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**T.C.**
**TURKISH-GERMAN UNIVERSITY**
**INSTITUTE OF THE GRADUATE STUDIES**
**IN SCIENCE AND ENGINEERING**

# PREDICTION OF PSYCHOLOGICAL DISORDER LEVELS WITH DEEP LEARNING MODELS BASED ON ELECTROENCEPHALOGRAPHY (EEG) SIGNALS

**Master's Thesis**

**Oğuzhan MEMİŞOĞLU**

**ISTANBUL 2024**

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**M.Sc., Robotics and Intelligent Systems, Turkish-German University, 2024**

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**Submitted to the Institute of the Graduate Studies in Science and Engineering in partial fulfillment of the requirements for the Master's degree**

**ISTANBUL 2024**

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## DECLARATION OF AUTHENTICITY

I declare that I completed the master thesis independently and used only the materials that are listed. All materials used, from published as well as unpublished sources, whether directly quoted or paraphrased, are duly reported. Furthermore, I declare that the master thesis, or any abridgment of it, was not used for any other degree-seeking purpose and give the publication rights of the thesis to the Institute of the Graduate Studies in Science and Engineering, Turkish-German University.

Oğuzhan MEMİŞOĞLU

## ABSTRACT

PREDICTION OF PSYCHOLOGICAL DISORDER LEVELS WITH DEEP LEARNING MODELS BASED ON ELECTROENCEPHALOGRAPHY (EEG) SIGNALS

Psychological disorders, diverse and complex, paint a spectrum of challenges across the human experience. Depression is one of the life-threatening psychological disorders that impacts millions of individuals worldwide. Traditional diagnosis depends heavily on subjective reports, which inhibits objectivity and accuracy. This study investigates the potential of deep neural networks (DNNs) in detecting and characterizing depression severity using electroencephalography (EEG) data. In this study, an open-source dataset is examined, which includes resting state and task-driven EEG recordings of 60 subjects to classify to predict severity of depression, based on self-rating depression scale (SDS) score. Severity of subjects are labeled by the ranges of SDS score. Using the significant feature extraction capabilities of DNNs, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), it is aimed to classify depression severity level using EEG data itself and extracted features from EEG data proposed in the literature. Accuracies of different input representations are obtained. It is observed that using combinations of feature representations of EEG data shows promising results in the above-mentioned networks.



**Keywords:** *Deep Learning; Machine Learning; Depression; EEG; Mental Disorders*

# ÖZET

## ELEKTROENSEFALOGRAFİ (EEG) TABANLI SİNYALLER ÜZERİNDEN PSİKOLOJİK BOZUKLUK DÜZEYLERİNİN DERİN ÖĞRENME MODELLERİ İLE TAHMİNİ

Çok çeşitli ve karmaşık olan psikolojik bozukluklar, insan deneyimi boyunca karşılaşılan zorlukların bir spektrumunu çizer. Depresyon, dünya çapında milyonlarca bireyi etkileyen ve yaşamı tehdit eden psikolojik bozukluklardan biridir. Geleneksel teşhis büyük ölçüde öznel raporlara dayanır ve bu da nesnelliği ve doğruluğu engeller. Bu çalışma, derin sinir ağlarının (DNN) elektroensefalografi (EEG) verilerini kullanarak depresyon şiddetini tespit etme ve karakterize etme potansiyelini araştırmaktadır. Bu çalışmada, kendi kendini derecelendiren depresyon ölçeği (SDS) puanına dayalı olarak depresyon şiddetini tahmin etmek için sınıflandırmak üzere 60 deneğin dinlenme durumu ve görev odaklı EEG kayıtlarını içeren açık kaynaklı bir veri kümesi incelenmiştir. Deneklerin ciddiyeti SDS puan aralıklarına göre etiketlenmiştir. DNN'lerin, özellikle de evrişimli sinir ağları (CNN'ler) ve tekrarlayan sinir ağlarının (RNN'ler) özellik çıkarma kabiliyetleri kullanılarak, EEG verilerinin kendisi ve literatürde kullanılan, EEG verisinden çıkarılan özellikler kullanılarak depresyon şiddet seviyesinin sınıflandırılması amaçlanmaktadır. Farklı veri girdi şekillerine göre sınıflandırma doğruluk oranları elde edilmiştir. EEG verilerinden elde edilen bazı özelliklerin ve bu özelliklerin kombinasyonlarının yukarıda bahsedilen ağlarda iyi sonuçlar verdiği gözlemlenmiştir.

**Anahtar Sözcükler:** *Derin Öğrenme; Makine Öğrenmesi; Depresyon; EEG; Ruhsal Bozukluklar*

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| | |
|---|---|
| 1D | One-dimensional |
| 2D | Two-dimensional |
| ANN | Artificial Neural Network |
| CNN | Convolutional Neural Networks |
| DNN | Deep Neural Network |
| DWT | Discrete Wavelet Transform |
| EEG | Electroencephalography |
| EOC | Electrooculogram |
| ESS | Epworth Sleeping Scale |
| FFT | Fast Fourier Transformation |
| Hz | Hertz |
| LSTM | Long Short-Term Memory |
| NYC-Q | New York Cognition Questionnaire |
| PLI | Phase Lagging Index |
| ReLU | Rectified Linear Unit |
| RMSE | Root Mean Square Error |
| s | Seconds |
| SAS | Self-rating Anxiety Scale |
| SDS | Self-rating Depression Scale |
| SVM | Support Vector Machine |
| SVM RBF | Support Vector Machine classifier with Radial Basis Kernel Function |

# 1. INTRODUCTION

## 1.1 Mental Disorders

A mental disorder is a syndrome that manifests as a malfunction in the biological, psychological, or developmental processes that underpin mental functioning and is defined by a clinically significant disturbance in a person's behavior, emotion regulation, or thought processes. Significant distress or impairment in social, professional, or other key tasks is typically linked to mental disorders [1].

According to Global Burden of Disease Study 2019, in 2019 13.04% of global population affected from mental disorders, in which 2.49% of global population affected from major depressive disorder and 4.05% affected from anxiety [2].

Major depressive disorder is a prevalent mental disorder, which affects an estimated 5% of adults worldwide and can result in suicide [3].

The understanding and diagnosis of mental disorders have been advanced through various technological approaches, including the analysis of neural activity on brain.

## 1.2 EEG

EEG is a record of neural activity from the brain [4]. It is recorded at scalp of human brain (Figure 1.1). Records from the brain can be used for the classification of emotions, mental workload, motor imaging, seizure detection, event-related potential detection, and sleep scoring [5]. Moreover, mental disorders can be detected from EEG signals via biomarkers from the brain [6].

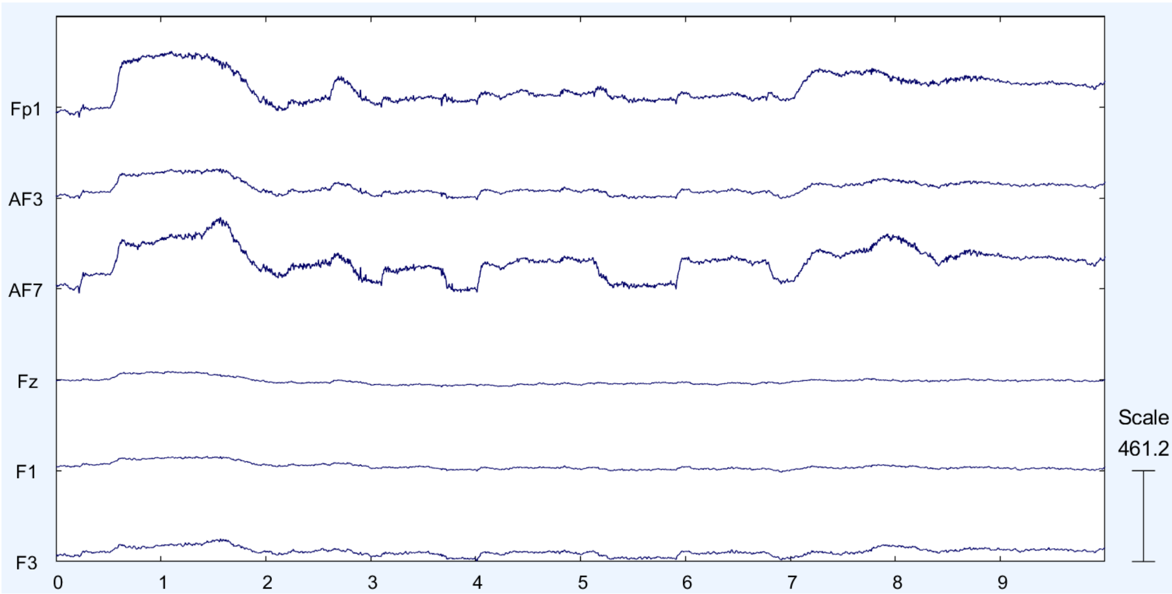

Figure 1.1: Example EEG signal representation

The use of EEG in mental health research allows for a non-invasive examination of brain function, enabling the identification of patterns and abnormalities associated with different mental disorders. Processing EEG signals by deep learning methods provides valuable insights into the neural signatures of conditions such as major depressive disorder and anxiety.

### 1.3 Deep Learning

Deep learning, a subfield of machine learning, has emerged as a powerful tool for automatically learning complex representations from data. In the area of mental health, deep learning techniques, particularly deep neural networks, have gained prominence for their ability to extract complex patterns from neuroimaging data.

Researchers have applied deep learning to tasks such as the analysis of EEG signals to detect and classify mental disorders [4]. By leveraging the hierarchical features learned by deep neural networks, these approaches enhance the accuracy and the efficiency of identifying subtle patterns associated with various mental health conditions.

The integration of deep learning methodologies with EEG analysis holds promise for developing more precise and efficient diagnostic tools for mental disorders, contributing to a deeper understanding of the underlying neural mechanisms.

