1.ABSTRACT

We know that our brain functions with various signals. These signals are generated with every activity that we do, even in our sleep. We basically capture these signals by putting electrodes on our scalp and then in the EEG it is recorded as wave patterns. Normal activity would have the usual pattern but abnormal EEG has some distinguishable features. Doctors can identify abnormal EEG from the normal ones after some observation.

Although EEGs helps us differentiate between Normal and Abnormal, it is still heavily dependent upon the examiner to give the last judgement. In order to interpret the signals captured by EEG, we need the help of an expert in this field. Our main objective is to lessen the burden on examiner and reduce the time of examination.

The final goal of this project is to automate the whole process of examination of classifying EEGs. We have now focused only on classifying an EEG into its appropriate type. This automation will help reducing the overall time required to identify the EEG and help the examiner.

2.PROBLEM STATEMENT

To classify EEG signals into Normal and Abnormal EEG Signals using various technique and compare the results.

3.INTRODUCTION

Brain is a complex as well as significant part of human. It also holds many secrets such as how the memories are stored in our brain, how different abnormalities like seizures etc. Now we have come to such point of research that we are much closer to discovering the mysteries of brain.

Among the various measures of analysis, electro-encephalogram is one the most used in the research. Normally outpatient EEG diagnosis takes about 20 min. But this duration is not always sufficient for the analysis of epilepsy or other seizure disorders.

Here comes the question-How do we capture EEG? Basically EEG is the brain waves which captured by metal disc placed on the scalp. Whenever we use our brain, brain emits signal and the metal disc, i.e electrodes, captures this signal and store them in the record as waves.

EEG reports are manually diagnosed by medically certified physicians. As it is performed manually, it may take a lot of time to analyze each of the report thoroughly. Not only this, the analysis is purely based on the subjective interpretation of the examiner. This may lead to some errors.

As we can see that there can be various issue when manually analyzing, we can try to approach this issue using automation of the process. The thought of fully automating the process is interesting. But in order to do that we have to solve the individual module separately and accurately. So in this project, we are focusing on how to filter the EEG reports into normal and abnormal cases.

We want to proceed with first pre-processing the data with various methods to learn the distinguishable features in those EEG. Then comes the training of various models. In order to do that we are hoping to use pre-trained models with traditional machine learning algorithms.

Given that deep learning is unbiased towards the features currently used in visual inspection and is able to learn from raw data, it can be an alternative to visual inspection and traditional machine learning methods for EEG analysis.

4.LITERATURE SURVEY

There are many researches that are already being done for this EEG classification.

Among these the most prominent ones are:

1. Automated Identification of Abnormal EEGs. By Lopez, S. (2017). Temple University.

2. Deep Learning Enabled Automatic Abnormal EEG Identification. by Subhrajit Roy, Isabell Kiral-Kornek, and Stefan Harrer, IEEE Senior Member

3. Automated detection of abnormal EEG signals using localized wavelet filter banks. by Manish Sharma , Sohamkumar Patel , U. Rajendra Acharya

4. A new feature extraction and classification mechanisms For EEG signal processing. by Hemant Choubey, Alpana Pandey

1.

For the first paper, we can see that it was first introduced by the Temple university Hospital. As the EEG classification by Human Examiner takes a lot of time, they first proposed that automation of this process would be much beneficial in the medical science.

Their main approach was to implement a classifier based on Hidden Markov Model (HMM) , Convolution Neural Network – Multiple Layer Perceptron (CNN-MLP), KNN and Random Forest Ensemble Classifier.

The performance is as follows in their research:

Table 1. Summary of the performance for all the evaluated systems

System Description	Error (%)
kNN (k=20)	41.8%
RF (Nt=50)	31.7%
PCA-HMM #GM = 3 #HMM States = 3)	25.6%
GMM-HMM (#GM = 3 #HMM States = 3)	**17.0%**

2.

For the Deep Learning based Automatic Abnormal EEG Identification, they have introduced an approach of using deep neural network in order to classify the data into normal and abnormal. They have used some pre-processing techniques in order to extract features. They didn't use hand-engineering techniques to extract the feature but learn the features.

They have used some deep learning techniques to learn the features. We have also introduced this technique in our project.

They have pre-processed the data into three types –

- Direct using the time series wave signal
- Converting the signal into visual spectrogram
- Converting the signal into GAF

Now after processing the data, they have introduced some classifier models to predict the EEG Signals such as

- Logistic Regression
- MLP Classifier
- 1-D CNN
- 2-D CNN
- 1-D CNN-RNN
- TCNN-RNN

The result obtained by their research work is given as:

Algo. / Pre. proc.	Log. Reg.		MLP		1D-CNN		2D-CNN		1D-CNN-RNN		TCNN-RNN	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Time-series	83.72%	49.09%	69.64%	54.15%	82.04%	76.90%	N/A	N/A	**99.16%**	**82.27%**	N/A	N/A
Spectrograms	N/A	N/A	N/A	N/A	N/A	N/A	86.31%	70.39%	N/A	N/A	95.22%	71.48%
GAF	N/A	N/A	N/A	N/A	N/A	N/A	79.46%	68.61%	N/A	N/A	92.55%	67.02%

TABLE I: Comparison of performance for combination of pre-processing techniques and learning algorithms.

