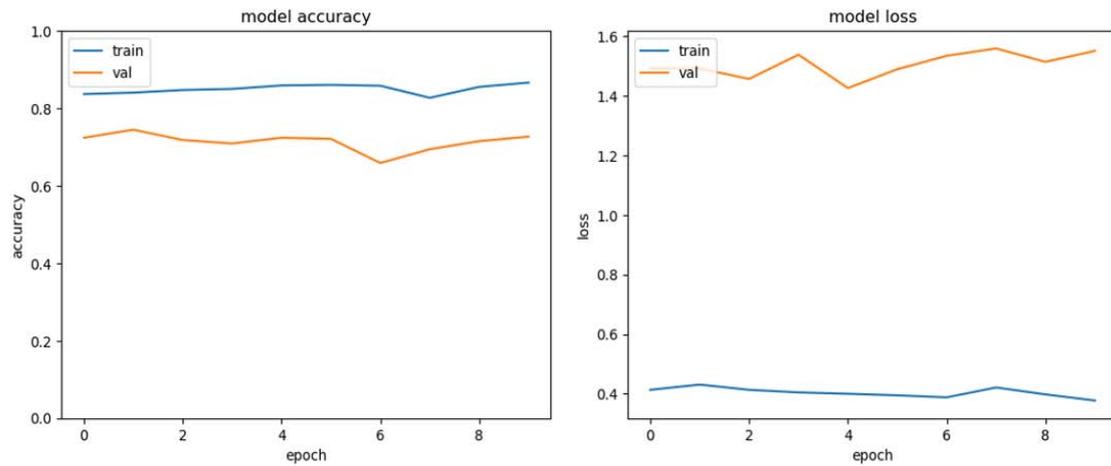
**Figure 9. Best model accuracy and loss graph for experiment 1**

**Table 3. Normalize Confusion Matrix for Experiment 1**

| Classes | 0 | 1 | 2 | 3 |
|---|---|---|---|---|
| 0 | 0.78571429 | 0.03149606 | 0.02272727 | 0.04477612 |
| 1 | 0.08571429 | 0.77165354 | 0.10227273 | 0.05970149 |
| 2 | 0.08571429 | 0.09448819 | 0.78409091 | 0.01492537 |
| 3 | 0.04285714 | 0.1023622 | 0.09090909 | 0.88059701 |

**Table 4. Accuracy Score for Experiment 1**

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.79 | 0.92 | 0.85 | 119 |
| 1 | 0.77 | 0.8 | 0.78 | 123 |
| 2 | 0.78 | 0.73 | 0.76 | 94 |
| 3 | 0.88 | 0.69 | 0.77 | 86 |

Validation accuracy: 0.80

Experiment no 2:

No of feature after dimension reduction: 100

```
Search space summary
Default search space size: 5
n_hidden (Int)
{'default': 2, 'conditions': [], 'min_value': 0, 'max_value': 8, 'step': 1, 'sampling': 'linear'}
n_neurons (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 256, 'step': 1, 'sampling': 'linear'}
learning_rate (Float)
{'default': 0.0001, 'conditions': [], 'min_value': 0.0001, 'max_value': 0.01, 'step': None, 'sampling': 'log'}
optimizer (Choice)
{'default': 'sgd', 'conditions': [], 'values': ['sgd', 'adam'], 'ordered': False}
input_units (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 256, 'step': 32, 'sampling': 'linear'}
```

**Figure 10. search space summery for expriment 2**

| conv1d_input | input: | [(None, 100, 1)] |
|---|---|---|
| InputLayer | output: | [(None, 100, 1)] |

| conv1d | input: | (None, 100, 1) |
|---|---|---|
| Conv1D | output: | (None, 98, 192) |

| activation | input: | (None, 98, 192) |
|---|---|---|
| Activation | output: | (None, 98, 192) |

| max_pooling1d | input: | (None, 98, 192) |
|---|---|---|
| MaxPooling1D | output: | (None, 49, 192) |

| flatten | input: | (None, 49, 192) |
|---|---|---|
| Flatten | output: | (None, 9408) |

| dense | input: | (None, 9408) |
|---|---|---|
| Dense | output: | (None, 251) |