### 1.3.1 Deep Neural Networks

Neural networks are networks which consists of connected neurons conveying information to one another, if an activation threshold is satisfied, mimicking neural connections of brains [5]. One set of neurons that takes inputs from the previous set and outputs to another set is called a layer of neural network. Multiple layers of neurons that take input from previous layers and gives output to the next layers establishes a deep neural network (Figure 1.2).

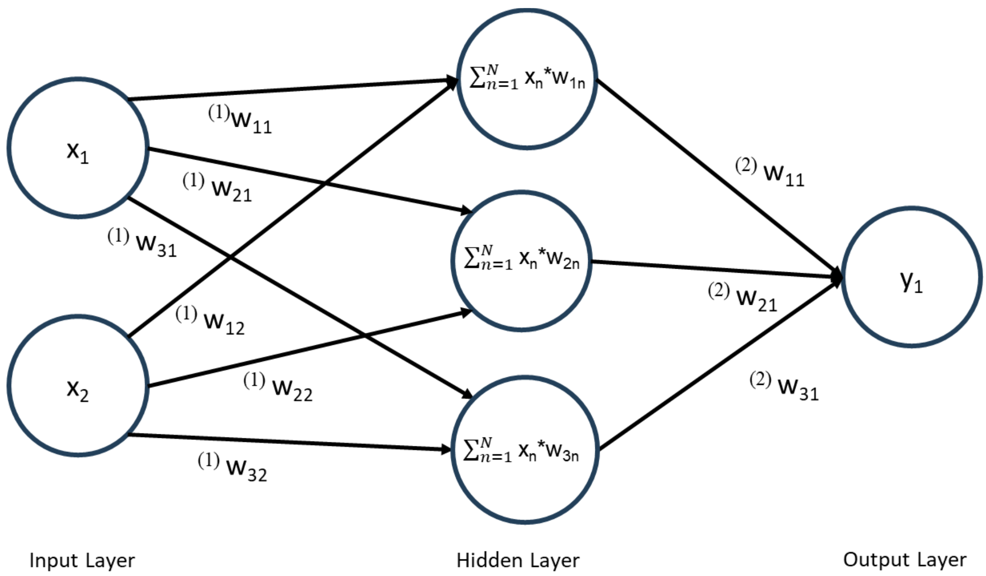


Figure 1.2: Deep neural network

Inputs taken from previous layer are multiplied by weights in every connection between current neuron and previous neurons and summarized to get the input value of current neuron. Output value is calculated by an activation function. Some of the most commonly used activation functions include ReLU, Leaky ReLU, Tanh, and softmax (Figure 1.3).

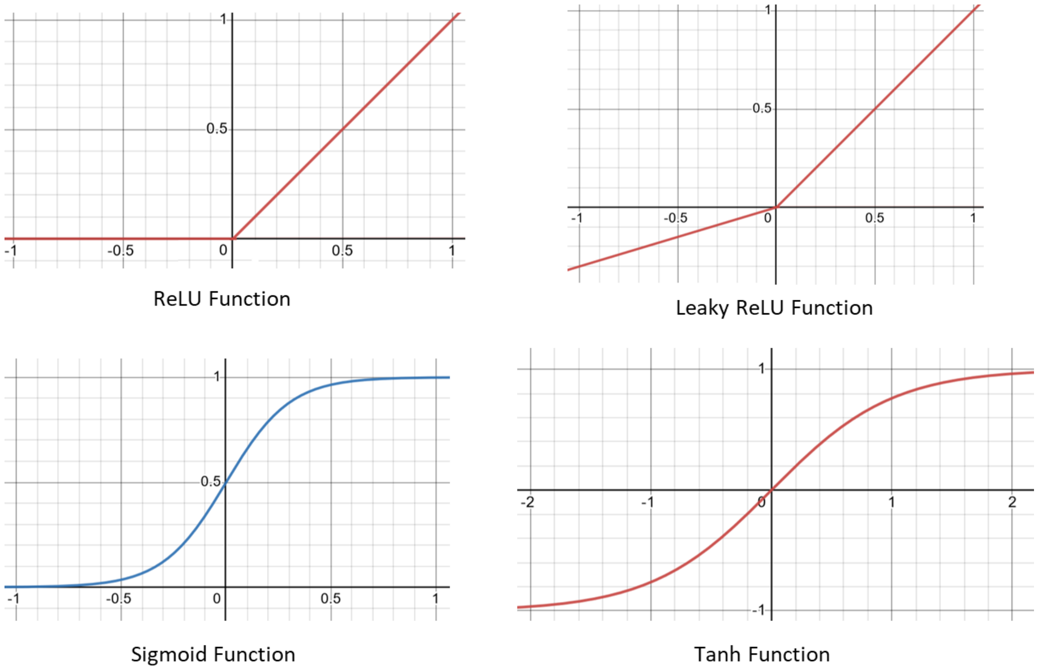


Figure 1.3: Activation Functions

Neural networks can learn to classify data by adjusting weight parameters multiplied by outputs and inputs of neurons. By adjusting weight parameters, predicted outputs of networks are compared to the actual value expected by loss functions such as cross entropy and mean squared error. Calculated loss values of input data are then backpropagated into the network by using derivatives of weights, determining how much the connection between two neurons are contributing to the output of the last neuron. Each layer is backpropagated step by step by feeding the training dataset to the network multiple times.

### 1.3.2 Convolutional Neural Networks

CNNs combines the convolution operation on images or timeseries data and varying values of convolution masks that enables tuning filter weights rather than using fixed numbers to convey static feature maps extracted from original data (Figure 1.4). CNNs also includes pooling, flatten and fully connected layers.

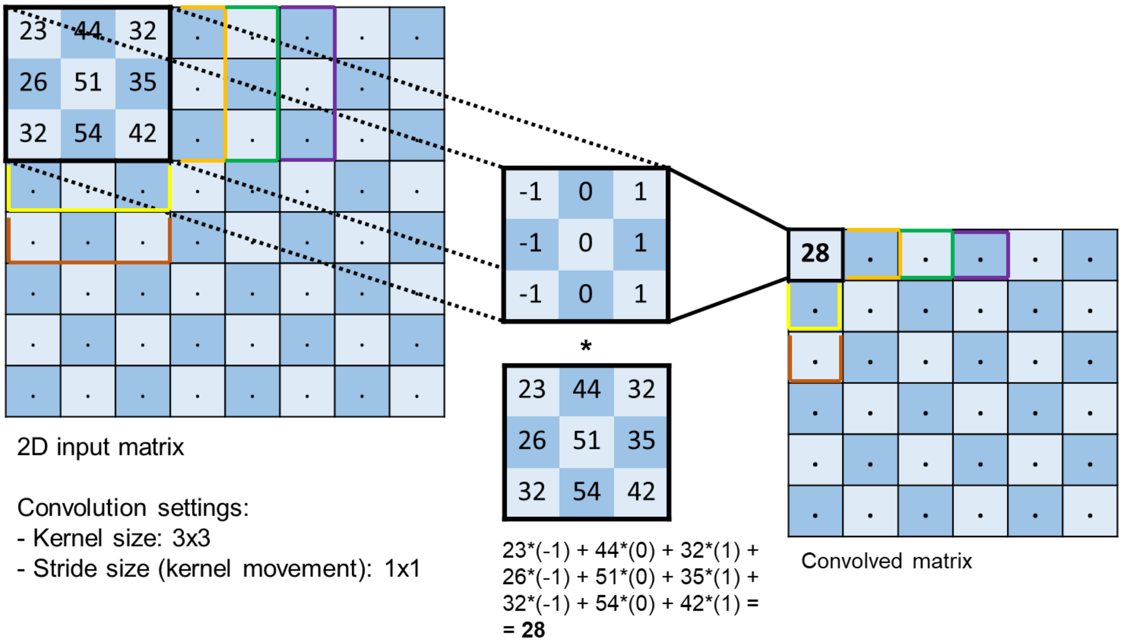


Figure 1.4: Convolution operation

Pooling layers extract most significant values according to the selected property such as minimum, maximum, or average value inside a selected kernel. The deep learning model used in this study uses maximum pooling. Maximum pooling layers extract the biggest value in each kernel size, moving along the axes by stride size (Figure 1.5).

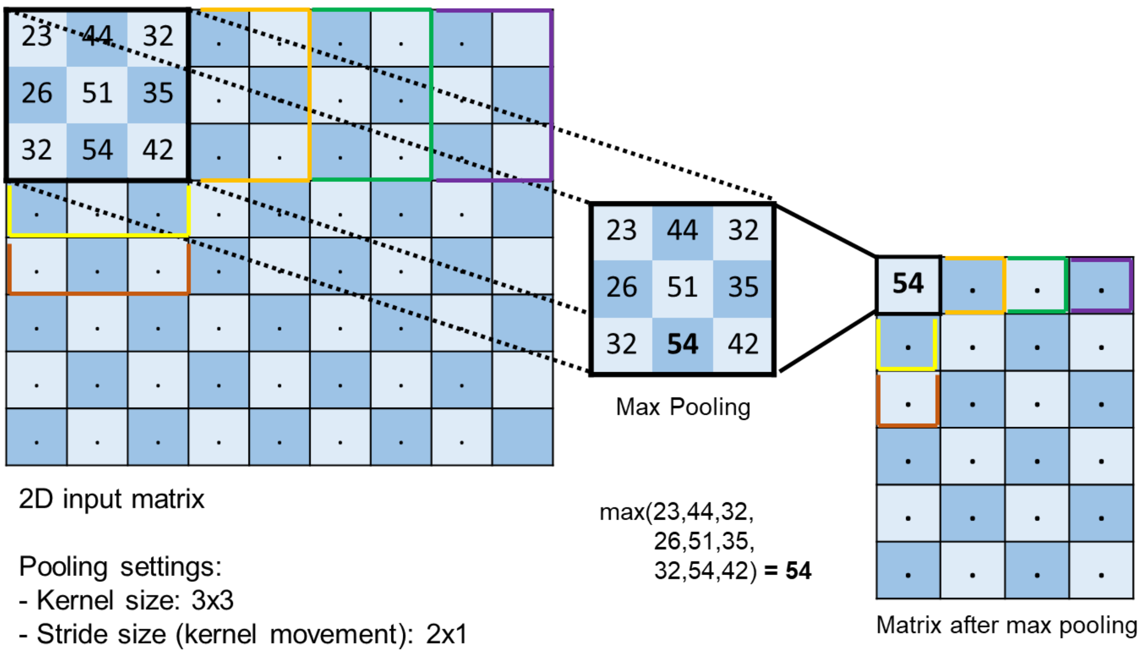


Figure 1.5: Max pooling operation

In CNN, the last 2D pooling or convolutional layer is flattened into 1D vector to convey information into fully connected layers, in which the learning of classification occurs (Figure 1.6).