3.

For the next paper, they have introduced another research approach as novel stop-band energy (SBE) minimized orthogonal wavelet filter bank. After using this method they have used SVM classifier to classify the EEG signals into abnormal. They have used unorthodox method to implement this classifier.

4.

For the next paper, they have proposed a method of extracting the features using Masking and Check-in based Feature Extraction Technique (MCFET) and an integrated K-Means with K-Nearest Neighbour classification algorithms to classify the EEG Signals into Normal and Abnormal Signals.

For this method of extracting, first mask is generated , then the check in function is calculated, upper and lower envelops are calculated. Finally the features are extracted from this.

After obtaining this feature, they have used knn classifier to classify the signals into normal and abnormal EEG Signal.

5.1.PROPOSED METHODOLOGY

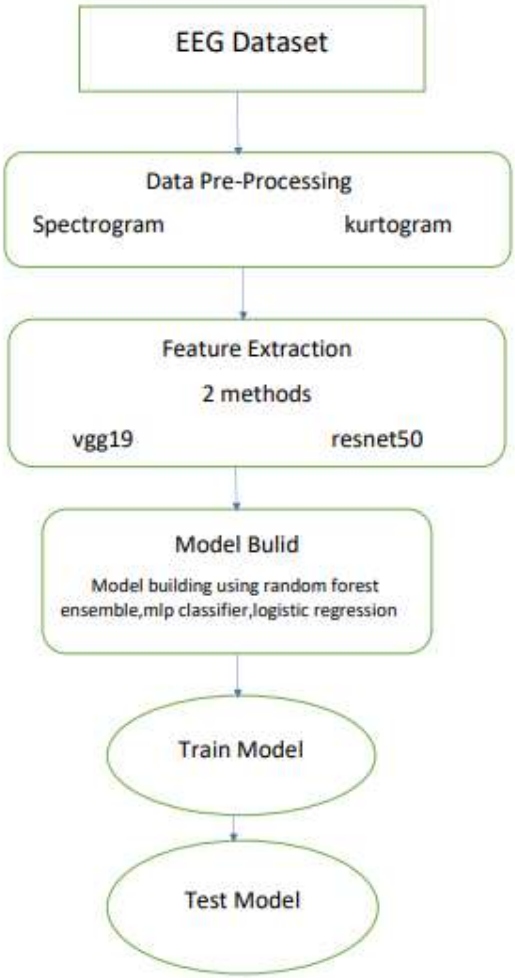
To classify the EEG wave signals into two classes, i.e. normal and abnormal EEG signal, we introduced a three-step architecture.

In the first step, we saw that there are several nodes that captures the brain signal and plot it into EEG. In a single session performed by the examiner, we can see that one patient has about 30 to 40 such nodes associated with his EEG report. To store the EEG report there is a specific data format used. Its name is EDF. Now we have raw data in EDF format and to make use of this data, we have process it according to our needs. So, the first step will be Data Pre-processing.

In the second step, we have to extract features from the processed data. In order to do that we intend to use some techniques and take the best technique after we get the desired result.

In the final step, we have to build some classifier model and train it using the features that we extracted from the previous step. After that we have to test the classifier using the test data that we have and get the desired accuracy we need in order to classify the EEG signals into Normal and Abnormal EEG signals.

5.2.BLOCK DIAGRAM



In this block diagram, we can see the basic Block Diagram of our work-flow.

5.2.1.

First Block of our diagram is the dataset and for this block of our work-flow, we are mainly focusing on how the data is situated as EDF format. How this data is then converted as matlab data array.

5.2.2.

Second Block of our diagram is the data pre-processing. In this flow of our work-flow, we basically pre-processed the data into suitable data to obtain temporal frequency spectrum. Our main intuition was that the data is basically signal with temporal axis. So, temporal frequency spectrum would be appropriate for data pre-processing.

5.2.3.

Third block of our block diagram is feature extraction. In this stage, we used pre-trained model to extract features. in that case we used 2 models, i.e VGG19 and ResNet50 model. In convolution neural network, we see that in each convolution layer the model tries to obtain new features from the image and tries to recognise more complex feature. Using that intuition, we used these 2 pre-trained models to extract features from our dataset.

5.2.4.

In the fourth block, we built our main classifier model that would classify our data into Normal and Abnormal EEG signals. There are many binary classifier that are available. We used random forest ensemble, logistic regression and MLP classifier.

5.2.5.

In the next step, we used our extracted feature vector to train our 3 models.

5.2.6.

After that, we tested our test data to obtain how much accuracy our model can gain. This part concludes our project.

6.1.DATASET

In order to implement our project, we needed a dataset of EEG signals and their classification of Normal and Abnormal. For this we got the "Temple University Hospital EEG Data Corpus" that was provided by our respected mentor, Dr. Rishav Singh.

In this dataset, the EEG signals are obtained by taking a EEG session of about 15 minutes of several patients and observing the brain signals with the help of metal discs placed on the scalps of the patients. These signals are thereafter stored in the data format of EDF. These EDF data format consists the name of the nodes from where the signals are coming from, the sampling rate of the signal, signals in form of wave and etc.

The distribution of the dataset is given below:

Table 1. File statistics for the full evaluation set.

