DECEPTION DETECTION OF FAMILIAR/UNFAMILIAR FACES USING EEG SIGNALS

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JAYPEE INSTITUTE OF INFORMATION TECHNOLOGY, NOIDA

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(II)
DECLARATION

I/We hereby declare that this submission is my/our own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Place : Noida

Date : 16-12-2019

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(III)
CERTIFICATION

This is to certify that the work titled “**Deception Detection of familiar/unfamiliar faces using EEG signals**” submitted by “**Akash Gupta, Ajay Kumar and Saurabh Gupta**” in partial fulfillment for the award of degree of B. Tech of Jaypee Institute of Information Technology, Noida has been carried out under my supervision. This work has not been submitted partially or wholly to any other University or Institute for the award of this or any other degree or diploma.

Signature of Supervisor : …………………….

Name of Supervisor : Ms. Indu Chawla

Designation : Professor (Senior Grade)

Date : 16-12-2019

(IV)

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(V)
SUMMARY

Deception detection, brain signals are useful in lie detection. As Electroencephalogram signals reveal fine features of state of mind of subject and thoughts of subject make it better tool for lie detection.

The main purpose of this project is to enhance the existing methods for classifying the familiar and unfamiliar face images. There are numerous experiments were done on visual stimuli based EEG signals.

In this project we will try to classify the familiar and unfamiliar visual stimuli obtained in the form of EEG from subject. As the EEG signals are bi-logical and non stationary in nature and time series, we will try to obtain the, component of EEG though some data driven approaches by decomposing them. We try to build new deep learning model for the classification of familiar and unfamiliar images.

Brain signals were started to use in deception detection process from last few years.

EEG signals can reveal many important features of our thought which make it as a better tool for deception detection.

A number of experiments were done in terms of visual stimuli based EEG signals.

The purpose of this paper is to improvise the existing methods in the classification of familiar and unfamiliar faces which can be used as a basic model in deception detection. In this paper, we proposed a deep learning based classification of

EEG signals for the given visual stimuli. In this experiment, the subjects were shown by familiar and unfamiliar face.We build a model for classification of such problem porposed . By training the model properly which is far better than the models using conventional machine learning methods. Our model achieved the state of the art results for classification of familiar and unfamiliar EEG signals.

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LIST OF SYMBOLS & ACRONYMS

S. No.	Acronyms/Symbols	Meaning
1	EEG	Electroencephalography
2	MRI	Magnetic Resonance Imaging
3	BCI	Brain-Computer Interface
4	KNN	K-Nearest Neighbour
5	K-D Tree	K-Dimension Decision Tree
6	PET	Positron Emission Tomography
7	ERP	Event Related Potential
8	ANFIS	Adaptive Network Fuzzy Interference System
9	SVM	Support Vector Machine
10	ICA	Independent Components Analysis
11	PCA	Principal Component Analysis
12	GKT	Guilty Knowledge Test
13	CQT	Control Question Test
14	MLP	Multi Layer Perceptron
15	FFT	Fast Fourier Transform
16	FIR	Finite Impulse Response
17	RNN	Recurrent Neural Network
18	LSTM	Long Short Term Memory

Chapter 1
Introduction

1.1 General Introduction

Electroencephalography (EEG) is the measurement of electrical activities inside the brain to different stimuli given, which will be measured by using electrodes placed on the scalp. EEG is cheap and easy to acquire in comparison to other signals in the brain. Also it is risk free for user receiving these signals. They are used for in exploration and clinical motives.

The study of brain using analysis of EEG signals has many advantages in comparison to other methods. The cost of hardware required for devices that acquire EEG signal is very considerably lesser than the other different techniques. The EEG sensors are very easy to place on the scalp due to their light weight. Because of its high temporal resolution, EEG will always measure in milliseconds. The signal is peak to peak voltage with amplitude range in between 0.5 to 100 µV. In comparison to other brain related brain-related signal acquisition techniques EEG has many advantages in acquiring and analysing. EEG can respond to all complex neural activities happening inside the brain within milliseconds after the stimulus occurred.

Fig 1.1 Setup of a polygraph test

Deceiving is one of the central characteristics of the human, and because of this reason, humans developed various techniques to find deception and for knowing the truth. i.e., the researches on finding a reliable tool for detecting deception has a very long history. Lie detection is the most challenging task which is still an open problem among the psycho-physiologists. To gain a better precision for detecting deception, we need to analyze each verbal and non-verbal cues and need to be tested against a ground truth which was taken from the subject when there is no reason to lie for them. Polygraph is the traditional technique used for the detection of deception while doing a criminal investigation which was introduced on 20th century.

In the mentioned technique, there were a total of almost five to six sensors used because of using these multiple sensors, the method known as `poly' graph. In this test, the examiner records different physiological signals - blood pressure, pulse, skin conductivity, etc. - using the sensors and analyzes this signal to conclude that whether the convict is telling the truth or not.

Always among the researchers, the reliability and trustworthy of polygraph was a big question. The polygraph measurement has many limitations and it cannot get a direct view of the complex underlying brain processes.

1.2 Problem Statement

Lie Detectors are a prevalent device used in many criminal investigations all over the world. Most modern polygraph devices were patented, made a simplified construction which is sensitive and also could be used without causing pain. Also, this device is inexpensive compared to conventional methods at that time. But by the time being new methods were introduced and the device got better. By 1960s polygraph technique used more in the US and also so many other countries started to use this technique for deception detection in criminal investigations . Modern polygraphs test use digital devices to record the physiological signals and there is a need for an expert to analyze the signal and to conclude whether the convict is telling a lie or not. A trained convict can easily manipulate the signals and sometimes due to the highly tensed situation based on the signals from innocent people wrongly classified as a lie. Accuracy of the polygraph is always a variable one, and it's still an open question among the research world. Some of the techniques to beat a polygraph test are -

• By controlling the breathing rate

• Thinking about some mysterious things

• Performing some mental calculations

1.3 Significance/Novelty of the problem

Our main objective of the proposed model is here is to keep the precision and accuracy maximum and to give substantial solution for the proposed problem.
EEG signal analysis for the study of brain function has more advantages than other existing methods. Like, the hardware cost for EEG signal acquisition devices is significantly less than the majority of the different techniques. Also, EEG sensors are very weightless and easy to place on the scalp. Always EEG will measure and analysis in the order of millisecond not in second because of its high temporal resolution. Comparing to the brain-related signal acquisition techniques like MRI, fMRI, PET, etc., EEG has many advantages over these signals. The acquisition of EEG is not a sophisticated technique, and EEG can respond to all complex neural activities happening inside the brain within milliseconds after the stimulus occurred.

1.4 Empirical Study

While EEG technology has been around for the better part of the last century, it wasn't until fairly recently that it was made available to the general public.

Until a few decades ago only clinicians and expert neuroscientific researchers were able to setup and analyze recordings under strictly controlled laboratory conditions with electrode caps containing 64 channels or more. These high-density electrodes evenly spaced across the human scalp were used to help researchers discover the underlying neural mechanisms involved in actions, cognition or emotional processing were completely unknown.

Recent advancements in computer hardware and processor technology have enabled researchers all around the globe to vastly expand the existing knowledge about the complexity of the human brain and gain deeper insights into brain processes and structures.

Now that this cornerstone has been set, EEG (Electroencephalography) can be used for various applications. Below is a list of the six most common applications of EEG technology:

Neuromarketing:

In the field of neuromarketing, economists use EEG research to detect brain processes that drive consumer decisions, brain areas that are active when we purchase a product/service, and mental states that the respective person is in when exploring physical or virtual stores.

Human Factors:

Originating from Psychology, the field of Human Factors focuses on workplace optimization; both with respect to tools and interfaces as well as social interaction. In this area, EEG research is used to identify brain processes related to specific personality traits such as intro-/extroversion or social anxiety. Additionally, brain processes reflecting cognitive and attentional states during human-machine-interaction are heavily studied using EEG, primarily using wireless headsets with long-term monitoring capabilities.

Social Interaction:

Humans are social agents – we spend a majority of our lives interacting with others. In social interaction research, brain processes related to social perception, self-evaluation, and social behavior are investigated. Importantly, social interactions and communication are not passive forms of processing incoming stimuli. Whenever we talk to others or solve problems together, we have to “sync up” with our partners. To study the brain processes underlying the synchronization of conversations and actions, EEG researchers use a method referred to as "hyperscanning" to record data from multiple people at once, allowing them to gain deeper insights into leadership and team interactions.

Psychology and Neuroscience:

Most generally, psychological studies utilize EEG to study the brain processes underlying attention, learning, and memory. How do we perceive the world? How do our expectations shape the way we see our surroundings?

Based on massive trial repetition, event-related potentials (ERPs) are extracted from the continuous stream of EEG data, which allows characterizing brain processes triggered by the events on a very detailed timescale (tens of milliseconds). ERPs can be characterized by their amplitude (in millivolts, with positive and negative going waves labeled "P" and "N", respectively), timing (in ms relative to event onset), and voltage distribution across all electrodes (topography). Specific ERPs have been identified for the processing of faces (N170), words and meaning (N400), surprise (P300), or memory recall (P600).

Clinical and Psychiatric Studies:

Whenever brain processes are impaired (e.g., lesions, genetic dysfunctions, diseases), deficits in behavioral, attentional and cognitive processing can be observed. Clinical and psychiatric fields use EEG to evaluate the patients' cognitive states, determine lesion sites, and classify symptoms.