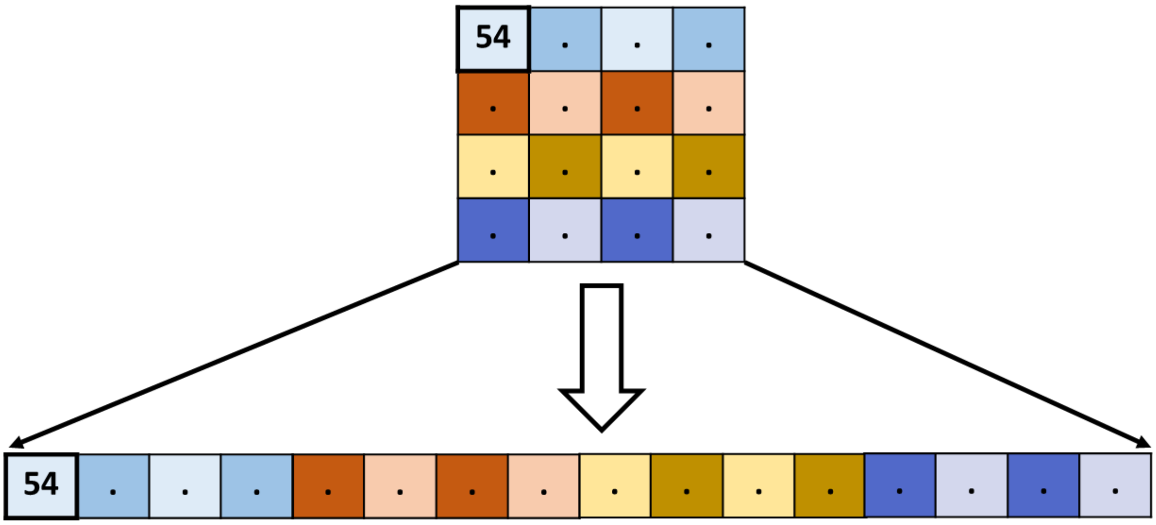


Figure 1.6: Reshaping into 1D

### 1.3.3 Recurrent Neural Networks and Long Short-Term Memory

Recurrent neural networks are a type of neural network that transmits its output back into itself, as many times as the size of its input vector. RNNs can output the values in each recurrence iteratively or deliver the final calculated value (Figure 1.7).

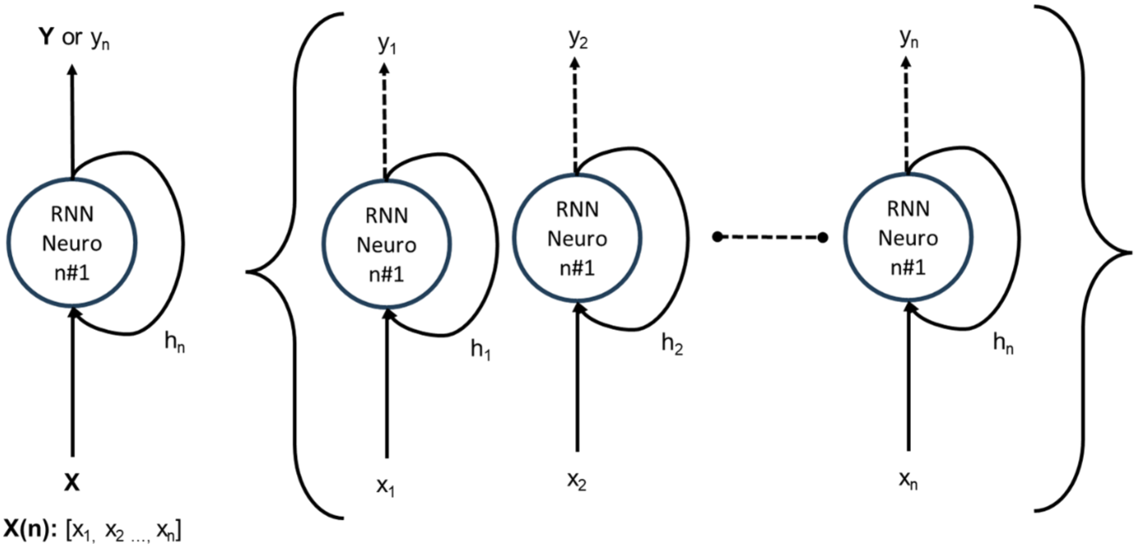


Figure 1.7: Recurrent layer with one neuron

Long short-term memory is a type of RNN network that aims to convey information from previous inputs in a series of data to overcome vanishing gradient descent problem [6].

Vanishing gradient problem occurs when multiple derivatives of neuron weights are calculated. The more the derivatives are calculated over the same weights, the less the calculated derivatives become smaller and therefore the learning in networks nearly stops.

One LSTM neuron consists of one input and one output, two hidden state inputs and outputs, and activation functions which control the amount of inputs transmitted to the recurrent input into the same neuron (Figure 1.8).

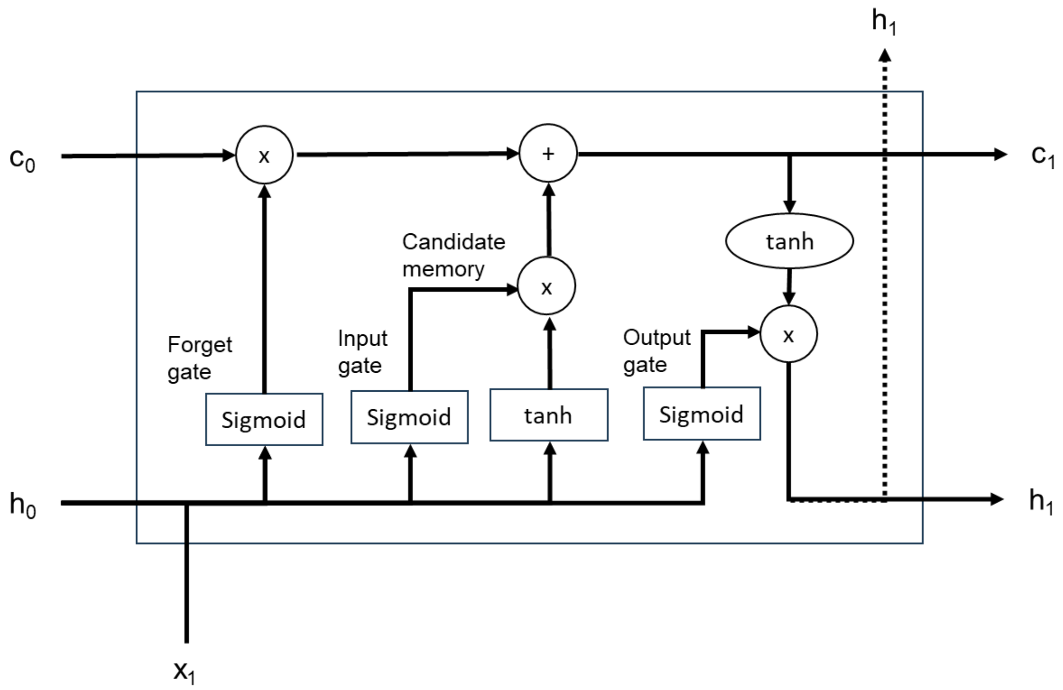


Figure 1.8: Inner structure of LSTM Cell

Activation gates control the amount of information passed through one cell to the next instance of hidden inputs and next input in series of data. $h_0$ denotes the short-term hidden state, which controls how much of the long-term hidden state $c_0$ is going to forwarded into the next recurrence.

## 1.4 Related Work

Classification of mental disorders like major depressive disorder, bipolar disorder and anxiety disorder has been conducted by machine learning and deep learning approaches on EEG data or extracted features.

Different input formulations, EEG data from different tasks and different deep neural networks have been used to classify depressive disorder patients.

In [7], the use of machine learning techniques to predict vulnerability to depression based on EEG data is explored, where an accuracy of 91.42% in predicting vulnerability to depression using task-based EEG is achieved using a long short-term memory model. In this study, the accuracy achieved by a 1D convolutional neural network amounts 98.06% using raw resting state EEG data. Accordingly, machine learning models can effectively predict vulnerability to depression using EEG data from both resting state and task-based measurements.

In [8], extracted features from DWT of EEG signals and SVM are used to classify depressed subjects. EEG data of 30 recorded at 256 Hz over a duration of 5 minutes from left hemisphere of the brain were used. An accuracy of 88.92% is achieved by training SVM RBF model with ten-fold cross validation strategy.

Authors in [9] have used logistic regression with leave-one-out cross validation on three linear and three nonlinear features extracted from 5 minutes records of 30-channel EEG data. In this study, 13 depression patients and a control group of 13 healthy subjects participated. They reached an accuracy of 92% by using all features and argued that no single feature is sufficient to detect depression.

In [10], the statistical features extracted from 30 resting state EEG signals from left and right hemisphere of the brain over a duration of 5 minutes are used to train a LSTM model. Authors compared the proposed model with CNN-LSTM and ConvLSTM models to predict mean datapoints from EEG channels. Among other models, the proposed model has the least RMSE value.

In [11], authors used a combined network consisting of brain network and CNN to classify anxiety and depression. Adjacency matrices of PLI feature from five frequency bands of 31-channel EEG data are used as input to a combined network. A classification accuracy of 92% has been reached by the proposed network.