Evaluation

Description	Files		Patients		hours
Abnormal	126	46.4%	105	41.5%	48.9
Normal	150	53.6%	148	58.5%	55.4
Total	276	100.0%	253	100.0%	104.4

Table 2. File statistics for the full training set.

Training

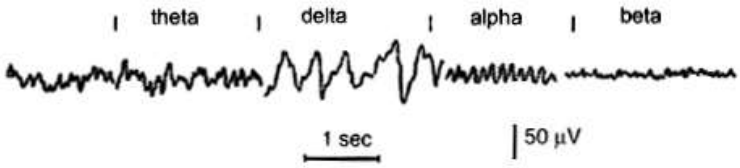
Description	Files		Patients		Hours
Abnormal	1346	50.2%	899	42.1%	546.4
Normal	1371	49.8%	1239	58.0%	518.3
Total	2717	100.0%	2138	100.0%	1064.7

EEG:

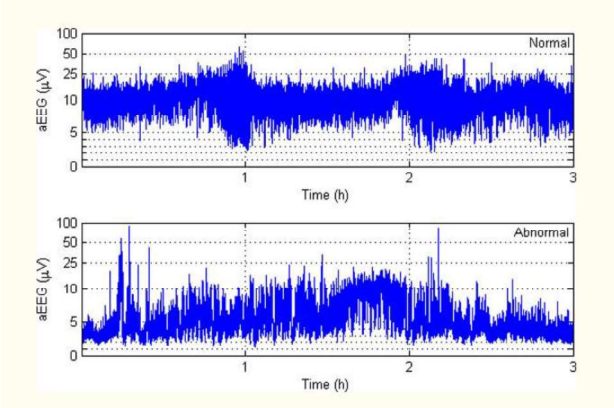
The electro-encephalogram (EEG) is a signal that is recorded by capturing the electrical activity of the brain by putting metal discs (known as nodes) on the scalp.

EEG activity is measured in micro-volt. It has 4 main frequency observed on human. They are:

1. **Delta:**
   It has a frequency of 3 Hz or below. It has the highest amplitude and the slowest waves. It is mostly found in frontal area in adult human.
2. **Theta:**
   It has a frequency of 3.5 to 7.5 Hz. It can be found on children upto the age of 13 and when an average human sleeps. But when it is found on adults when they are awake, it is abnormal.
3. **Alpha:**
   It has a frequency of 7.5 to 13 Hz. It occurs when we close our eyes and relax.
4. **Beta:**
   It has a frequency of 14 and greater. It is a fast activity.



Different EEG Frequencies obtained on human



Example of a Normal and Abnormal EEG

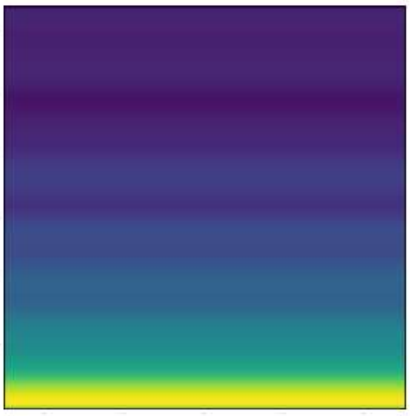
6.2.DATA PRE-PROCESSING

First of all, the dataset is in the form of EDF. So, to get the process this data into our useful data, we converted this EDF data into matlab array data. Now we have a matrix of data on which we can apply several pre-processing techniques.

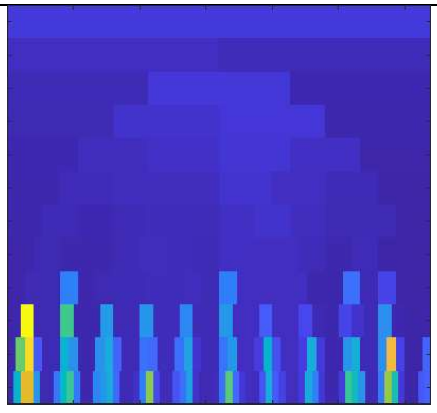
The dataset has many nodes from which 21 signals of each data-point are picked and for this our accuracy increased by 10%.

There are several pre-processing techniques that are available. As we wanted to use CNN based feature extraction in the next step, we had to use pre-processing techniques that would convert the signals into temporal frequency spectrum. Some of these techniques are spectrogram and kurtograms.

We used both of these techniques to pre-process the data into spectrograms and kurtograms and stored them for the next step. This temporal frequency spectrum would be helpful in order to extract the features.



Spectrogram



Kurtogram

In order to read the dataset in python, we have used “pyedflib” library in python. After reading the data in python, we obtained the signal in array and used that array to save in matlab array using the “scipy.io” and savemat() function.

After obtaining the matlab data array, we used matlab software to convert the array signal into spectrogram and kurtogram.

In order to obtain the spectrogram and kurtogram took a lot of time, one whole day to be precise. I think the time took such a long time as the processing of a single data was done at a time. For this reason, for converting 3k data points individually took such a long time.