Also, EEG is heavily used to evaluate the effect of medical and psychological treatment (e.g., cognitive-behavioral therapy). More and more therapies utilize virtual reality technology and record EEG data to monitor how the patients' brains improve over time.

Brain Computer Interfaces (BCI):

A relatively new but emergent field for EEG is brain-computer interfaces. Today, we know in much more detail which brain areas are active when we perceive stimuli, when we prepare and execute bodily movements, or when we learn and memorize things.

This gives rise to very powerful and targeted EEG applications to steer devices using brain activity. This can, for instance, help paralyzed patients steer their wheelchairs or move a cursor on a screen, but BCI technology is also used for military scenarios where soldiers are equipped with an exoskeleton and EEG cap, allowing them to move, lift and carry very heavy items simply based on brain activity.

1.5 Brief Description of the Solution Approach

Our experiment was to analyze how deep learning techniques are effective over the traditional machine learning methods for an effective deception detection model as we know that the deep learning is a part of machine learning - shown in the Venn diagram.

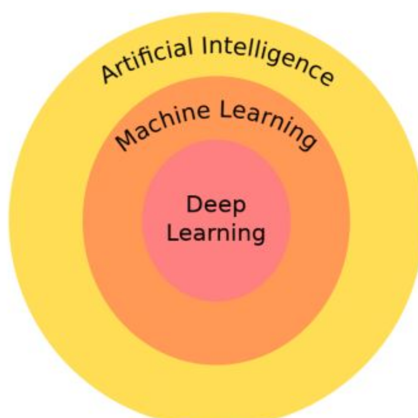


Figure 1.2: Venn Diagram of Artificial Intelligence

Signal processing is the most important step where we will eliminate all the artifacts and the noises included in the signal. Processing of EEG signal has a significant role at the time of classification. Since EEG signals are of shallow frequency and contain many unwanted signals like ocular, cardiac, powerline noise, etc., removal of noise is essential and should be done carefully without losing the useful information. Band pass filter is one of the significant artifacts in EEG, which reduces its signal to noise ratio.

We further did feature extraction via stationary wavelet transformation and trained our model using basic models like KNN, K-D Tree, Naive Bayes, SVM, Ransom Forest, etc.
Finally, these models were unable to provide desired results, so we reduced the dimensions of the dataset and applied deep neural network LSTM to achieve desirable accuracy.

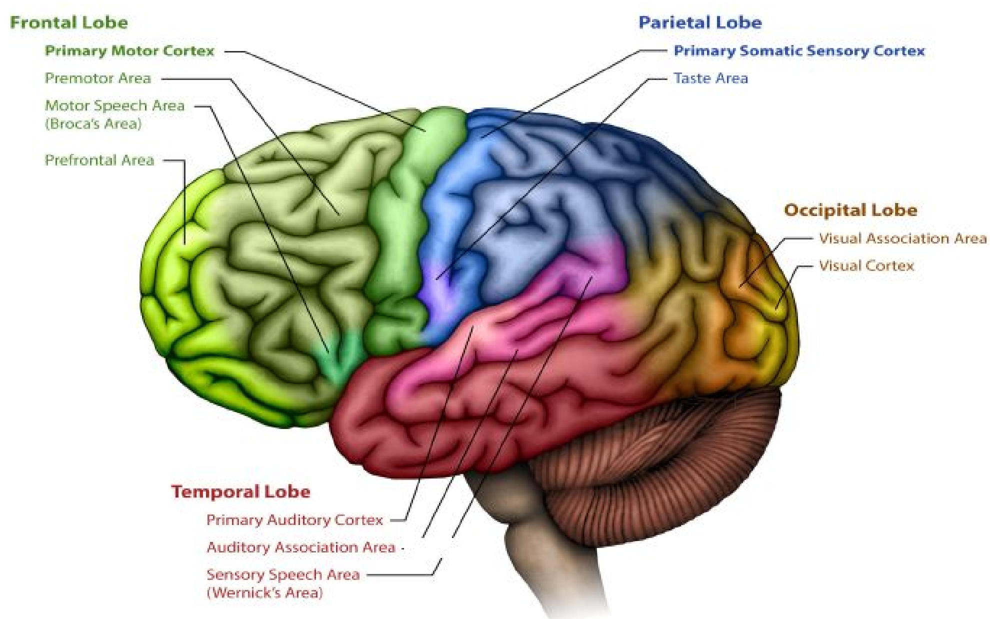


Fig. 1.3 Major Parts of the Brain

Chapter 2
Literary Survey

2.1 Summary of papers studied

Paper 1

Paper Title	**Better than random? A closer look on BCI results**
Authors	Gernot R. Müller-Putz, Reinhold Scherer, Clemens Brunner, Robert Leeb, Gert Pfurtscheller
Published in	International Journal of Bioelectromagnetism
Summary	Brain-computer interface (BCI) is a collaboration between a brain and a device that enables signals from the brain to direct some external activity, such as control of a cursor or a prosthetic limb. This paper is a basic comparison between Theoretical approach and Simulation(Practical) approach of BCI for the case of 2-class paradigm. The theoretical approach states that the probability of correctly classified trial in a 2-class paradigm of N trails follows a binomial distribution with p = 0.5, i.e, both classes are equally likely to occur. In this context a BCI experiment consisting of trials (50 per class), the expected chance level would be at exactly 50 correctly classified trials (with equally probable classes). If the reported accuracy of a classifier is 59 correctly classified trials (or alternatively, 59%), it is straightforward to see that this probability does not lie within the theoretical limits of 40.39% and 59.61% (for a confidence of). Thus, it can be assumed that the given classifier does not significantly differ from a random one. The theoretical results for BCI of a 2-,3-,4- and 8-class are 50%, 33.3% 25% and 12.5% respectively. However, the Simulation results vary from the theoretical for N = 80, the results of 2-,3-,4-,8-class BCI are 57.5%, 39.6%, 29.7% 15.2% for a significance level α=5%. Concluding, we want to take into account the proposed considerations and to check their results also in relation to the real level of chance and not only to the theoretical one.

Paper 2

Paper Title	Classification of EEG Signals by using Support Vector Machines
Authors	K. Sercan Bayram, M. Ayyüce Kızrak, Bülent Bolat
Published in	ResearchGate
Summary	In this work, EEG signals were classified by support vector machines to detect whether a subject's planning to perform a task or not. Various different kernels were utilized to find the best kernel function and after that, a feature selection process was realized. EEG recordings of four different mental states was classified by using five classifiers. In this work, the best result was obtained by using a resilient back propagation method as 95%. With the help of multilayer perceptron(MLP) it was recognised whether a person was sleeping or was awake by using EEG signals. The five different metal activities were also classified with Support Vector Machine with maximum accuracy of 72%. The accuracy for using a quantum neural networks was 81.33%. Another classifier used was neural networks had an accuracy of 80%. The ID3 classifier had an accuracy of 71%. The final classifier used was fuzz rough ID which correctly classified 76.2% of the data. In the first step of the work, the dataset classified by linear and nonlinear SVMs, and the best kernel function was determined. Based on the results, the best choice is radial basis function (RBF) kernel for $\sigma=1.2$ with 71.43% accuracy. By applying the SFS on data, the result had the accuracy of 72.53%. The SBE gave the best result as 74.73%. At last t-scores and p-values were calculated. The accuracy range of t-score varied from 67 to 71.43% and that of p-value varied from 70.33 to 71.43%.

Paper 3

Paper Title	**Analysis of EEG Signals for Deception Detection**
Authors	Roshani J. Khandelwal, Juilee D. Mahajan, Ujjwala P. Bombatkar, Snehal G. Badhe
Published in	International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering
Summary	Prominent deception detection approaches include the standard polygraph which monitors the signature changes in autonomic responses and the cognitively more central EEG. .Deception detection is the practice of attempting to determine whether someone is lying. The common signs of deceptive behavior are body language, emotional gestures and contradiction, interactions and reactions, verbal context and content,facial micro-expressions, change of topic etc. These deception techniques are used by police, forensic psychologists, security experts and other investigators to help prevent them from being a victim of fraud or scams and other deceptions. Throughout history, it has often been assumed that lying is accompanied by a change in the body's physiological activity. The polygraph is a set of equipment that accurately measures various sorts of bodily activity such as heart rate, blood pressure, respiration, and palm sweating. Lying causes a conflict between lie and the truth within the brain. The increased activity can be detected by F- MRI which records brain activity by identifying changes in brain blood flow and the metabolic rate. The radar based procedure which could perform remote, unobtrusive, non-invasive and stealthy lie detection is when an UWB radar pulse passes through the human thorax it gets echoed back by the cardiac structure i.e. the heart wall. Heart rate variability is the physiological phenomenon of variation in the time interval between heartbeats i.e. the variation in the beat-to-beat interval. HRV is also an indicator of the emotional arousal. Several morphological features were extracted to know the various parameters and distinguish truth from lie telling. Classification is done by Euclidean distance method, which will calculate the minimum value between the vectors to display the output. The output is generally displayed with a message as "lie EEG signal" or "true EEG signal".