In [12], authors used imaging asymmetry matrices calculated from 19 EEG channels to obtain recordings for both eyes-closed and eyes-open states of 30 normal and 34 depressed subjects to classify depression with a 2D CNN model. Here, a classification accuracy of 98.85% has been achieved. It is mentioned that to increase the reliability of deep learning models, correlation of classification results to various depression scoring inventories can be used in further research.

In [13], authors extracted relative wavelet energy values of different frequency bands and entropy from EEG signals to train an ANN model. The model consists of 20 individual input neurons for 20 features and two output neurons for classification. A classification accuracy of 98.11% has been reached. It is concluded that depression is essentially limited to the low frequency range of 0 – 4 Hz.

In [14], a combined model of CNN with GRU is proposed to predict depression from a public dataset (MODMA dataset [15]) by using brain maps containing frequency and temporal data as input. A prediction accuracy of 89.63% has been achieved on the open-source dataset. It has been concluded that a greater number of patients and other types of data rather than EEG are required to achieve higher accuracy rates.

In [16], authors introduced a graph convolutional network for classification of depressed patients from resting state EEG data. Hjorth parameters and power spectral density features are extracted from EEG signals to be used as input to the network. An accuracy rate of 96.50% has been achieved with the proposed model with a 10-fold cross validation strategy.

In [17], a CNN network with two separate convolution lines connected at the end of convolution layers is proposed to classify three categories of medicated patients, unmedicated patients and normal subjects. An accuracy of 79.08% has been achieved with a 10-fold cross validation.

### 1.5 Original Contributions

The severity level of major depressive disorder can be classified as mild, moderate and severe [1]. Identifying severity level of depression at early stages can provide more specialized treatment to patients and prevent deaths related to major depressive disorder. Therefore, this study investigates the performance of CNN and RNN for classifying the severity level of depression. To achieve this goal, preprocessed EEG data and optimal features identified from literature are used to train deep neural network models and compared with different data formulations.

### 1.6 Organization of the Thesis

In Section 2, dataset, preprocessing steps, and input representation of dataset fed into a classification model based on CNN and RNN are explained.

In Section 3, results obtained from different input representations fed into the proposed CNN model are presented.

In Section 4, the results are discussed, and further research objectives are addressed.

## 2. MATERIALS AND METHODS

In this study a test-retest dataset which includes resting state and cognitive state EEG recordings has been used to classify subjects having mild depression and no depression [18]. A flowchart of the procedures conducted in this study has been shown in Figure 2.1.

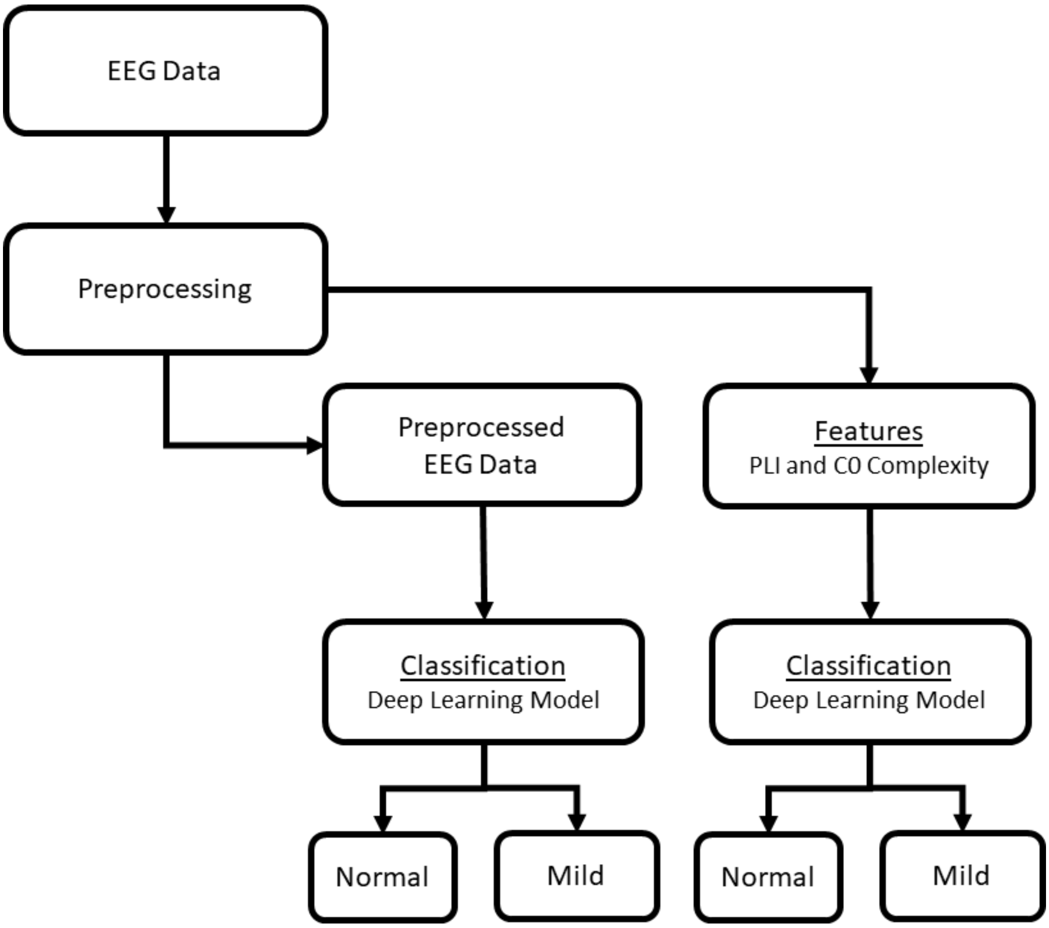


Figure 2.1: Procedures in this study

### 2.1 Dataset

Participants selected for the data acquisition have no psychological or neurological disorder diagnosis and no psychiatric drugs taken within 3 months prior to the recording.

EEG data has been recorded from 60 participants in 3 sessions. First two sessions are conducted 90 minutes apart from each other in their first visit and last session is conducted after one month of their first visit.

### 2.1.1 Test Procedure

In each session two resting state (eyes open and eyes closed) tasks and three cognitive (memory, music and subtraction) tasks have been requested from participants to accomplish. Before EEG recordings, participants were informed of procedures they are going to take and filled SDS, SAS and ESS. Then, participants were directed to EEG recording room to attend resting state and cognitive tasks (Figure 2.2).

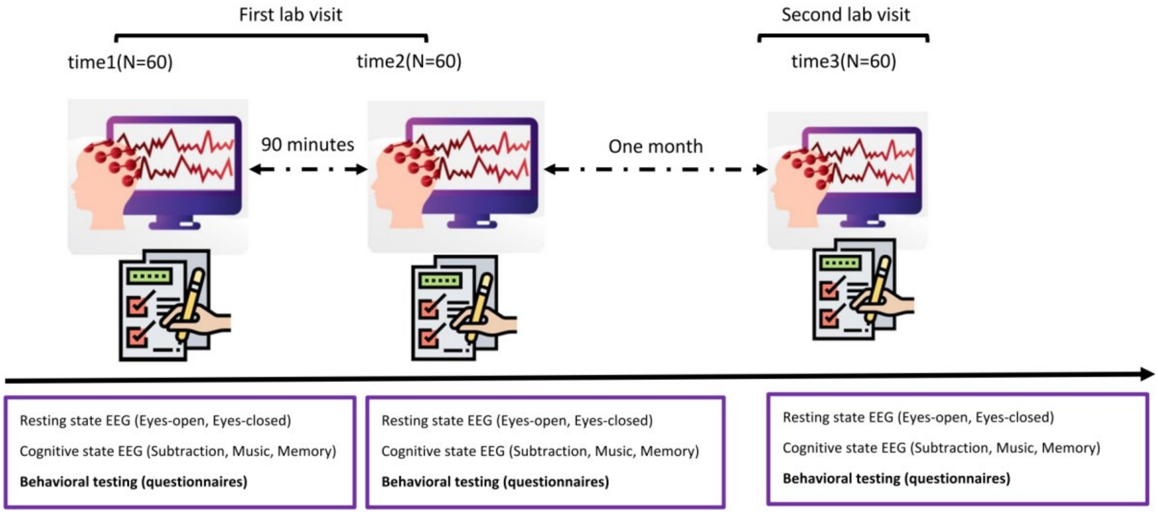


Figure 2.2: Procedure of experiment [18]

In resting state tasks, participants are asked to sit quietly in the recording room for five minutes both in eyes closed and eyes open states.

In memory task, participants were instructed to subtract repeatedly by 7 beginning from 5000. Then, they are asked to sing their favorite song in their heads. Lastly, they were requested to recall their day until they arrive at the laboratory. Between each cognitive task, participants filled mini NYC-Q.

### 2.1.2 EEG Acquisition

For acquisition of EEG data, an elastic cap with 64 electrodes according to the international 10-20 placement system is being used. Two channels were used to record

EOC to detect and filter eye movements affecting other channels and one channel as reference. The recordings were sampled at 500 Hz. 61-channel of EEG data for each task and subject per session is collected (Figure 2.3).