6.2.1. SPECTROGRAM

The spectrogram contains a compromise between time resolution and frequency resolution: the large window provides less local processing at a time and more discrimination at times. The window receives a piece of signal, where the spectral features are almost invariant

the found parts move the timer window at a certain interval. The spectrogram is defined as the size of S (m, k), represented as A (m, k), as a show in equation

$$A(m,k)=\frac{1}{N}|S(m,k)|^2.$$

Spectrogram adjustment can be improved to change the window length; The long window offers the best solution for frequency, but the worst time fix. A shorter window, however, offers better timing but better resolution resolution. Good visibility in the spectrogram depends on choosing the right window length and spacing. Figure 2 shows the signal spectrogram, which is a multi-signal signal display. Spectrum programming is usually as follows: x-axis represents time, y-axis represents frequency, and the third dimension is the amplitude (visual content) of the frequency, which is encoded. This three-dimensional data can also create a 3D structure, where power is represented as height on z-axis but a 2D chart provides better understanding.

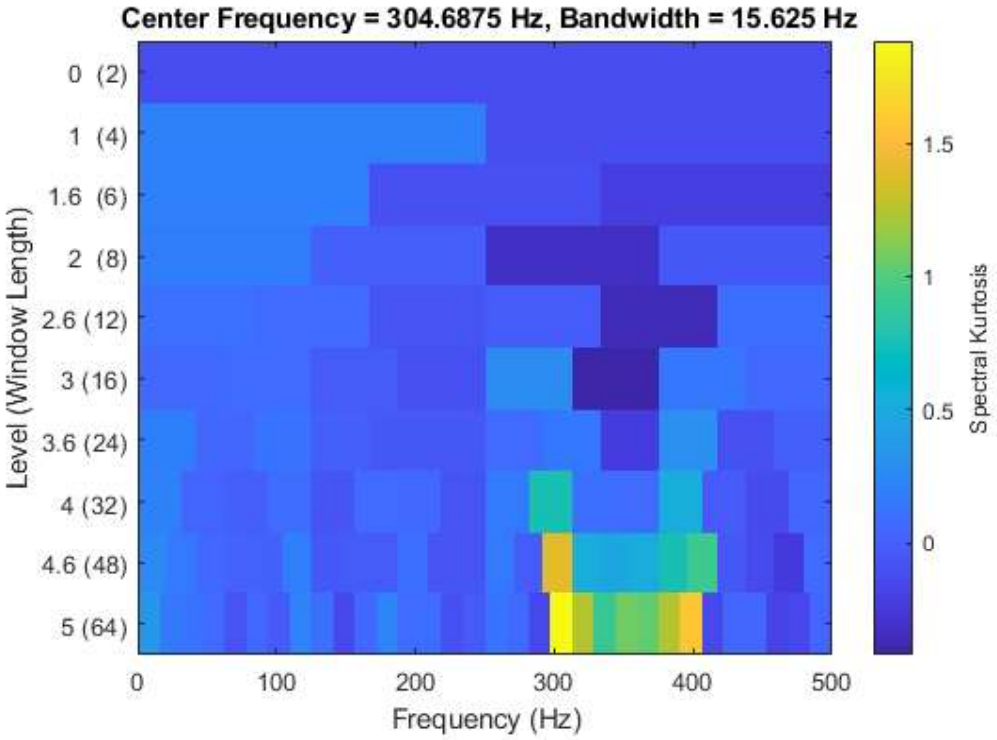
Spectrogram of

An EEG signal

6.2.2. KURTOGRAM

A kurtogram is a spectral analysis tool used to detect irregularities in the signal area. It can be used effectively to find a suitable filter to remove the feature element from the vibration damp, because error signal-induced signal times can be considered static. However, the efficiency of the kurtogram decreases when the signal is collected in a structure that operates under various speed conditions.

A kurtogram is a newly developed spectral analysis tool for the fourth order to detect and mark non-signal objects. The paradigm is based on the premise that each temporal type is associated with the correct dyad {frequency (frequency / frequency) dyad {} which increases its kurtosis, hence its detection. However, a complete overhaul of all aircraft () is a daunting task that is incomparable to online industrial applications.



7.FEATURE EXTRACTION

For the second step of our project, we intended to use CNN based pre-trained model for extracting the features from the spectrograms and kurtograms. For our project we used VGG19 and RESNET50 pre-trained model.