Paper 4

Paper Title	**Evaluation of P300 based Lie Detection Algorithm**
Authors	Syed Kamran Haider, Malik Imran Daud, Aimin Jiang, Zubair Khan
Published in	IEEE
Summary	We extract the desired features from the brain signals acquired through sixteen electrodes using various extraction techniques. Then, they have implemented linear discriminant analysis (LDA) classification technique to differentiate the positive and negative samples from the signals obtained from sensors in order to achieve a decision for either guilty subject or innocent subject accordingly. Twenty subjects (15 males and 5 females, ages between 20-25 years) that were generally universities students and all had good health with stable psychological behaviour participated in the study. They recorded data of over 15 to 20 subjects. In one scenario, some precious items were placed in front of some subjects. Those subjects were not informed about the scenario and the subject can be any random person. Another person called as Subject-2 intended to perform this test come and stole that item that was placed in front of person called as Subject-1. It can be any person but suggestively that can be his/her close friend. As this test was performed in university, university authorities would handle the case of that stolen item. This was done only to put our subject under pressure for lie and truth response. First some obvious questions were asked that everybody would answer the obvious answers, i.e., the true answer. The brain signals were recorded with the sample rate of 128 samples per second. After applying pass band filter on EEG signals, each continuous subject record is divided into single sweep as per the times known by stimulus presentation. The total length of each single sweep is 1000ms, and contains 128 samples. Then the signal pattern recognition technique includes special features extraction and features selection. After that apply classification method on the signals to assess the detection rate. It should be noticed that, in all cases related to P300 ERP the Pz is the prime location where P300 can be monitored maximal and therefore visual related experiments were performed only on Pz data.

Paper 5

Paper Title	**Lie Detection Based EEG-P300 Signal Classified by ANFIS Method**
Authors	Arjon Turnip, M. Faizal Amri, M. Agung Suhendra, and Dwi Esti Kusumandari
Published in	Springer
Summary	The lie detector is an instrument that is often discussed or researched by scientists and experts. Because of a number of problems posed by lies and frauds, which be able to lead to criminal activities, lie detector needs to be improved. This shows the importance of tools that can differentiate between a subject who is lie or not. Once the signals recording was complete, the continuous EEG data from each subject were inspected and filtered for artifacts using band-pass filter and Independent Component Analysis (ICA), respectively. Parts of the signals that contained noises by task-irrelevant movement or artifact be cut by band-pass filtered using 0.1 Hz and 30 Hz cut-offs and then the noises were removed by ICA. Discrete wavelet transform (DWT) is used as an extraction method. The reason why the wavelet transform has been selected because the component of ERP signal-to-noise ratio (SNR) is low and not stationary. The DWT uses multi filter banks and special wavelet filters for the analysis and reconstruction of signals. The DWT provides a compact representation of a signal in time and frequency that can be computed efficiently. The method calculates the wavelet coefficients at discrete intervals of time and scale instead of at all scales. An Adaptive Network Fuzzy Interference System (ANFIS) is used as a classifier after signals extraction.The results of signal from three stimuli responses which are produced through signal processing, response from P stimuli has the most important information in determining whether subjects are lying or not. Before we got the signal features that affected by P stimuli, preprocessing signals and feature extraction had been through. The ANFIS method applied at the features classification step has the advantage of much less training time is achieved. The results indicated that the existing method in this article had great result for lie detection. The ANFIS method is able to separate lying subjects from honest subjects based on EEG-P300 signals with an accuracy of 64.27%.

Paper 6

Paper Title	**Wavelet analysis for EEG feature extraction in deception detection**
Authors	Anna Caterina Merzagora, Scott Bunce, Meltem Izzetoglu and Banu Onaral
Published in	28th IEEE EMBS Annual International Conference
Summary	By interfacing the brains signals directly, it is possible to design brain computer interfaces to control devices without mechanical interfaces. Especially direct controlling the prosthetic organs is very important for disabled people. The most common brain activity monitoring device is electroencephalogram (EEG). A primary emphasis in this study was to examine the capacity for physiological measures to differentiate among the cognitive elements of truth and deception, i.e. the knowledge that one is lying. The task was designed to elicit high motivation to escape detection, but to minimize participants' anxiety about being deceptive. To accomplish this end, the task was framed as a form of poker-like card game in which it is socially acceptable to "bluff," or to lie, minimizing feelings of anxiety about lying. Participants were given a total of 5 cards, four of which (one from each suit) were face-up on the computer screen (the 'hand'). Participants were informed that the identities of these four face-up cards, as in some forms of poker, were known by the participants, as well as the researchers. Participants were then asked to choose a fifth card from among three sealed envelopes, each of which contained a playing card which they kept in their hand ('target' card) and $50. Participants were informed that only they knew the identity of this card, and the experimenter would be attempting to learn the identity of this card by alternately presenting a series of cards, asking the question "Do you have this card?", and examining their brain responses. They were told that if they were successful in concealing the identity of the card, that would be able to keep the $50, in addition to their participation remuneration ($25). Quadratic B-spline wavelets were used in the wavelet analysis due to their near optimal time frequency localization properties. Moreover, their waveform is similar to the waveforms to be detected in the EEG signal; hence extraction of EEG components is more likely to be successful.

Paper 7

Paper Title	**Deception Detection of EEG-P300 Component Classified by SVM Method**
Authors	K. Sercan Bayram, M. Ayyüce Kızrak
Published in	IEEE
Summary	By interfacing the brains signals directly, it is possible to design brain computer interfaces to control devices without mechanical interfaces. Especially direct controlling the prosthetic organs is very important for disabled people. The most common brain activity monitoring device is electroencephalogram (EEG). The ability to measure noninvasively the related brain activity of lying within an individual subject could offer a significant improvement over currently available tools to detect deception A vast variety of approaches to the classification of quantitative features from an EEG signals. SVM have become extremely successful discriminative approaches to pattern classification and regression problems. In other words, SVM is a technique used to obtain the most probable hyperplane to separate two classes. It is done by measuring the hyperplane's margin and determines its maximum point. Margin is defined as distance between the corresponding hyperplane and the nearest pattern from each class. To enhance signal noise ratio of P300 components, the independent component analysis (ICA) method was adopted to separate non-P300 (i.e. artifacts) and P300 components from every single trial. Then the P300 waveforms with high SNR were reconstructed. And then group of features based on time, frequency, and amplitude were extracted from the reconstructed P300 waveforms. Finally, two different class of feature samples were used to train a support vector machine classifier because it has higher performance compared with several other classifiers.

Paper 8

Paper Title	**An Improved Approach for EEG Signal Classification using Autoencoder**
Authors	Abhijith V Nair∗, Kodidasu Murali Kumary, Jimson Mathew
Published in	IEEE
Summary	Electroencephalography (EEG), being one of the major brain signal using in Brain-Computer Interface (BCI) applications and in many others also. Comparing to other brain signals, it is very easy to acquire and very cheap. Also, there will be no risk for the user while acquiring the EEG signals and also it is a non-invasive technique. EEG signals are used for clinical as well as research purposes. Analyzing the Event Related Potentials (ERPs) triggered while the subject is exposed to different faces, N170 and P2 waves gave the degree of familiarity effects with small amplitude signals after 170ms and 250ms respectively. Independent Component Analysis (ICA) as the signal processing tool. Due to the low Signal-to-Noise ratio (SNR) value of EEG components, using of ICA enhance the conditioning thus by reducing the noise component. By finding the suitable linear combinations of mixed variables helps for the calculation of independent components. ICA is not a commonly used one, comparing to Principal Component Analysis (PCA). But it is better for signals having multiple recordings at the same time. Based on the property of non-linear feature extraction technique of autoencoders, we designed a classifier for classifying the familiarity and unfamiliarity of the images.

Paper 9

Paper Title	**Classification of EEG Signals by using Support Vector Machines**
Authors	K. Sercan Bayram, M. Ayyüce Kızrak
Published in	IEEE
Summary	By interfacing the brains signals directly, it is possible to design brain computer interfaces to control devices without mechanical interfaces. Especially direct controlling the prosthetic organs is very important for disabled people. The most common brain activity monitoring device is electroencephalogram (EEG). Support vector machine (SVM) is a statistical learning theory based classification method. For a given two-class linearly separable classification problem, SVM tries to find a hyperplane which separates the input space with a maximum margin. The first group which called as filters deals each features independently form the others. Due to their nature, filters are fast and computationally cheap. On the other hand, filter methods can't interpret the relations between features, and this disability limits the filters' performance. Wrappers consist of a searching algorithm and a classifier. The search algorithm searches new solutions through the feature space while the classifier produces a fitness function to the search algorithm. The most common algorithms are genetic algorithms, particle swarm optimization, The algorithm starts with the entire dataset. In every step, existing features are removed from the dataset one by one. The feature that gives the least decrease on the accuracy is excluded from the dataset. The algorithm continues until the stopping criterion is reached To raise the accuracy and to find the most relevant features, four different feature selection algorithms applied to the dataset.