| dense_1 | input: | (None, 251) |
|---|---|---|
| Dense | output: | (None, 4) |
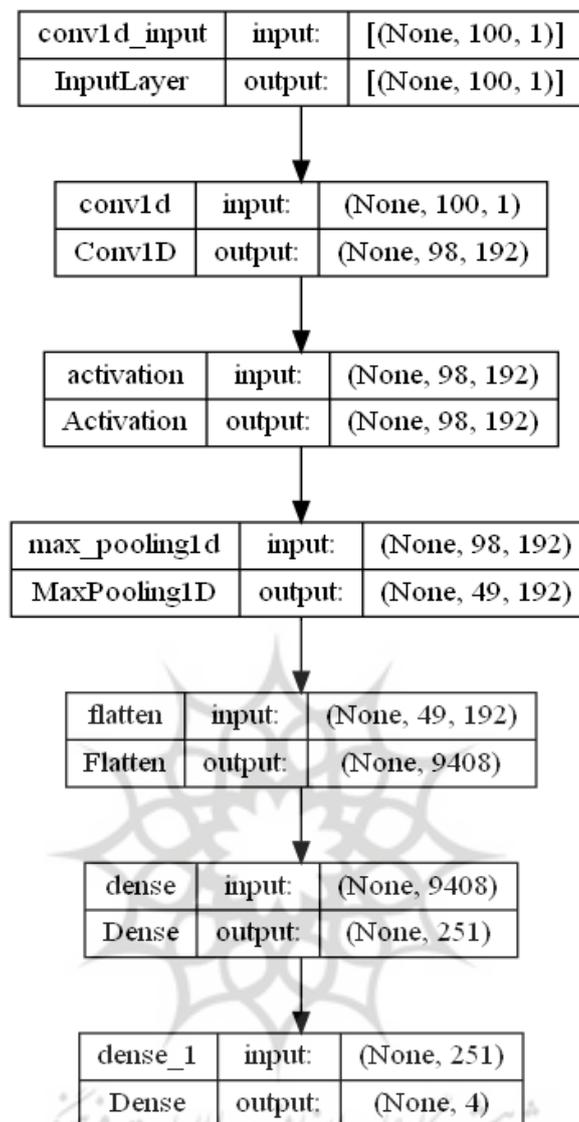
**Figure 11. best model for experiment 2**

```
Model: "sequential"

_____
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 98, 192)           768

 activation (Activation)     (None, 98, 192)           0

 max_pooling1d (MaxPooling1D  (None, 49, 192)          0
 )

 flatten (Flatten)           (None, 9408)              0

 dense (Dense)               (None, 251)               2361659

 dense_1 (Dense)             (None, 4)                 1008

=================================================================
Total params: 2,363,435
Trainable params: 2,363,435
Non-trainable params: 0
_____
None
```

**Figure 12. best model summery for experiment 2**
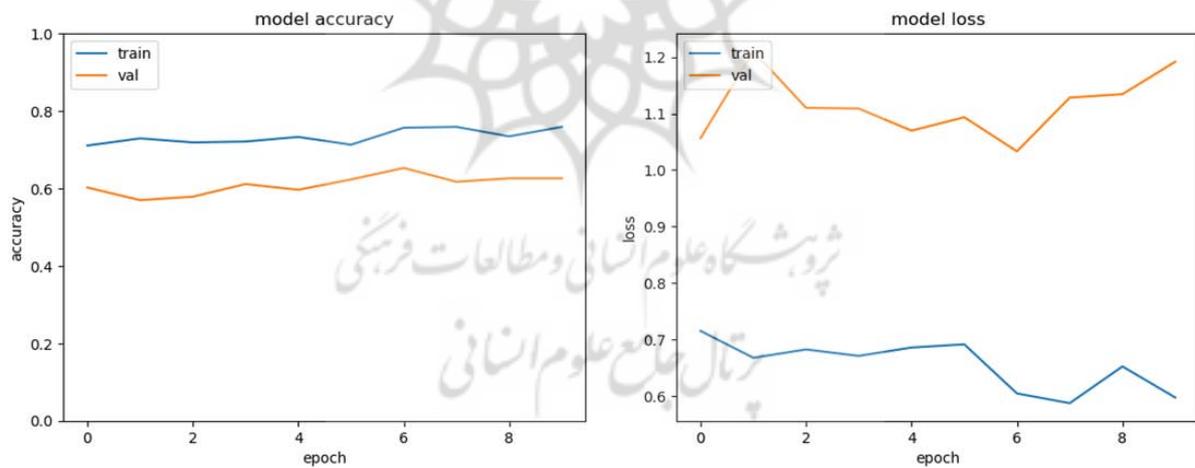


**Figure 13. model accuracy and loss graph for experiment 2**

**Table 5. Normalize Confusion Matrix for Experiment 2**

| Classes | 0 | 1 | 2 | 3 |
|---|---|---|---|---|
| 0 | 0.83505155 | 0.13402062 | 0.10869565 | 0.08235294 |
| 1 | 0.07216495 | 0.53608247 | 0 | 0.14117647 |
| 2 | 0.07216495 | 0.17010309 | 0.89130435 | 0.15294118 |
| 3 | 0.02061856 | 0.15979381 | 0 | 0.62352941 |