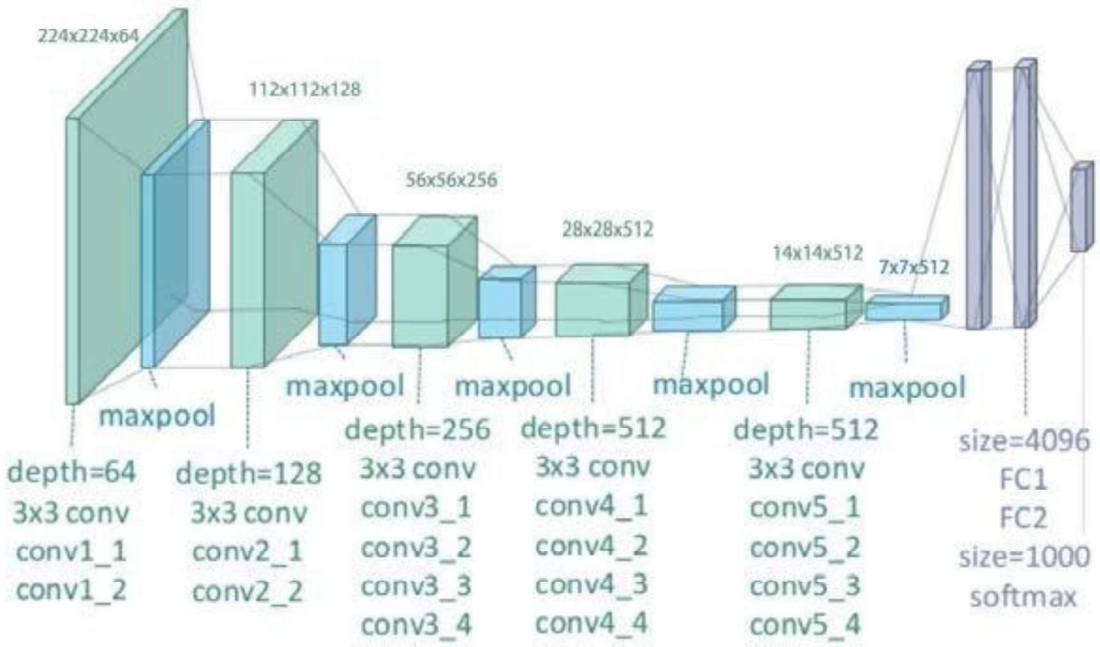
VGG19 pre-trained on "Imagenet" dataset consists of 8 convolution layers and with fully-connected layers total 11 layers. In the case of VGG19, we used "block4_conv1" layer output as the extracted feature. After obtaining the feature, we flattened the feature and made it into a feature vector and will use it in the next step as training data.

ResNet50 consists of 5 stages each with a convolution block and an identity block. Each Convolution block has 3 convolution layer and each identity block also has 3 convolution layers. For our project, we used some of the layers such as "conv3_block2_add".

After extracting the features, we flattened the output layer and got the desired featured vector. Now we shall use this to train our classifier model to get the accuracy.

7.1. VGG19:

For the VGG19 model, the architecture is given as:



VGG19 contains total 19 layers of which 16 layers are convolution layer, 3 layers are fully connected layer and 5 max-pool layer and 1 softmax layer.

Convolution Layer:

Convolution layer is the layer which uses convolution operation to extract features from the image. Convolution operation is done on the image by several filters or kernels. These filters learn the features and make the whole convolution process successful.

Fully Connected Layer:

Fully connected layer is a popular and frequently used layer in Convolutional Neural Network. It represents a matrix vector multiplication. It is used to change the dimension of the vector.For example dense layer applies scaling, rotation , transform of the vector etc.

Max Pool Layer:

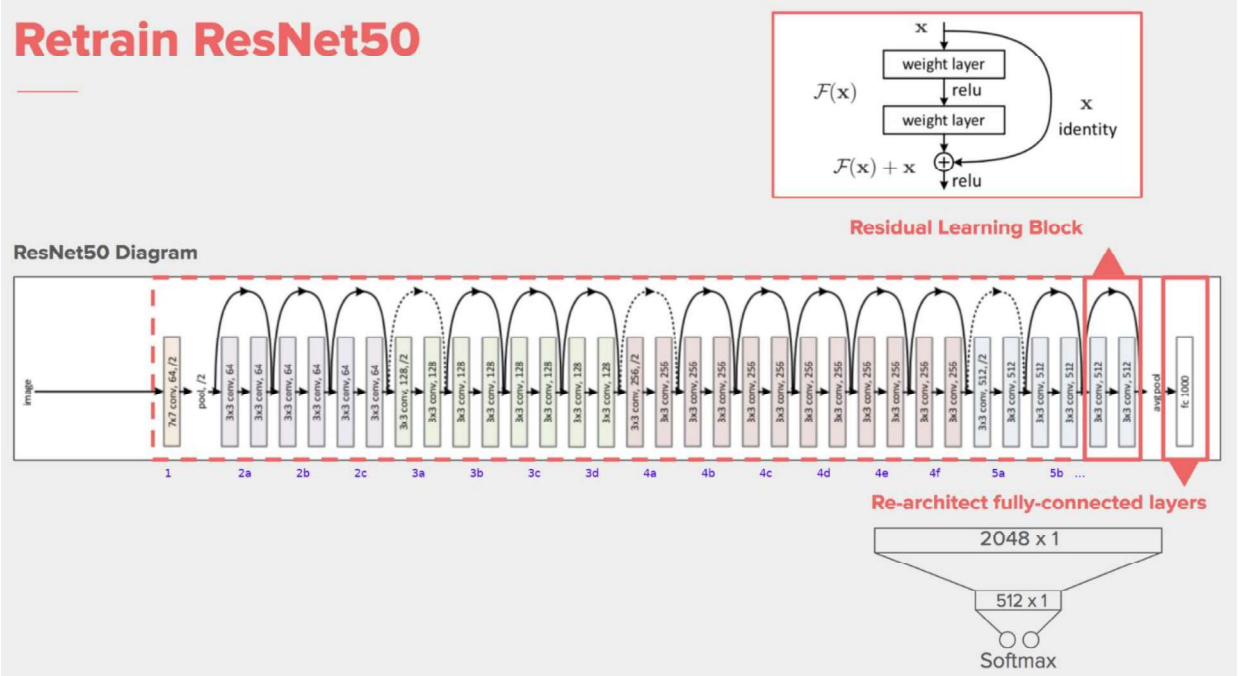
Max Pool Layer is the layer that summarizes the features present in the region of the feature map generated by a convolutional layer. It is used to reduce the dimensions of the feature maps. Therefore, it reduces the number of parameters to learn and the amount of computation performed in the network. It uses max as a pool function meaning that the max value will be pooled onto the next layer.