2.2 Integrated Summary of papers:

In the papers we realised that the EEG Signals which we measured from Brain is not a categorical data so here Naive Bayes model will not work effectively. In this project due to lack of features we extracted the features by wavelet transformation and we have eight dimensional input data with their labels so it have very complex functions some spiral data points so logistic regression and support vector machine is also not able to some this problem and KNN is also not able to deal with this model because of highly dimensional data.Most of papers they use the ERP and ICA analysis but in that model can be manipulated by the subjects.Some recent papers they applied some Deep learning models which work better than previous paper models but some basic mlp models was used in the paper which didn't give good results because they don't have memory to save previous

Chapter 3
Requirement Analysis and Solution Approach

3.1 Overall Description of the project

Electroencephalography (EEG), is the measurement of electrical activities inside the brain to different stimuli given, which will be measured by using the electrodes placed on the scalp. Humans have the unique ability to express their every emotion,and this emotion, thinking skills were conveyed through the neurons in the brain. Neurons, also called as brain cells communicate with the neuron cells in the central nervous system in electrical pulse form. This presence of electrical currents in the brain was discovered by Richard Caton, a British physician in 1875. The German neurologist Hans Berger revealed that the weaker currents from the brain could be measured even without opening the scalp. Berger called the name ‘electroencephalogram’ for the electrical potentials from the brain. There are two modes of measurement of EEG - either EEG from the cortical surface directly known as electrocorticogram or with the help of depth probes called electrogram. We were focused on the EEG measurement from the scalp surface. By comparing to other brain signals, it is effortless to acquire and very cheap. Also, there will be no risk for the user while receiving the EEG signals, and it is a non-invasive technique.

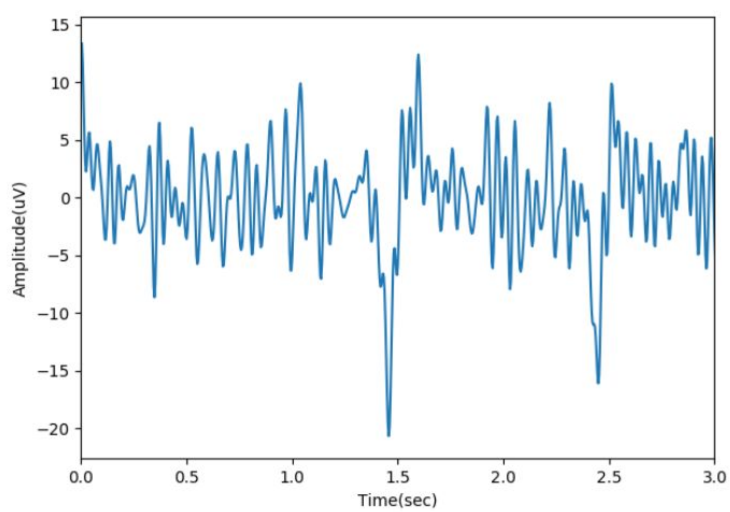


Fig 3.1 EEG Signal recorded during a cognitive experiment

EEG sensors are very weightless and easy to place on the scalp. Always EEG will measure and analysis in the order of millisecond not in second because of its high temporal resolution. Usually, the signal is measured in terms of the peak to peak voltage with amplitude ranges in between 0.5 to 100 µV. We can use both dry and wet EEG electrodes to measure the signal that is postsynaptic potentials of neurons. The standard size of an EEG electrode is always below 10mm diameter. This size of the electrode will make a better connection between the conducting fluid of tissue where the electrical signal was generated and the amplifier circuit.

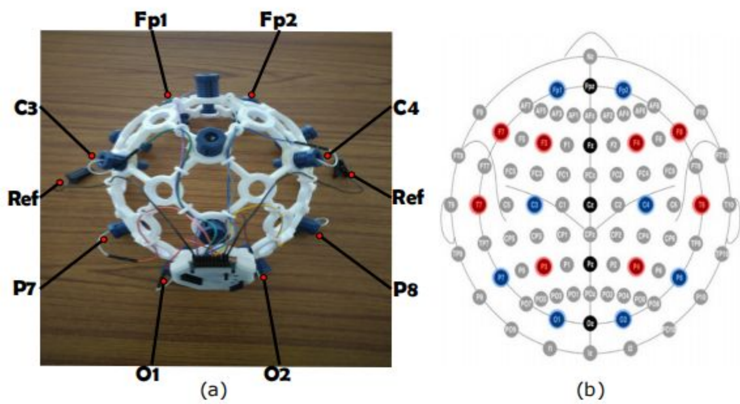


Fig 3.2 OpenBCI Ultracortex Mark IV used for the data collection

Bandpass Filtering : The brain wave patterns have a sinusoidal shape. This brain waves changes concerning the change in emotions, thoughts, and actions of a person. Each such change inside the brain has a particular unique brain wave pattern. While doing the power spectrum analysis of the brain wave, we can see that the signal is a combination of sine waves in different frequencies, and this spectrum ranges from 0.5Hz to 100Hz. Major brain wave components are :

1. Delta Waves : 0.5 - 4Hz
2. Theta Waves : 4 - 7Hz
3. Alpha Waves : 8 - 15Hz
4. Beta Waves : 16 - 31Hz
5. Gamma Waves : >32Hz

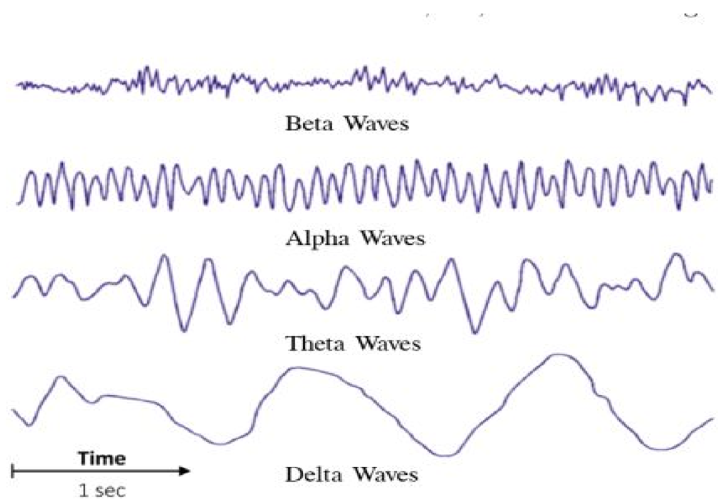


Fig 3.3 Different brain wave components

We applied bandpass filter to extract theta waves from the dataset. Then, due to lack of features we could not get the accuracy on training.

Feature Extraction and Classification : Feature extraction and classification of EEG were done on the basis of application. There were many different traditional techniques for this along with the modern deep learning methods. Mostly the features related extracted from the EEG were based on time-frequency domain. Time-frequency features were extracted from the signal that got while the subjects are shown to the visual stimuli (familiar and unfamiliar). Using the Continuous Wavelet transform the time-frequency features were extracted from the EEG band of 4-7Hz. First we took a dataset of 13 subjects containing 4 probe values and label for familiar or unfamiliar images.

So we applied stationary wavelet transformation to extract the features by decomposing signals into approximate(low frequency) and detailed(high frequency) coefficients. The approximate coefficient is decomposed as level increases. Now we trained our data using LSTM deep learning model to classify into familiar and unfamiliar images.

LSTM Model : The first step in our LSTM is to decide what information we're going to throw away from the cell state. This decision is made by a sigmoid layer called the "forget gate layer." It looks at ht−1 ht−1 and xt, and outputs a number between 0 and 1 for each number in the cell state Ct−1. A1 represents "completely keep this" while a 0 represents "completely get rid of this."

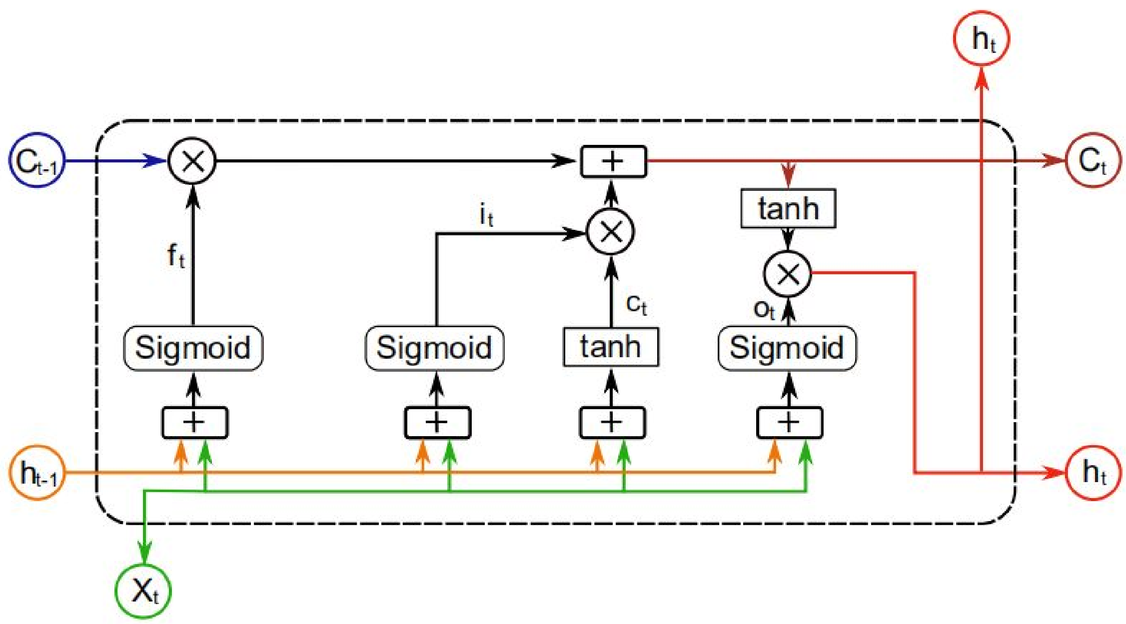
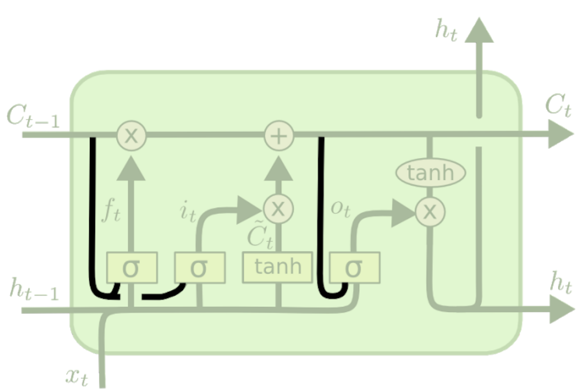
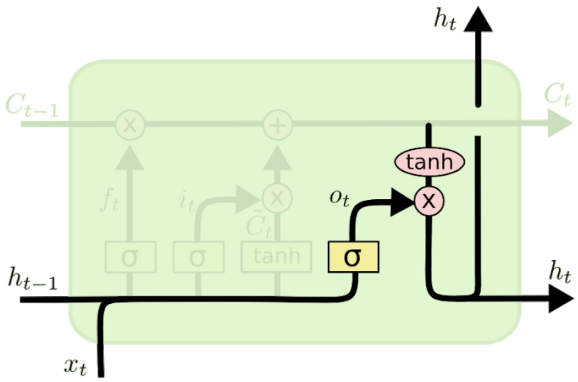