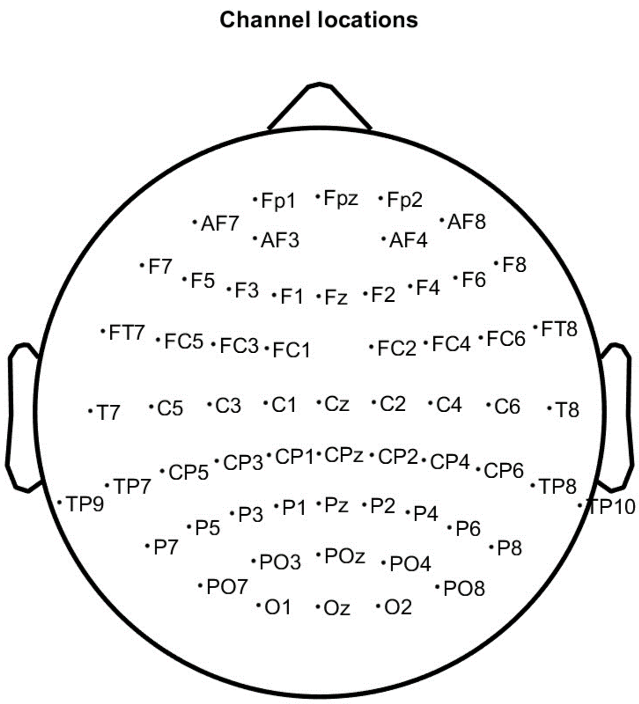


Figure 2.3: Channel locations of EEG data

## 2.2 Data Selection

Table 2.1: SDS Score Ranges

| Severity of Depression | SDS Score Range |
|---|---|
| Normal | 25-43 |
| Mild | 50-59 |
| Moderate | 60-69 |
| Severe | 70 and over |

According to [19], for classifying severity of depression, SDS scores of subjects are divided into 4 groups (Table 2.1).

Due to the insufficient number of moderate and severe subjects, only normal and mild subjects were selected for classification (Figure 2.4).

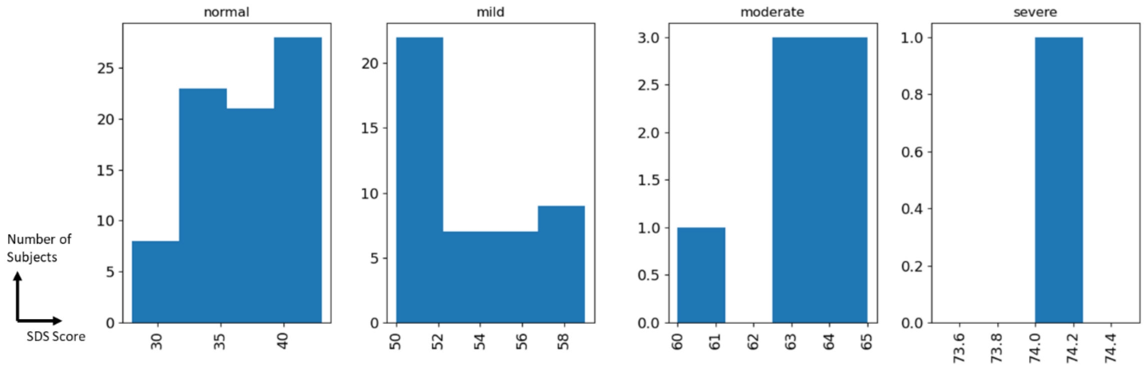


Figure 2.4: Histogram of all eyes closed sessions grouped by severity of depression

### 2.3 Data Preparation

Before classification step, EEG data has been preprocessed and two types of input data are prepared for the deep learning model (Figure 2.5).

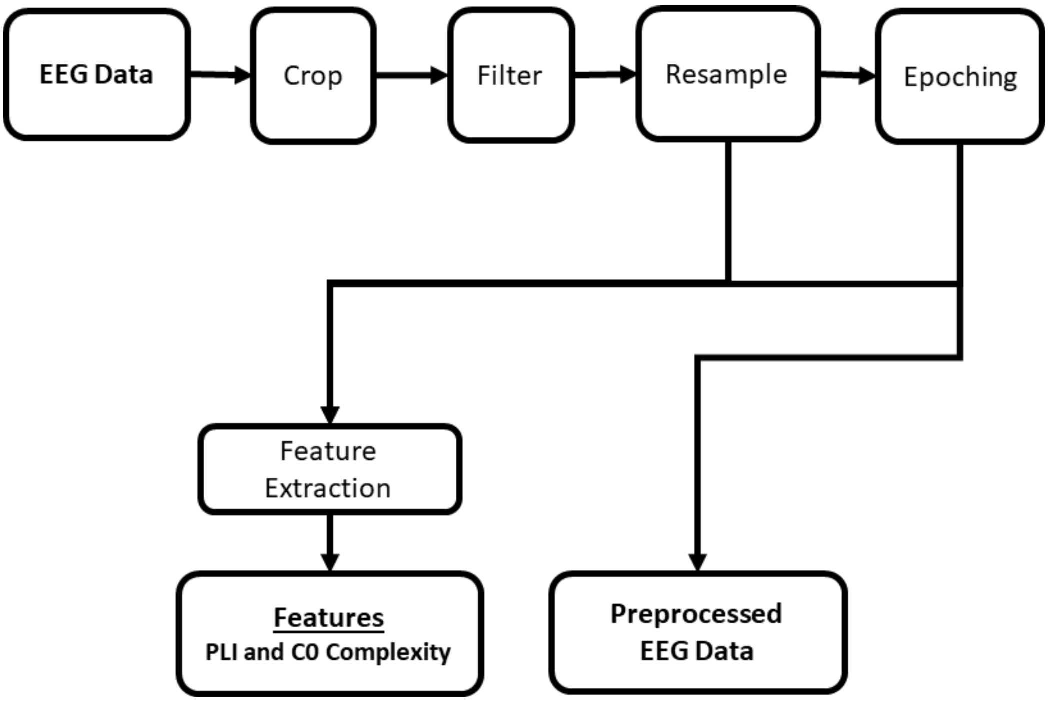


Figure 2.5: Flowchart of preprocessing steps

#### 2.3.1 Preprocessing

At the beginning, the first 30 seconds of EEG data of all participants has been cut from original data to have more stable EEG signals. The remaining data has been filtered at cutoff frequencies between 0.15 Hz and 45 Hz and thus 50 Hz power line and high frequency noise have been removed. Then, the data is resampled to 256 Hz. Finally, the EEG signals have been split into fixed length of epochs. Different epoch lengths are considered to examine the effect of epoch lengths and overlapping ratios on the prediction rate of the models (Figure 2.6).

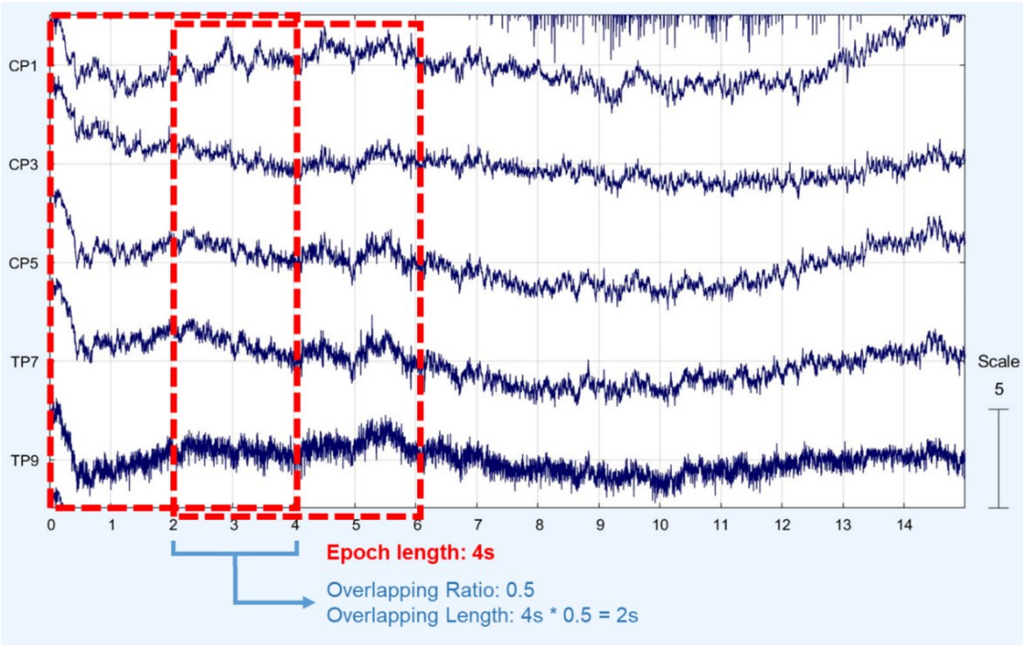


Figure 2.6: Fixed length epoch extraction with overlapping ratios

Authors in [20] specified PLI and C0-complexity as optimal features to detect depression from resting state EEG data by using feature selection methods. Therefore, PLI and C0-complexity are used separately and combined to form the input of the deep learning model. The features are extracted from fixed length epochs of EEG data and resampled EEG data.

### 2.3.2 C0-Complexity

C0-complexity is an indicator to the randomness of a time series signal [21]. It is the proportion of random activity to total complex activity. It can be applied both to short and long sequences of individual signals. The following steps are conducted to extract C0-complexity from each EEG signal of recordings.

The FFT of the EEG signal $x(n)$ is extracted as follows

$$X(k) = \frac{1}{N}\sum_{n=0}^{N-1} x(n)e^{-j\left(\frac{2k\pi n}{N}\right)}.$$

Then, the mean square value of each datapoint in FFT is calculated:

$$G_N = \frac{1}{N}\sum_{k=0}^{N-1} |X(k)|^2 .$$

Mean square value of datapoints is then used as a threshold to filter out datapoints. The output of the filter is given by

$$Y(k) = \begin{cases} X(k) & |X(k)|^2 > G_N \\ 0 & |X(k)|^2 \leq G_N \end{cases} .$$

Finally, filtered FFT datapoints are then transformed to time domain $y(n)$ and C0-complexity can be calculated as follows:

$$C0 = \frac{\sum_{n=0}^{N-1} |x(n) - y(n)|^2}{\sum_{n=0}^{N-1} |x(n)|^2} .$$

Calculated C0-complexity values are used as an input vector for the deep learning model.

### 2.3.3 PLI

PLI is a functional connectivity feature that values between 0 and 1 to indicate difference in phases of two signals [22]. PLI is calculated in each fixed length epochs without overlapping according to its proposed equation and mean value of PLI calculated for each channel pair is used to construct 2D connectivity matrix:

$$PLI = |\langle \text{sign } [\Delta\phi(t_k)] \rangle|$$

$\Delta\phi$ denotes the phase difference between two signals at a frequency.