Softmax Layer:

It is the layer that produces output. It basically assigns probability to each of the classes that are present in the model. After assigning the probability, we can simply see that the class having highest probability would be the predicted class.

7.2. ResNet50:

For the ResNet50 model, the architecture is as follows:



It has 48 Convolution layer and 1 max pool and 1 average pooling layer.

Residual Learning:

In deep cnn, several convolution layer, fully connected layer, pooling layer are stacked upon each other. They learn several features at the end of layers. But in residual learning, instead of learning features, it learns residuals. Residuals can be simply described as subtraction feature learned from that input layer. ResNet does this learning by connecting nth input layer to the input layer of (n+p)th layer. By this concept ResNet50 is implemented.

$$Y(L) = H(X_L) + F(X_L, W_L)$$

$$X(L+1) = G(Y_L)$$

F is a stacked non-linear layer and G is a Relu activation function. It has been found that when $G(Y_L)$ and $H(X_L)$ are identity mappings, the signal can be directly sent to any other unit whether backward or forward.

Convolution Layer:

Convolution layer is the layer which uses convolution operation to extract features from the image. Convolution operation is done on the image by several filters or kernels. These filters learn the features and make the whole convolution process successful.

Max Pool Layer:

Max Pool Layer is the layer that summarizes the features present in the region of the feature map generated by a convolutional layer. It is used to reduce the dimensions of the feature maps. Therefore, it reduces the number of parameters to learn and the amount of computation performed in the network. It uses max as a pool function meaning that the max value will be pooled onto the next layer.

Average Pool Layer:

Max Pool Layer is the layer that summarizes the features present in the region of the feature map generated by a convolutional layer. It is used to reduce the dimensions of the feature maps. Therefore, it reduces the number of parameters to learn and the amount of computation performed in the network. It uses average as a pool function meaning that the max value will be pooled onto the next layer.

8.MODEL BUILD

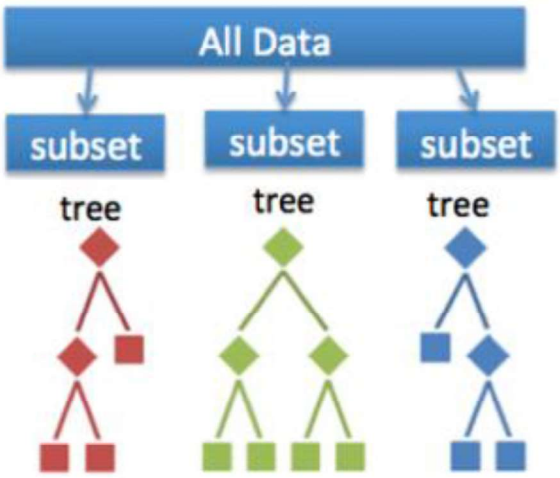
For our classifier model, we used several models. These models are mainly Random Forest Classifier, Logistic Regression and MLP Classifier.

8.1. Random Forest Classifier:

A random forest algorithm with supervised sections and a regression algorithm. As the name suggests, this random algorithm creates a forest with several trees.

Usually, as the trees grow in the forest, the forest becomes stronger. Similarly, in random forest planning, as the number of trees in a forest grows, the results are more accurate.

In simple terms, a random forest forms multiple decision-making trees (called forests) and combines them to produce more accurate and stable predictions. The constructive forest is a collection of Decision Trees, trained in the form of bagging.



The random forest ensures that the performance of each tree is not significantly related to the behavior of any other tree in the model by using the following two methods:

- Bagging or Bootstrap Aggregation
- Random feature selection

- Bagging or Bootstrap Aggregation:

Decision trees are more sensitive to the data they have been trained on, a small change in the training data set can lead to a very different tree construction.

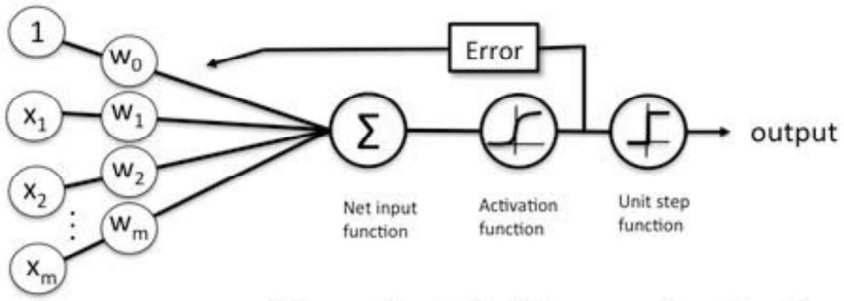
The random forest takes advantage of this by allowing each tree to randomly sample in the database by inserting another, which results in a variety of trees. This process is called Bagging.

- Random feature selection:

each tree in a random forest can only select from a random subset of features. This forces a very large difference between the trees in the model and ultimately leads to lower connections in the trees and more division.

So in a random forest, we end up with trees trained in different sets of data and use a variety of factors to make decisions.