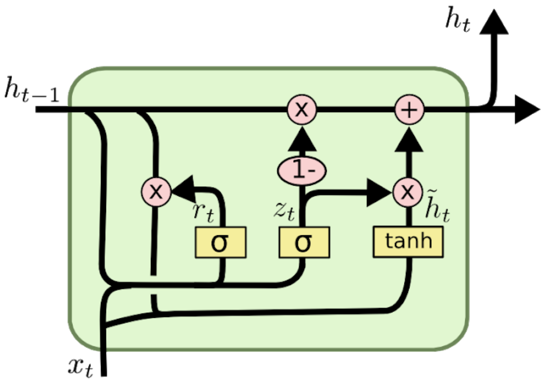
Fig 3.4 LSTM Cell Architecture



$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \;+\; b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \;+\; b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \;+\; b_o\right)$$



$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$



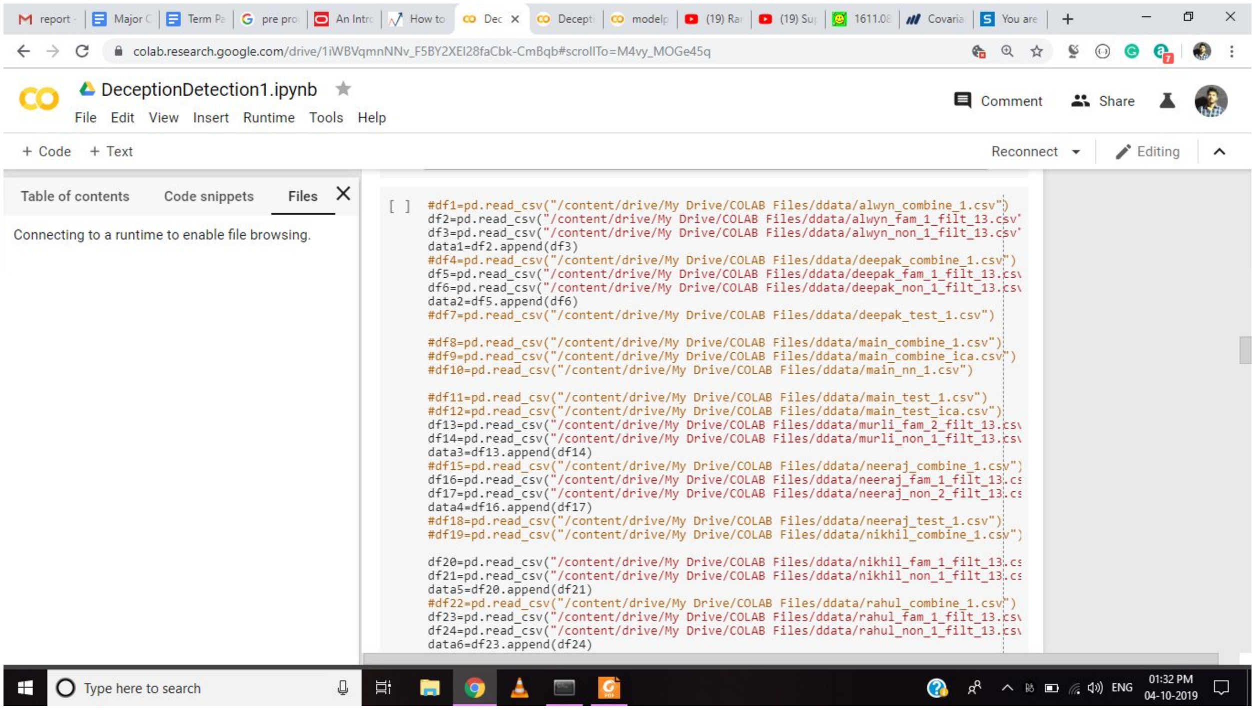
$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Fig 3.5 Peephole Connection in LSTM