Extracted 2D connectivity matrix is reshaped into input vector for the deep learning model.

## 2.4 Deep Learning Models

Deep learning models used to train preprocessed EEG data and feature vectors are based on a CNN named DeprNet [23] and a RNN with LSTM layers.

DeprNet consists of 5 convolutional and max pooling layer pairs and 2 hidden dense layers are used to classify depressed patients and normal control subjects (Figure 2.7). Convolution kernel sizes are adjusted to convolve only individual channels and at the end of convolutional layers and max pooling layers, only the size of the data point axis is reduced. After convolutional and max pooling layers, all extracted 2D maps are reshaped into 1D and used as input to the fully connected layers to classify normal and depressed subjects.

The input shape of the model is changed with varying fixed epoch sizes of the preprocessed EEG data and 1D feature vectors. In output layer, 2 neurons are used to classify mild and normal subjects using softmax as activation and categorical-cross entropy as loss function related to softmax activation function.

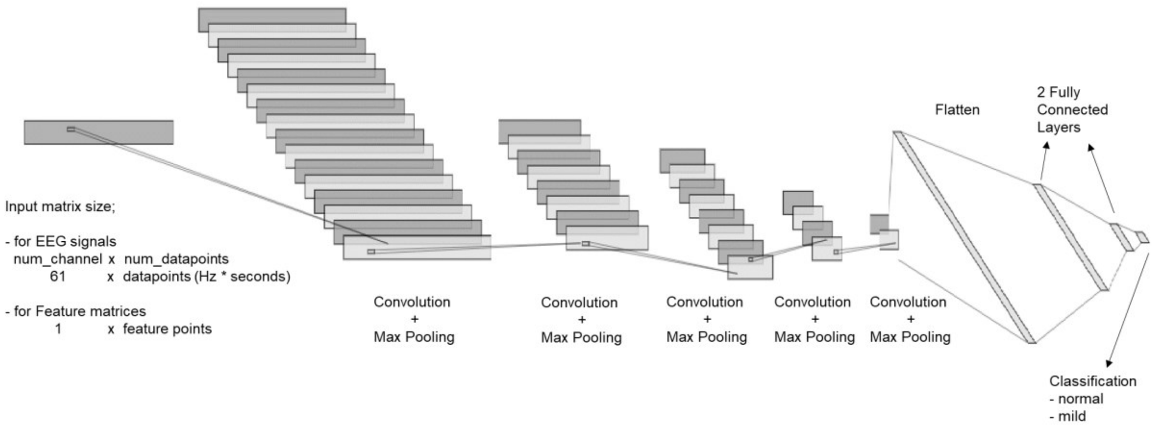


Figure 2.7: Overview of the CNN model

RNN used by preprocessed EEG data and feature vectors consists of 2-layer LSTM. The output of LSTM layers is reshaped into 1D vector and fed into 3 fully connected layers. The output of the network has 2 neurons, in which softmax activation is applied to classify data as normal or mild depressed.

## 2.5 Training

Training a deep learning model requires to feed training data multiple times to adjust weight parameters inside the model. One pass of the whole training set through the model is defined as epoch, differing from epoching an EEG data to have multiple data from a long sequence recording. Update of the model weights are done in batches, feeding a limited amount of data from training dataset to calculating an average of loss values and then updating weights of the model. Trainings with preprocessed EEG data are used a batch size of 32 and 100 epochs. Trainings with extracted features are used a batch size of 4 to maintain multiple learning steps in one pass of selected dataset.

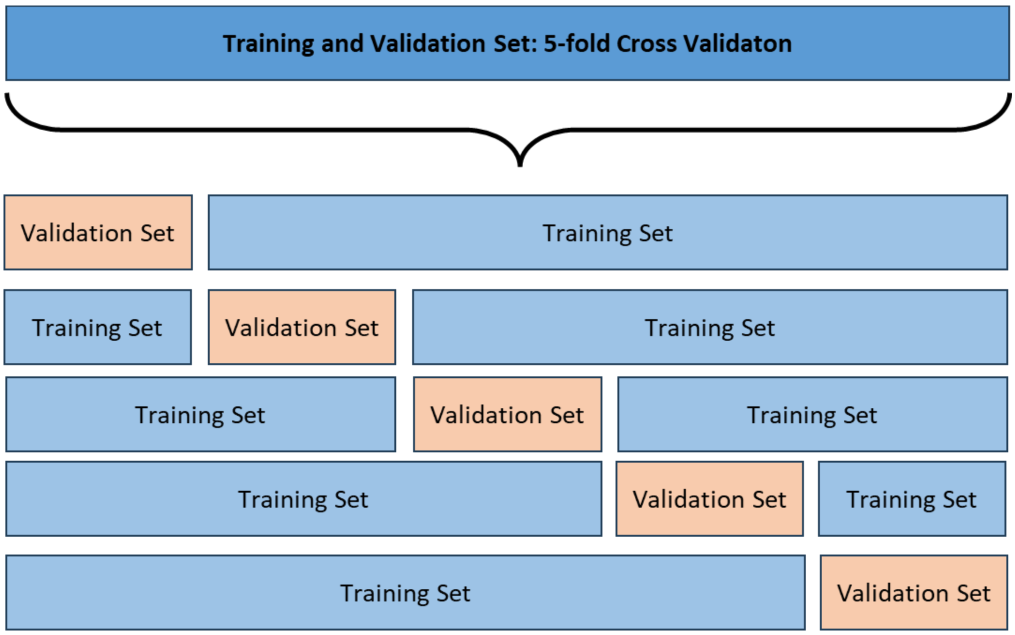


Figure 2.8: K-fold cross validation

5-fold cross validation is being used to train the deep learning model. Subjects in one session are split into training and validation sets, where each fold consists of a different validation set (Figure 2.8). Accuracy rates calculated in validation step are averaged and compared with different input formulations and networks.

In all networks, Adam optimizer is used, and all networks have 2 output neurons and softmax activation functions to classify subjects as normal or mild. Categorical cross-entropy is selected as the loss function of networks.

# 3. RESULTS

In this study, the efficiency of the proposed deep learning models with different inputs formulations are investigated and compared. Here, different adjustments such as overlapping ratio, EEG epoching length are considered. The model and the input form delivered the best performance are obtained.

## 3.1 Classification with Preprocessed EEG Data

In the last step of preprocessing, EEG data is split into fixed length epochs with different overlapping ratios. The split EEG data increases the amount of data to train and validate the deep learning model. The length of epochs and the resampling frequency affect the number of datapoints fed into neural networks. For each epoch length and resampling frequency, the number of datapoints of the combinations at 256 Hz are given in Table 3.1.

Table 3.1: Epoch lengths and corresponding data points

| Epoch Length (seconds) | Data Points |
|---|---|
| 2 | 512 |
| 4 | 1024 |
| 6 | 1536 |
| 8 | 2048 |

The combinations of epoch lengths and overlapping ratios are used to train and validate DeprNet (Table 3.1). It is observed that epoch duration of 4 and overlapping ratio of 0.0 provides the best accuracy value of 76.9% (Figure 3.1).

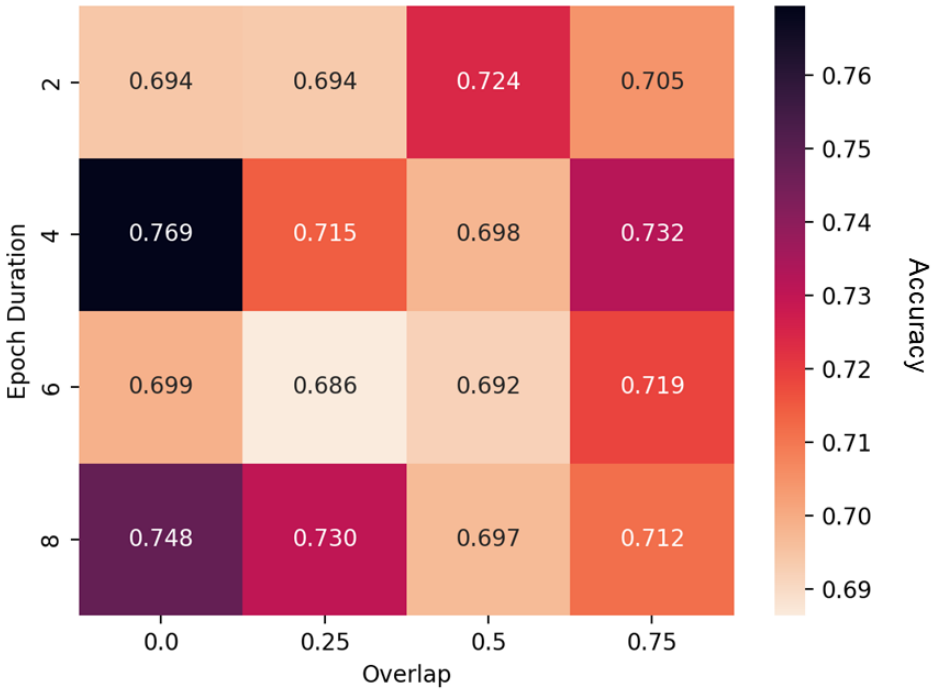


Figure 3.1: Accuracy heatmap of epoch and overlapping combinations

### 3.1.1 CNN with min-max Normalization

Using min-max normalization, data points epoch-overlapping combinations are scaled between values -1 and 1. All channels are used together to perform the normalization of each datapoint. Minimum and maximum values are chosen to represent negative and positive voltage values of datapoints.

DeprNet is used as the CNN to predict normal and mild depressed subjects (Table 3.2).