8.2. Logistic Regression:



Schematic of a logistic regression classifier.

In this figure logistic regression is represented as a single layer neural network.

The nodes are represented as neurons of the network and the node having 1 inside is called as bias and the weights w_i , $where\ i = 0,1,2,..m$ are the parameters of this logistic regression.

- The leftmost layer is the **Input Layer**. It contains the value of input vector x_i , $where\ i = 0,1,2 \ldots m$. x_0 is known as the bias. Here the node having 1 inside is known as x_0.
- The next layer is the **Output Layer.** It computes the weighted mean of the input vector and passes through the sigmoid activation function to get the value in the range of (0,1).

$$Y = F(W^T X + b) = F(\sum_{i=1}^{m} w_i x_i + b)$$

Where W is weight vector and X is the input vector, b is the bias. F(x) is the sigmoid function.

$$F(x) = \frac{1}{1 + e^{-x}}$$

Now the loss function of the model is binary cross-entroppy. That is:

$$L(w,b) = -\frac{1}{N}\sum_{i=1}^{N} y_i \log\left(f(o_i^{k+1})\right) + (1-y_i) log(1-f(o_i^{k+1}))$$

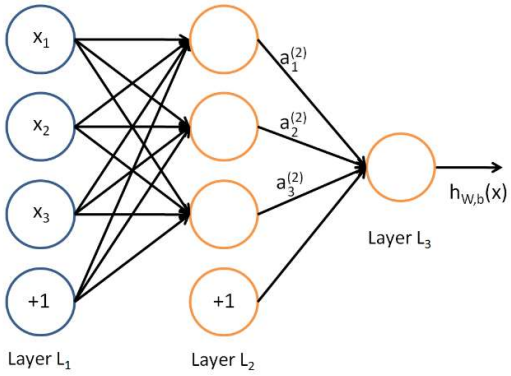
Now after calculating the loss function, we need to minimize it using back-propagation algorithm. The algorithm uses gradient descent to find the value of the parameters and update them by using the following equations:

$$W_{ij}^{(l)} = W_{ij}^{(l)} - \alpha \frac{\partial}{\partial W_{ij}^{(l)}} L(W,b)$$

$$b_i^{(l)} = b_i^{(l)} - \alpha \frac{\partial}{\partial b_i^{(l)}} L(W,b)$$

In this way, Logistic regression works. After that we take our test data to test our model.

8.3. MLP Classifier:



Multi Layer Perceptron

In this figure, the nodes are represented as the neurons of the network and the node having +1 inside denotes the bias of the network.

- The leftmost layer denotes the **Input Layer**. The nodes having $x_i, where\ i = 1,2,3$ denotes the input fed into the network.
- The next layer is known as the **Hidden Layer.** The parameters of these layers are learnt and not observed during the iteration. Hence its name hidden layer.
- The rightmost layer is known as the **Output Layer.** It gives the output of the model.

Algorithm:

In MLP the input layer mainly takes input vector and assigns it to each of the node of input layer $x_i\ , where\ i = 1,2,3, \ldots . n$

$$Model_{out} = f\left(W^T X + b\right) = f(\sum_{i=1}^{n}(w_i x_i + b))$$

Where W is the weight vector and X is the input vector, f(x) is the sigmoid activation function.

$$f(x) = \frac{1}{1 + e^{-x}}$$

In MLP there can be more than one hidden layer. For that, the main equation changes a bit. Let us assume that in kth layer there are n neurons and the sum of the weighted input of the ith layer is o_i^k. Now by using this we can find out the next output layer that is o_i^{k+1}.

For k=1, $o_i^{(2)} = \sum_1^n (w_{ij}^1 x_j + b_i^1)$

For k>=2,

$$o_i^{(k+1)} = \sum_1^n (w_{ij}^k f(o_j^k) + b_i^k)$$

Now the loss function of the model is binary cross-entroppy. That is:

$$L(w,b) = -\frac{1}{N}\sum_{i=1}^{N} y_i \log\left(f(o_i^{k+1})\right) + (1-y_i) log(1 - f(o_i^{k+1}))$$

Now after calculating the loss function, we need to minimize it using back-propagation algorithm. The algorithm uses gradient descent to find the value of the parameters and update them by using the following equations:

$$W_{ij}^{(l)} = W_{ij}^{(l)} - \alpha \frac{\partial}{\partial W_{ij}^{(l)}} L(W,b)$$

$$b_i^{(l)} = b_i^{(l)} - \alpha \frac{\partial}{\partial b_i^{(l)}} L(W,b)$$

Now in this way, MLP Classifier learns and give us output.

9.TRAINING THE MODEL

For the training of the models, we used the extracted feature vector and feed it into the several model that we had built. We built and trained our model in google collab using 25 GB Ram and 6 GB Graphics Memory. For training, we used two feature vectors. One obtained from VGG19 and another one from ResNet50.

9.1. Random Forest Classifier:

For the random forest ensemble classifier, we used maximum depth of 5000 and trained it till it reached completion. It took about 20 to 30 min with the help of our GPU.

We can see that we have used sklearn library to implement our Random Forest Classifier. The model is named as clf and we have fitted the model with our extracted features.

9.2. Logistic Regression:

For the Logistic Regression, we used iteration of 100 to 200 to train our model. It took about 30 min.