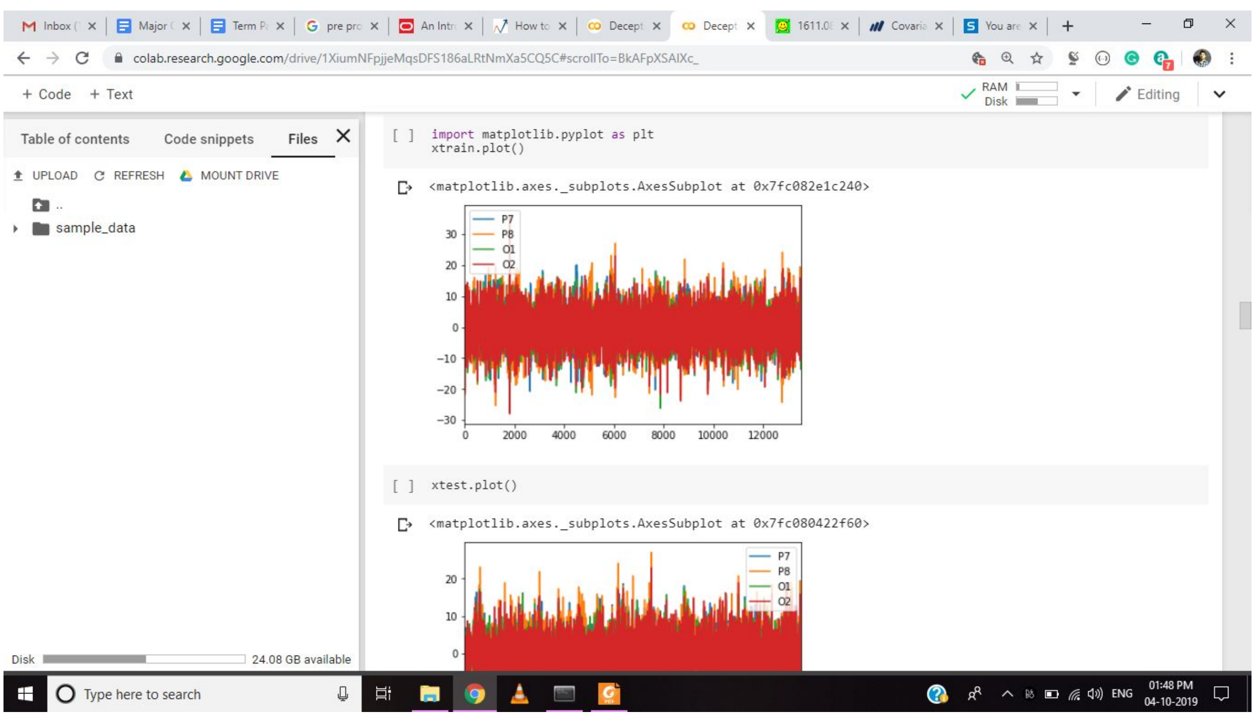
3.2 Requirement Analysis

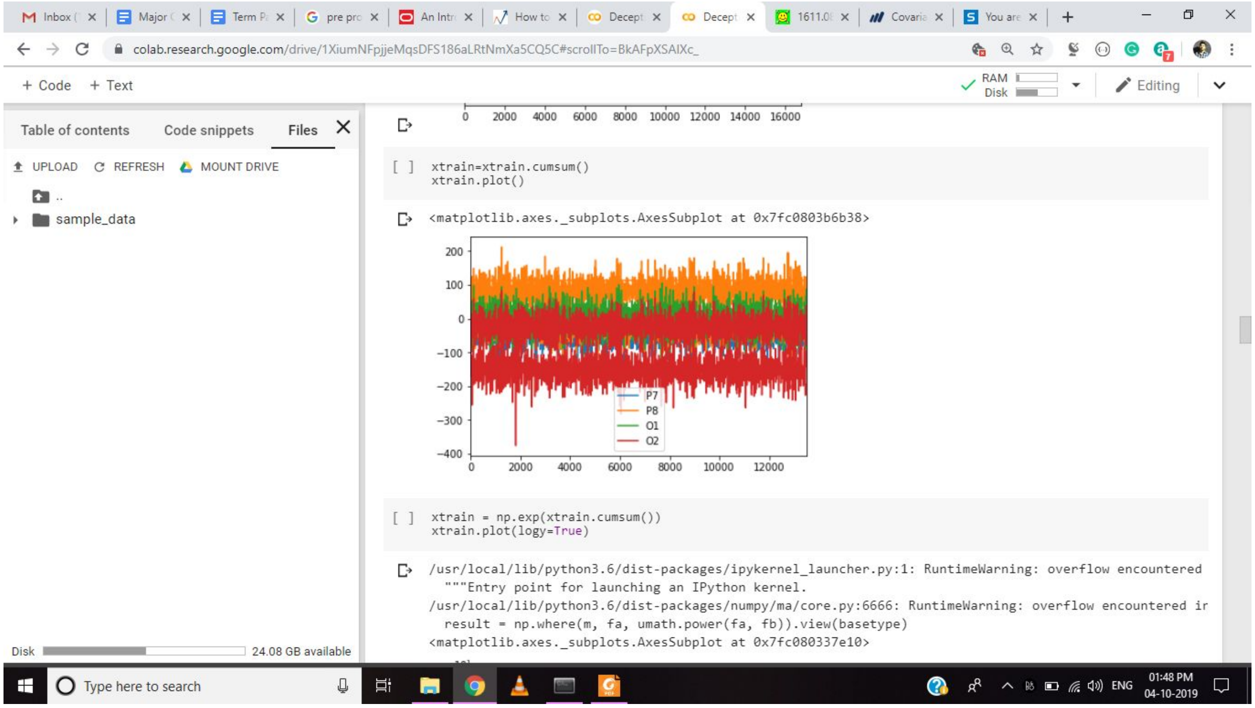
Dataset Source : For the collection of data, we chose 13 healthy subjects. We beforehand confirmed that all ten subjects have no health problems as well as neurological disorders. All the selected subjects were in the age of 22-25 years. All have a normal or normal to-corrected vision. Our primary target was to collect images that are very familiar to the subjects and unfamiliar images which should be completely strange to all of them. To subjects, we have a better awareness and instructions to follow while doing the data recording. All the subjects have good knowledge of the experiment. All were instructed to minimize their movements, and facial expressions to reduce the noise in the recorded signals. Since EEG have very less signal to noise ratio, we took care to minimize artifacts as maximum as possible.

Dataset :



Dataset visualisation:

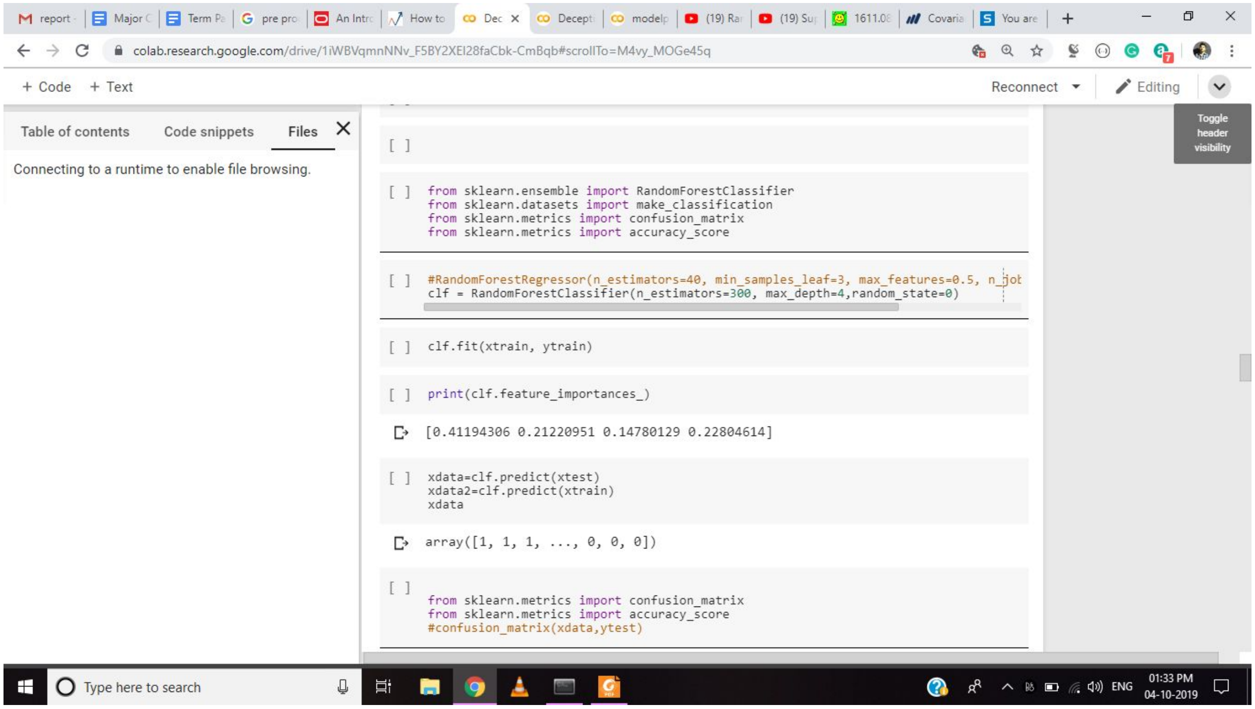


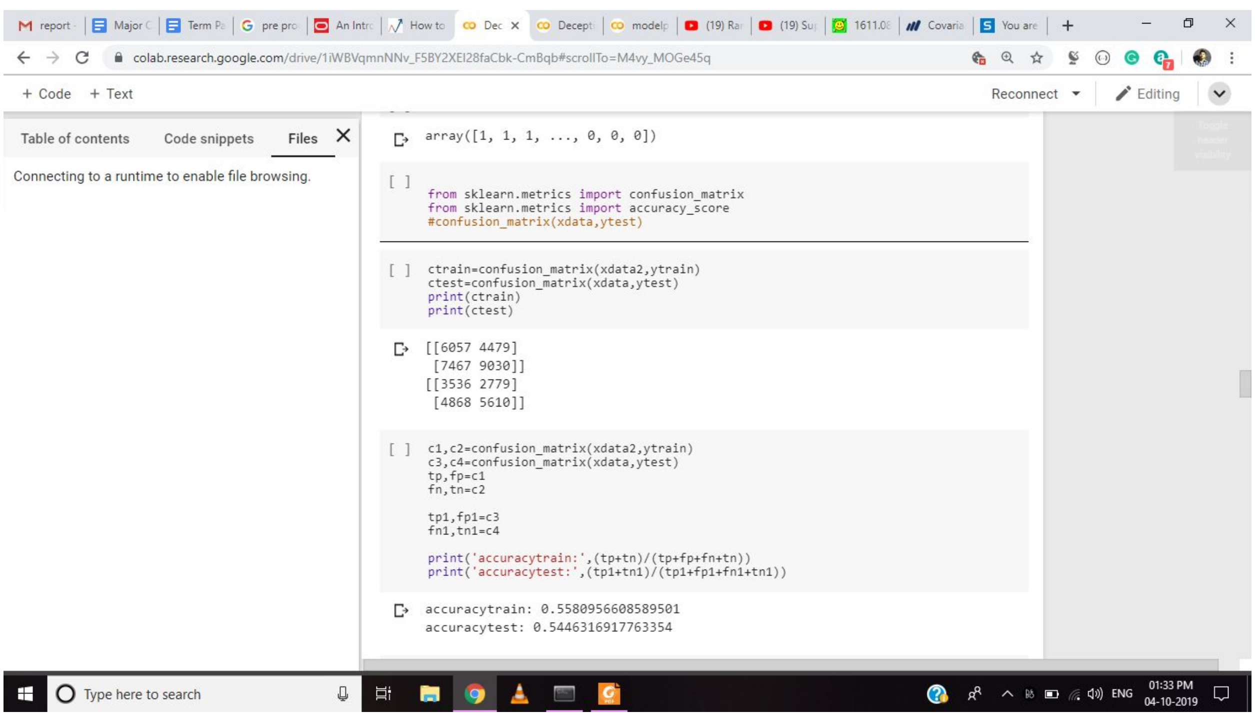


3.3 Solution Approach

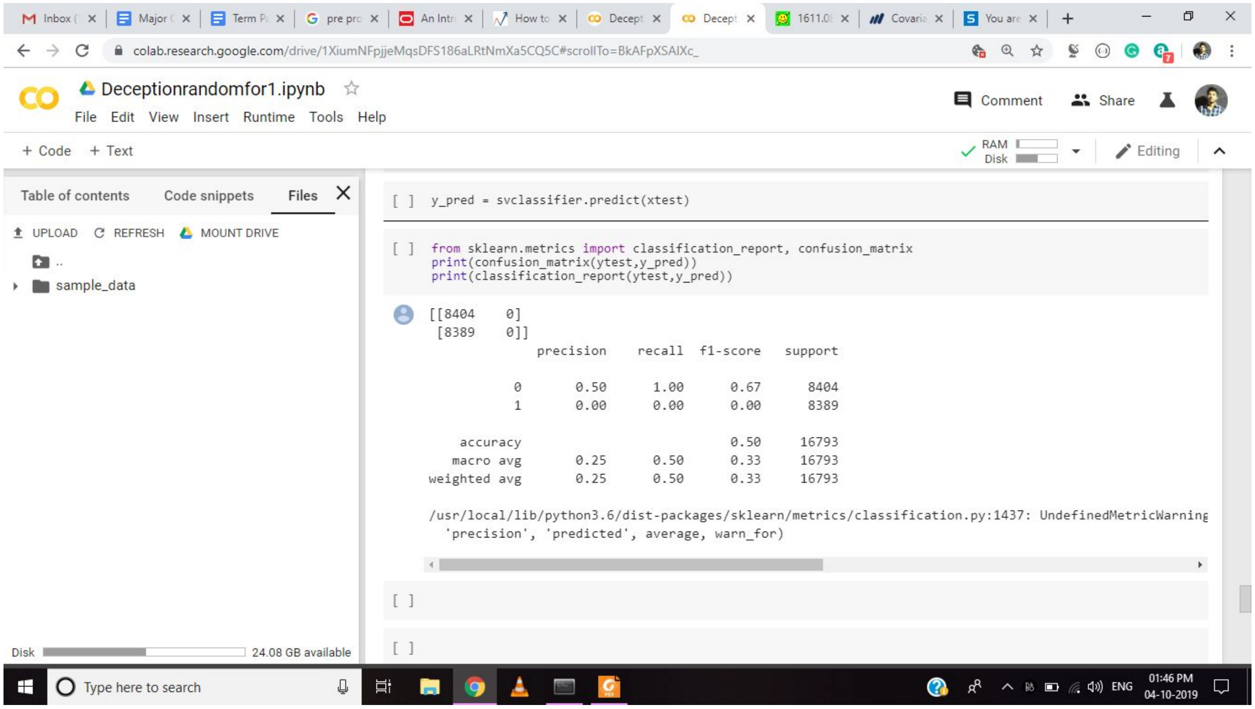
1. We evaluated how EEG signals responded to the familiar faces over the unfamiliar faces and analyzed using a correlated experiment.
2. We introduced deep learning models for the classification of familiar and unfamiliar EEG signal classes.
3. All the experiments designed by us depicts a very close relation to the real-life scene and can give the same impact as a crime scene for deception detection.
4. Our work shows how effectively we can use the raw neuro-signals, instead of going for Event-Related Potentials (ERPs).
5. We implemented a robust deception detector model efficaciously using the potential of the stateful LSTM network

Random forest:





SVM:



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print(classification_report(ytest,y_pred))
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[8389 0]]
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1 0.00 0.00 0.00 8389
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Chapter 4
Modelling and Implementation Details

4.1 Design Diagrams

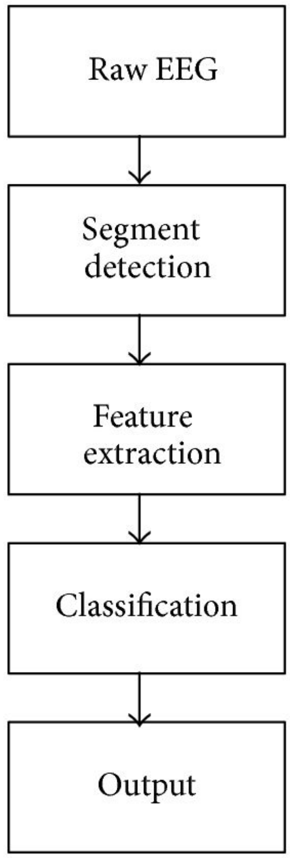


Fig 4.1 Activity Diagram

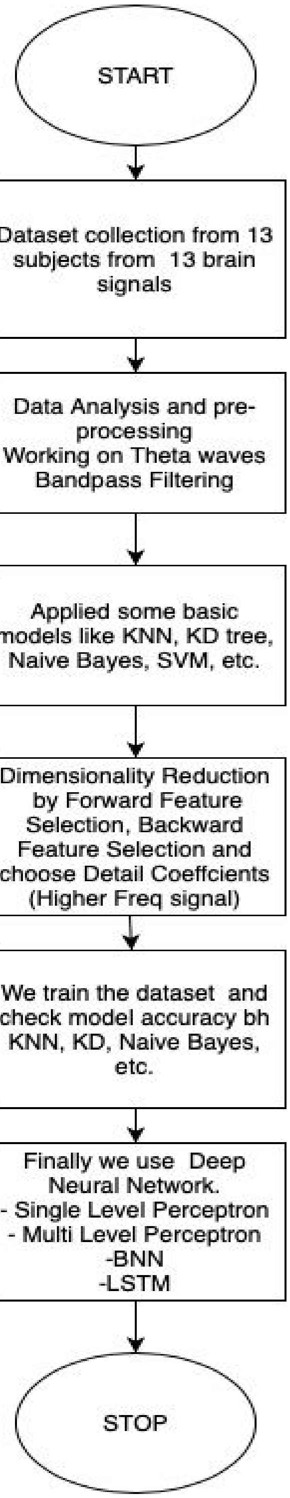


Fig 4.2 Control Flow Diagram

4.2 Implementation details and issues

- Thresholding :
  The soft thresholding is also called wavelet shrinkage, as values for both positive and negative coefficients are being "shrunk" towards zero, in contrary to hard thresholding which either keeps or removes values of coefficients.

- Random forest Classification :
  Random forest, like its name implies, consists of a large number of individual decision trees that operate as an ensemble. Each individual tree in the random forest spits out a class prediction and the class with the most votes becomes our model's prediction.
  The fundamental concept behind random forest is a simple but powerful one — the wisdom of crowds. In data science speak, the reason that the random forest model works so well is:
  A large number of relatively uncorrelated models (trees) operating as a committee will outperform any of the individual constituent models.

- Support Vector Machine :
  A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. In two dimensional space this hyperplane is a line dividing a plane in two parts where in each class lay in either side.

Long Short-Term Memory(LSTM):

Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. Unlike standard feedforward neural networks, LSTM has feedback connections. It can not only process single data points (such as images), but also entire sequences of data (such as speech or video). For example, LSTM is applicable to tasks such as unsegmented, connected handwriting recognition, speech recognition and anomaly detection in network traffic or IDS's.

Long Short Term Memory networks – usually just called "LSTMs" – are a special kind of RNN, capable of learning long-term dependencies. LSTMs are explicitly designed to avoid long-term dependency problem. Remembering information for long periods of time is practically their default behavior.