Table 3.2: DeprNet architecture for 4 seconds, 256 Hz input data

| # | Layer | Output Shape | # Maps | Kernel Size | Stride Size | Activation |
|---|---|---|---|---|---|---|
| 1 | **Input** | 61 x 1024 | 128 | - | - | - |
| 2 | **Convolution 2D** | 61 x 1020 | 128 | 1 x 5 | 1 x 1 | Leaky ReLU |
| 3 | **Batch Normalization** | 61 x 1020 | 128 | - | | - |
| 4 | **Max Pooling 2D** | 61 x 510 | 128 | 1 x 2 | 1 x 2 | - |
| 5 | **Convolution 2D** | 61 x 506 | 64 | 1 x 5 | 1 x 1 | Leaky ReLU |
| 6 | **Batch Normalization** | 61 x 506 | 64 | - | - | - |
| 7 | **Max Pooling 2D** | 61 x 253 | 64 | 1 x 2 | 1 x 2 | - |
| 8 | **Convolution 2D** | 61 x 249 | 64 | 1 x 5 | 1 x 1 | Leaky ReLU |

| | | | | | | |
|---|---|---|---|---|---|---|
| 9 | **Batch Normalization** | 61 x 249 | 64 | - | - | - |
| 10 | **Max Pooling 2D** | 61 x 124 | 64 | 1 x 2 | 1 x 2 | - |
| 11 | **Convolution 2D** | 61 x 122 | 32 | 1 x 3 | 1 x 1 | Leaky ReLU |
| 12 | **Batch Normalization** | 61 x 122 | 32 | - | - | - |
| 13 | **Max Pooling 2D** | 61 x 61 | 32 | 1 x 2 | 1 x 2 | - |
| 14 | **Convolution 2D** | 61 x 60 | 32 | 1 x 2 | 1 x 1 | Leaky ReLU |
| 15 | **Batch Normalization** | 61 x 60 | 32 | - | - | - |
| 16 | **Max Pooling 2D** | 61 x 30 | 32 | 1 x 2 | 1 x 2 | - |
| 17 | **Flatten** | 58560 | - | - | - | - |
| 18 | **Dense** | 16 | - | - | - | Leaky ReLU |
| 19 | **Dense** | 8 | - | - | - | Leaky ReLU |
| 20 | **Output** | 2 | - | - | - | Softmax |

Preprocessed EEG data of epoch and overlapping variations are fed into CNN. The accuracy heatmap is obtained and presented in Figure 3.2.

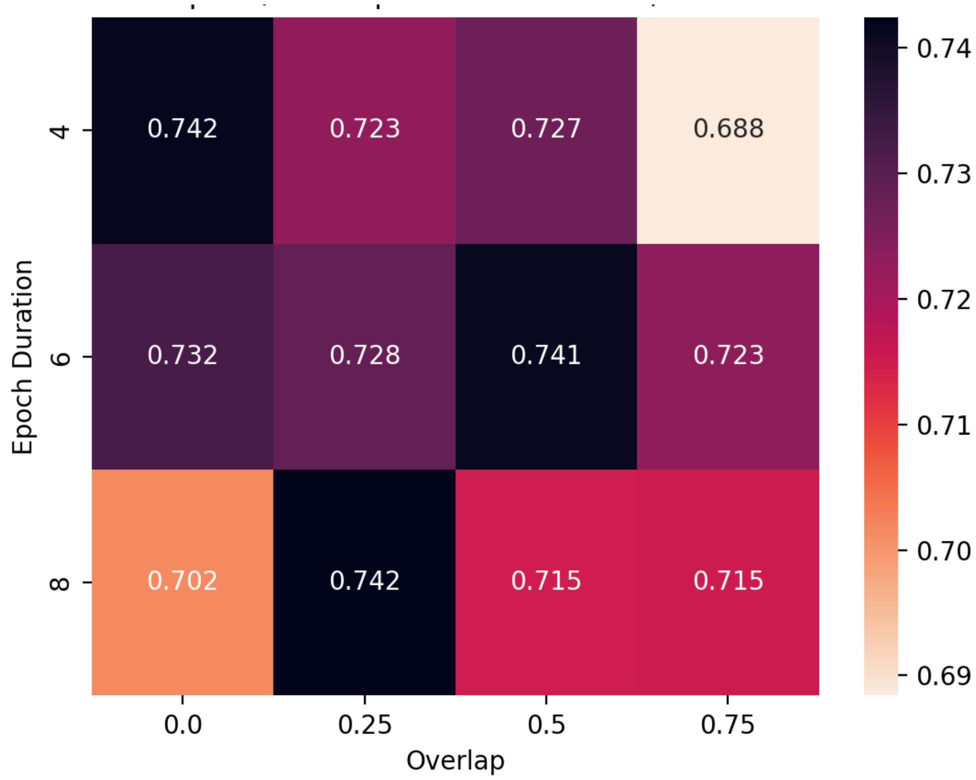


Figure 3.2: Accuracy heatmap with min-max normalization for DeprNet

### 3.1.2 LSTM with min-max Normalization

In literature, LSTMs are used to predict depression from EEG data. In this study, 2-layered LSTM network with fully connected layers are used to examine the effect of various epoch and overlapping combinations (Table 3.3).

Table 3.3: LSTM network layers

| Layer | Output Shape | Activation |
|---|---|---|
| Input | 61 x # Data Points | - |
| LSTM | 61 x 8 | Tanh |
| LSTM | 61 x 1 | Tanh |
| Flatten | 61 | - |
| Dense | 32 | Leaky ReLU |
| Dense | 16 | Leaky ReLU |
| Dense | 8 | Leaky ReLU |
| Output | 2 | Softmax |

Preprocessed EEG data with different epoch and overlapping values are fed into the LSTM network. Outputs of LSTM layers are reshaped into 1D and transmitted into fully connected layers. The accuracy heatmap of different epoch lengths and overlapping ratios are shown in Figure 3.3.

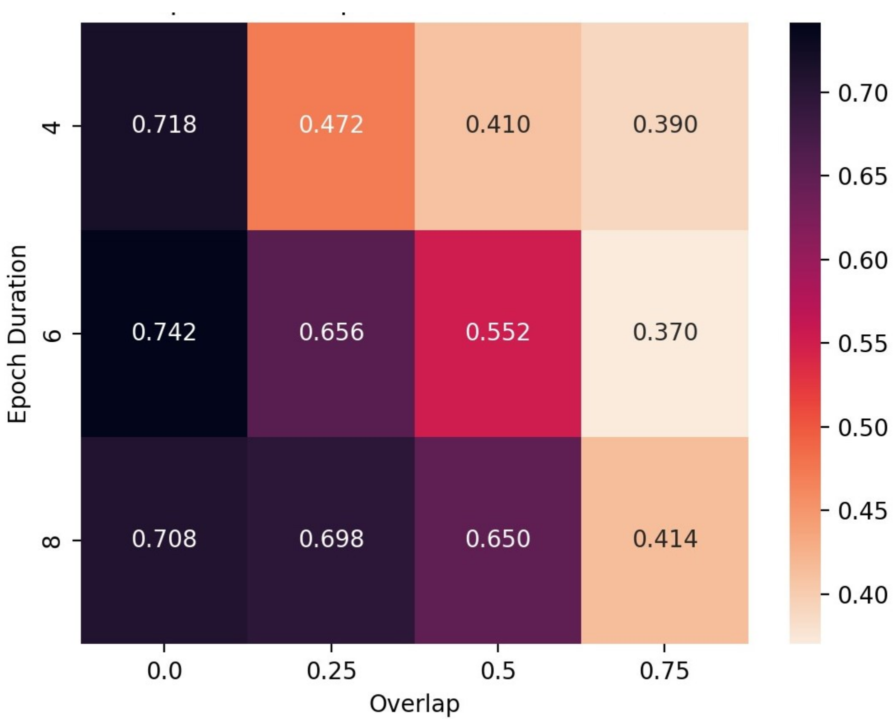


Figure 3.3: Accuracy heatmap for the 2-layer LSTM

It is observed that with increasing epoch duration and decreasing overlapping ratio, the accuracy increases.

### 3.2 Classification with Features

Features are extracted per subject. Therefore, there is a smaller amount of data in training and validation dataset.

PLI and C0-complexity features are used individually and combined to test classification performances of DeprNet and DeprNet with LSTM networks.

#### 3.2.1 PLI Frequency Variation

PLI is extracted from combinations of EEG channel pairs to create a connectivity matrix (Figure 3.4). The lower half triangle of PLI connectivity matrix is reshaped to be used as 1D vector input for the deep neural networks (Figure 3.4).

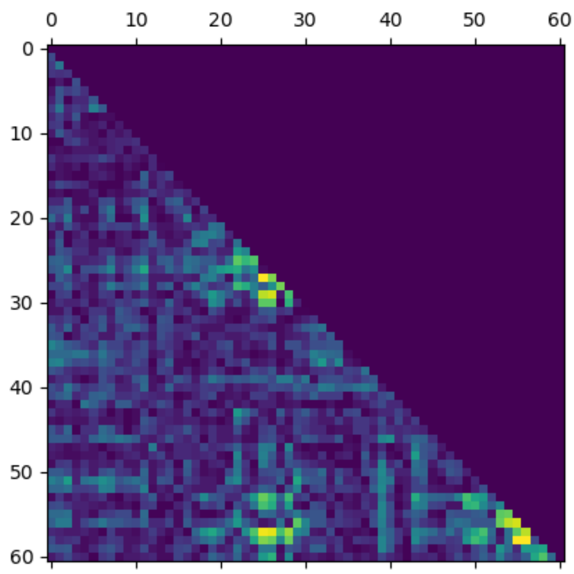


Figure 3.4: 2D RGB representation of PLI feature of 61-channel EEG data

PLI features extracted at different frequencies from 2 to 32 Hz are trained with DeprNet to investigate the impact of frequency (Figure 3.5).