We are able to see that we have used sklearn to implement our logistic regression. The model that we are using is having max iteration of 100. The solver that the model is using is sag. It converges faster for large dataset and also handles L2 or no penalty. For that reason, we have used sag as our solver. After that we have fitted that model with our feature vector.

9.3. MLP Classifier:

For the MLP Classifier, we used iteration of 100 to train our model. It took about 30 min to train.

We can see that the MLPClassifier model is implemented using sklearn library. After that it is having some parameters such as max iteration and so on. After that we have fitted the model using our extracted feature vector.

10.TESTING THE MODEL

For testing the test data, we had to go through with the same feature extraction that we had done for the training data. After we extracted the features from the test data, we used our several trained models to predict the output and compare the various test accuracy.

10.1. Random Forest Classifier:

We can see that for random forest classifier after fitting, we have used our test data extracted vector to predict if it is normal and abnormal. After that we have stored it into classifer_rf_pred array for generating the accuracy for later.

10.2. Logistic Regression:

We can see that for Logistic Regression after fitting, we have used our test data extracted vector to predict if it is normal and abnormal. After that we have stored it into logistic_regression_pred array for generating the accuracy for later.

10.3. MLP Classifier:

We can see that for MLP Classifier after fitting, we have used our test data extracted vector to predict if it is normal and abnormal. After that we have stored it into MLP_pred array for generating the accuracy for later.

11.RESULT

The several accuracies obtained by our models are given below:

11.1. VGG19 model based feature vector:

11.1.1. Random Forest Classifier:

```
print(str(sum(classifer_rf_pred==y_test1)/rftest.shape[0]*100)+"% Accuracy")
```

```
63.67%
```

In this case, we are able to see that the accuracy obtained is 63.67%.

11.1.2. Logistic Regression:

```
print(str(sum(logistic_regression_pred==y_test1)/bottleneck_test.shape[0]*100)+"% Accuracy")
```

```
60.34%
```

In this case, we are able to see that the accuracy obtained is 60.34%.

11.1.3. MLP Classifier:

```
print(str(sum(MLP_pred==y_test1)/bottleneck_test.shape[0]*100)+"% Accuracy")
```

```
61.27%
```

In this case, we are able to see that the accuracy obtained is 61.27%.

To summarise the accuracies for all the models, the beneath table is given:

Model	Accuracy
Random Forest Ensemble	63.67%
Logistic Regression	60.34%
MLP Classifier	61.27%

11.2. ResNet50 model based feature vector:

11.2.1. Random Forest Classifier:

```
print(str(sum(classifer_rf_pred==y_test1)/rftest.shape[0]*100)+"% Accuracy")
```

```
61.34%
```

In this case, we are able to see that the accuracy obtained is 61.34%.

11.2.2. Logistic Regression:

```
print(str(sum(logistic_regression_pred==y_test1)/bottleneck_test.shape[0]*100)+"% Accuracy")
```

```
59.08%
```

In this case, we are able to see that the accuracy obtained is 59.08%.

11.2.3. MLP Classifier:

```
print(str(sum(MLP_pred==y_test1)/bottleneck_test.shape[0]*100)+"% Accuracy")
```

```
60.25%
```

In this case, we are able to see that the accuracy obtained is 60.25%.

To summarise the accuracies for all the model the beneath table is given:

Model	Accuracy
Random Forest Ensemble	61.34%
Logistic Regression	59.08%
MLP Classifier	60.25%

From this above tables, we can see that VGG19 is better than ResNet50 to extract features from our Dataset. And the best model that gave the best accuracy is Random Forest Ensemble.

12.CONCLUSION

The division of deep learning has been used successfully in it many EEG activities, the burden of mental functioning, goals on the stage of sleep, the power associated with the event, and the functions of perceiving emotions. The design of these depths network studies differ significantly from input construction and network construction.

Many public databases are analysed in many studies, which have allowed us to directly compare the performance of categories based on their design. Generally, CNN's, RNN's, and DBN outperform other types of depth networks, such as SAEs and MLPNN's. In addition, CNN's best done using signal values or (spectrogram) images as input, and DBN has done very well when using it signal values or features are listed as input.

We also discussed in-depth network recommendations for each type of work. This recommendation diagram is provided with hope that it will guide the delivery of deeper education in EEG datasets in future research. Hybrid designs that include convolutional layers with repetitive or limited layers Boltzmann's equipment showed promise with precision in stages and transmission learning compared to conventional designs.

We commend an in-depth study of these compounds, especially the number and layout of various layers including RBM's, repetitive layers, convolutional layers, and layers that are fully connected. Without network design, We also encourage further research to compare how deep networks translate raw EEG and denoised raw, as this has not yet happened.

13.FUTURE SCOPE

From our project, we can see that the various models have tried to minimize the error rate and the best error rate is 36%. But it is still not sufficient though it reaches one of the state of the art accuracy. For further improvement, we can use other pre-processing techniques and make use of the other nodes that we didn't include in our project.

Also the temporal part of the several spectrums are much larger meaning that we are dealing with a session of above 15 min. Within this 15 min, the seizure where the EEG signal gets deviated from being normal happens for a small interval of time. For that we could check in which part the abnormality begins most of the times and try to check only that period of time and use our model to classify.