**Table 6. accuracy score for experiment 2**

|   | precision | recall | f1-score |
|---|-----------|--------|----------|
| 0 | 0.84 | 0.68 | 0.75 |
| 1 | 0.54 | 0.85 | 0.66 |
| 2 | 0.89 | 0.44 | 0.59 |
| 3 | 0.62 | 0.62 | 0.62 |

Accuracy: 0.62

The experiment mentioned above was carried out using different feature dimensions and hyper parameter. As stated in experiment, we achieved the maximum training accuracy of 0.69 percent, along with validation accuracy above 62 percent. We also obtain train-val losses of.43%-1.5%, respectively. This model exhibits a very good performance when compared to earlier pertinent efforts. Figure 13 shows the train and validation graphs, which display the values for accuracy and loss per epoch. Every epoch, training takes an average of 50 seconds. Additionally, in order to examine the discrepancy between the predicted and actual values, we also created a confusion matrix. This technique proved to be used as a tool to assess the effectiveness of multilabel categorization. The F1-Score and recall value of 0.92 indicate that this model has good performance. Below is comparison with previous work.

**Table 7. Comparison Chart with Previous on Same and Different Dataset**

| PREVIOUS WORK | DATASET | METHDOLOGY | ACCURACY |
|---------------|---------|------------|----------|
| (Tee et al., 2020) | 10 participants,128 Hz sampling rate | Binomial logical regression | 96.92% for 3 classes |
| (Dong et al., 2021) | 14 participants , 64 channel,500 Hz | a linear LR and a non-linear SVM | approx 59% for 2 classes |
| (Pandey & Prasad Miyapuram, 2020) | 24 meditators,64 channel | SVM, Logistic Regression | approx 88% for 2 classes |
| Classification into 4 classes using same Dataset | | | |
| (Singh et al., 2022) | 98 subject, 64 channel, dataset by Braboszcz et al. (Braboszcz et al., 2017) | Bagged Decision Tree | approx 33% for 4 classes |
| Proposed work | 98 subject, 64 channel, dataset by Braboszcz et al. (Braboszcz et al., 2017) | chi-square 1D-CNN | 62% for 4 classes |

After conducting numerous experiments, we've got solid evidence that the One-Dimensional Convolutional Neural Network functions remarkably well as a feature extractor for EEG signals. It efficiently identifies hidden patterns and features, making it a powerful tool in the field. Furthermore, our proposed method encompasses various steps, including preprocessing and classification tasks. The beauty of this approach is that it's designed to be light on memory consumption, ensuring smooth execution. The dataset with 64 channels was strategically chosen, and the results were astounding—our model trained at lightning speed, achieving convergence before hitting 100 epochs. These remarkable outcomes surpassed the performance of previously explored methods, all of which employed diverse preprocessing techniques and deep learning approaches for EEG feature extraction and meditation classification tasks. All the methods for meditation classification with dataset by Braboszcz et al. (Braboszcz et al., 2017) compared and illustrated in Table 7 but most of the author

classified into 2 classes (meditator and control), only author(Singh et al., 2022) and proposed methodology classified into 4 classes (types of meditation).

## Conclusion

In conclusion, the experimental setup involved splitting EEG data into 25-second chunks with overlaps to create a sequence of time splits. These chunks were used to create features for each subject, and various 1D convolutional neural networks (1DCNN) with different hyper parameters were trained on the data. The experiments focused on classifying 4-types of meditation using the EEG data. The results of the experiments showed that the proposed 1DCNN model achieved high accuracy in meditation type classification. Different experiments were conducted with varying numbers of features and hyper parameters, and the best models were selected for evaluation. The model achieved an accuracy of 69% on the training set and over 62% on the validation and test sets, demonstrating its effectiveness in classifying meditation types. Comparison with previous works on similar datasets revealed that the proposed method outperformed other approaches in terms of accuracy. The 1DCNN proved to be a powerful feature extractor, recognizing hidden patterns and features in the EEG signals effectively. Furthermore, the proposed methodology demonstrated its lightweight nature and fast training speed due to the use of a limited number of EEG channels. The experiments achieved convergence within a reasonable number of epochs without requiring large memory resources. Overall, the results suggest that the 1DCNN-based approach is a promising method for EEG signal analysis in meditation type classification. The study contributes to the field of brain-computer interfaces and provides valuable insights into EEG feature extraction techniques for various applications.

## Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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