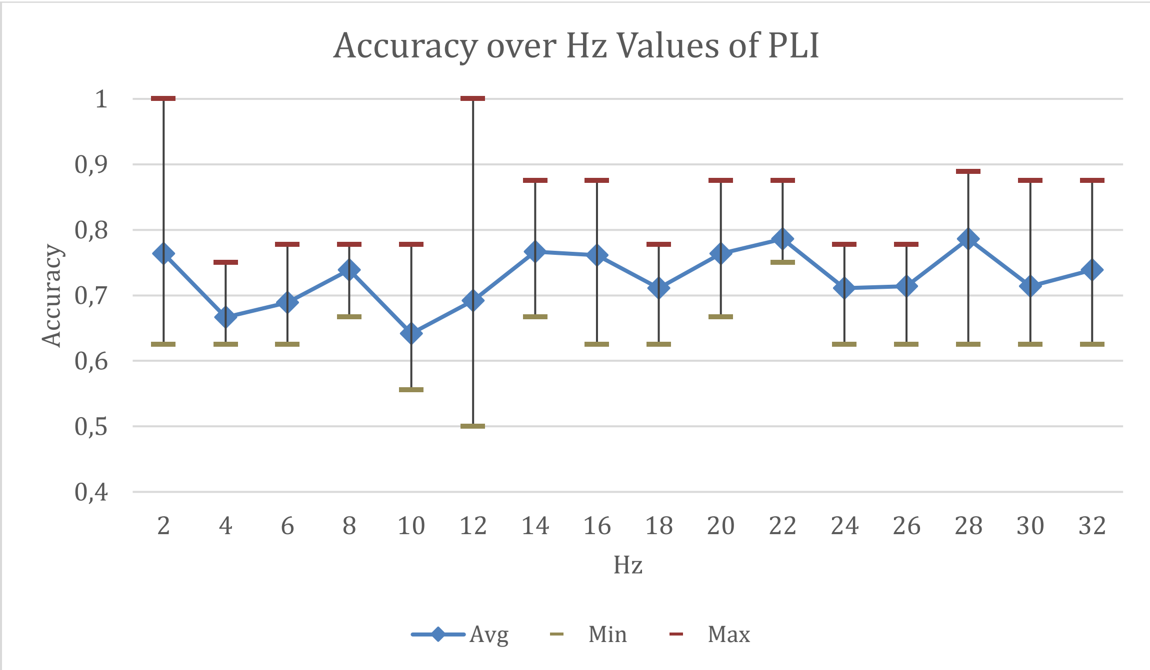


Figure 3.5: Accuracy of DeprNet using PLI features at different frequencies

It is observed that PLI features extracted from 16Hz and 22Hz are good candidates to use with C0-complexity features.

### 3.2.2 C0-Complexity Variations

C0-complexity is extracted from fixed length epochs of 2s, 4s, 8s and 40s for each EEG channel. Extracted C0-complexities are reshaped into 1D vector and used to train DeprNet and to compare accuracies with different epoch lengths of EEG channels. Accuracy rates obtained with different epoch lengths are shown in Table 3.4.

Table 3.4: Accuracies using C0-complexity at different epoch lengths

| **Epoch Length (s)** | **Accuracy** |
|---|---|
| 2 | 0.7168 |
| 4 | 0.7862 |
| 8 | 0.8334 |
| 40 | 0.7612 |

According to accuracy results, combinations of C0-complexity features from all tested ranges and PLI features at 16Hz and 22Hz are used to train deep neural networks.

### 3.2.3 PLI and C0-Complexity with CNN

PLI and C0-Complexity features are concatenated and fed into DeprNet. Accuracies are shown in a heatmap of PLI frequencies and C0-complexity epoch lengths (Figure 3.6).

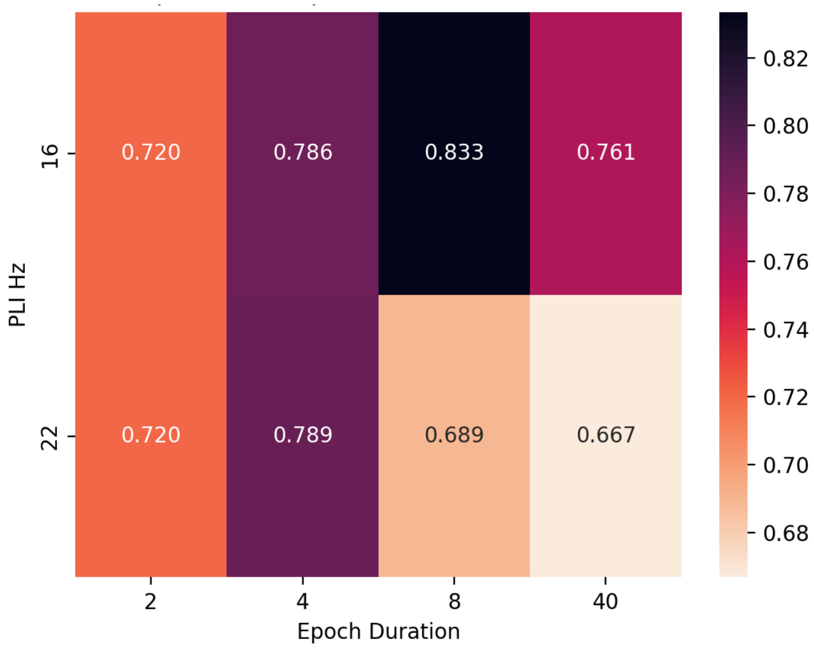


Figure 3.6: Accuracy heatmap of DeprNet using PLI and C0-complexity

It is observed that an accuracy of 83.3% is achieved by 16Hz of PLI and 8s epoch duration of C0-complexity.

### 3.2.4 PLI and C0-Complexity with CNN-LSTM

Further examination of PLI and C0-complexity is achieved by adding 1 LSTM layer between convolution layers and fully connected layers of DeprNet (Table 3.5).

Table 3.5: C0-complexity calculated for LSTM layer of 4s epoch

| Layer | Output Shape | Activation |
|---|---|---|
| After convolution and max pool layers | | |
| Flatten | 5856 | - |
| Reshape | 5856 x 1 | - |
| LSTM | 5856x 2 | ReLU |
| Flatten | 11712 | - |
| Dense | 16 | Leaky ReLU |
| Dense | 8 | Leaky ReLU |
| Output | 2 | Softmax |

Combined features are fed into the network as 1D vector and accuracy rates obtained for different frequency values of PLI and epoch lengths of C0-complexity are given in Figure 3.7.

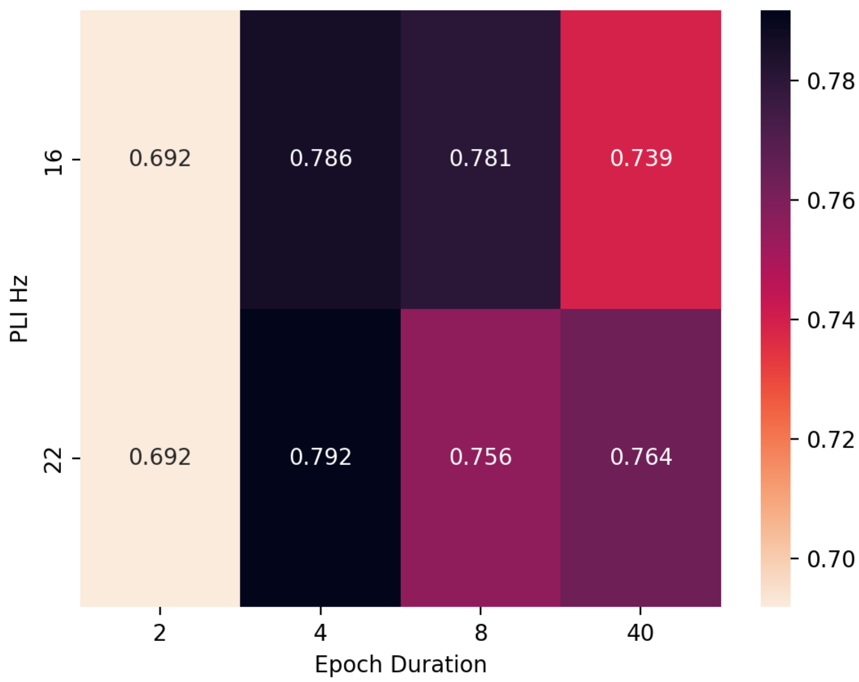


Figure 3.7: Accuracy heatmap of Deprnet with LSTM using combined features

It is observed that 16Hz and 22Hz of PLI with epoch length of 4s achieved the best 3 accuracy rates.

## 4. DISCUSSION AND CONCLUSION

In this study, the promising potential of DNNs in addressing the limitations of traditional depression diagnosis by leveraging electroencephalography (EEG) data with different input representations are examined.

Using a combination of extracted features from preprocessed EEG data, C0-complexity, combined input representation of C0-complexity and PLI yield the highest accuracy in identifying normal and mild depressed subjects. This suggests that capturing different aspects of brain activity provides a more comprehensive picture of the disorder. Furthermore, building different DNN structures trained to extract specific features, which has adjustable parameters, such as frequency of PLI, can lead to improved results. This approach can lead to more accurate and objective diagnosis of depression, enabling earlier intervention and improved treatment outcomes.

Calculated features are used as a 1D vector to train DNN models. Therefore, locations of features are not included in this study. Adding positional information of collected features from the brain can be examined.

Almost all areas of the cortex are affected by major depression disorder [24]. Therefore, in this study all channels of EEG data are used to classify subjects. Reducing number of channels by using channels associated with specific areas of the brain can be performed to observe the classification performance of DNNs.

Further research is needed to improve the classification performance of DNN models by examining different DNN structures. Additionally, exploring the interpretability of DNN models would provide valuable insights into the EEG signal patterns related to depression severity.

In this study, training of DNN models is based on self-rating scores of subjects. Using datasets with both self-rating score inventories and professional diagnosis of severity level of depression can provide more accurate results. Moreover, in this dataset, the number of subjects in each severity level of depression is not evenly distributed. An evenly distributed dataset of severity level of depression can enable a multi-class classification.

The classification of subjects is accomplished by only EEG data. Additional inputs from different sources such as facial expressions of subject during the EEG recording can be used for the classification.

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