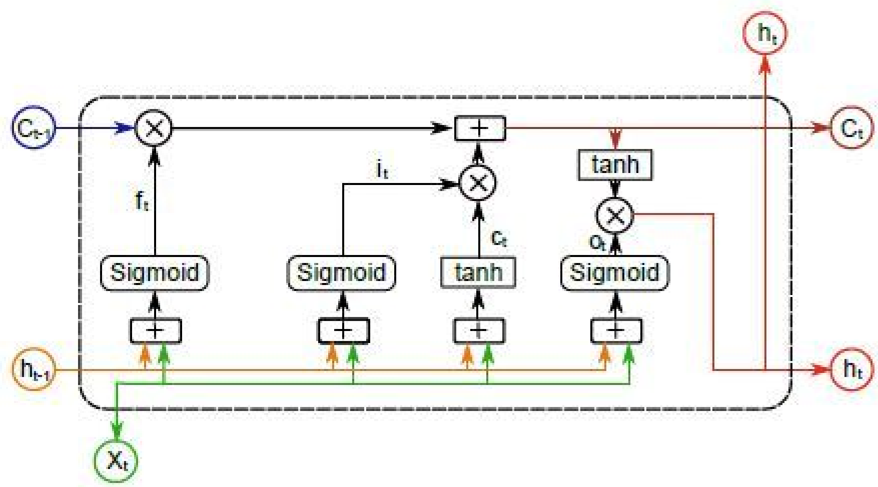


Fig 4.3 LSTM Model

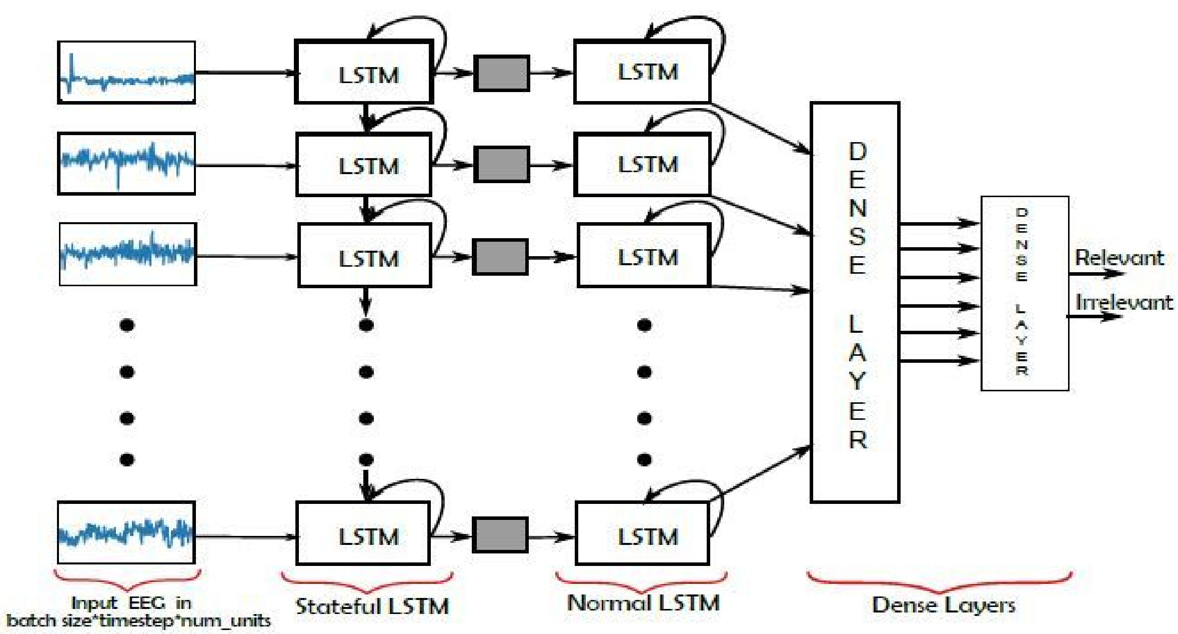
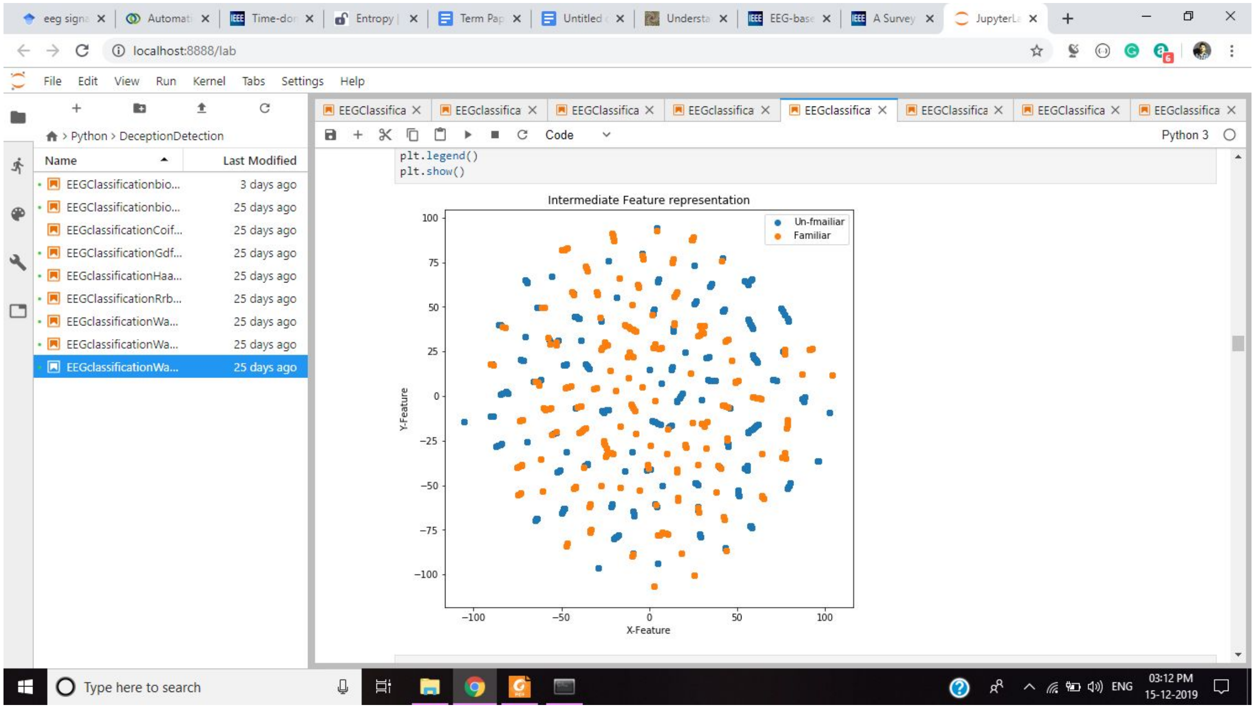


Fig 4.4 Implemented Stateful LSTM Model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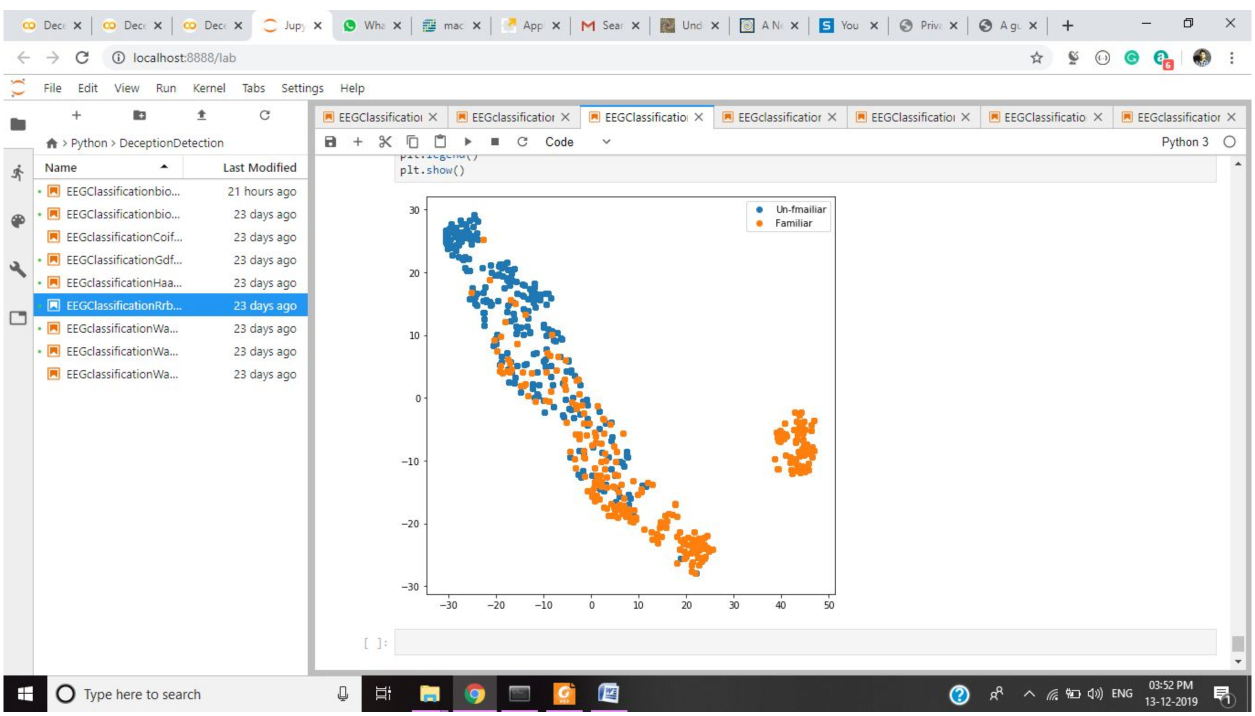
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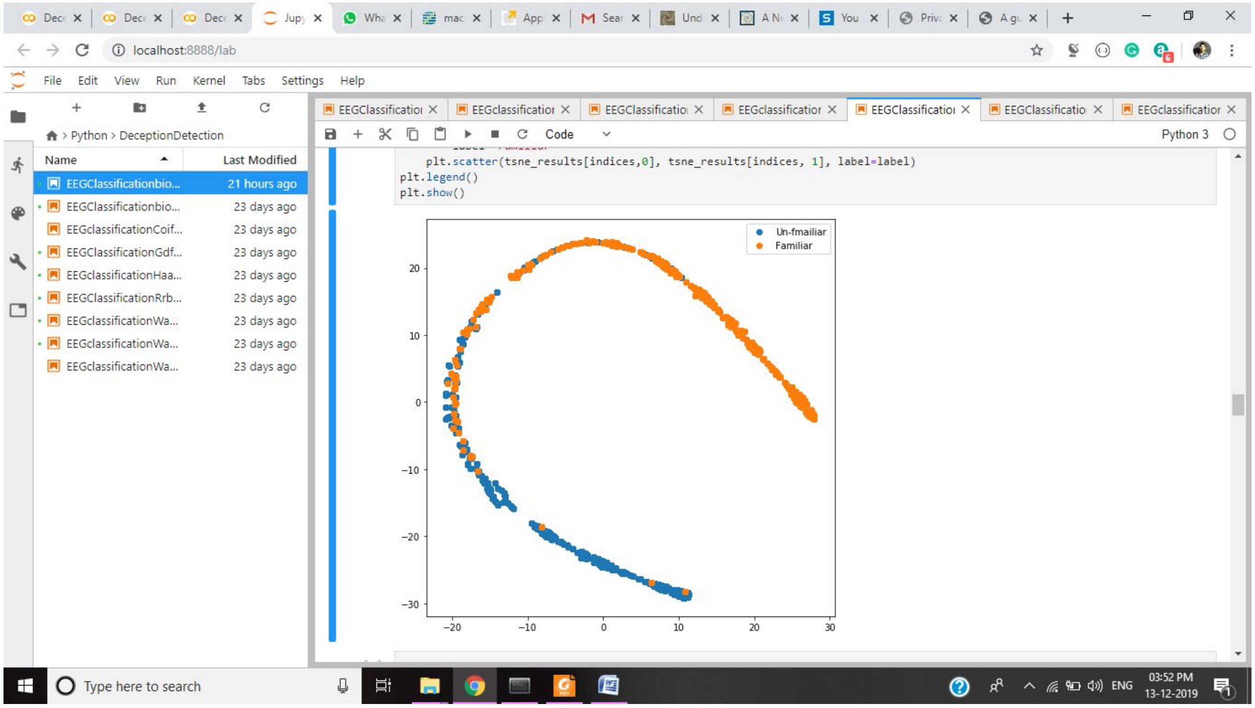
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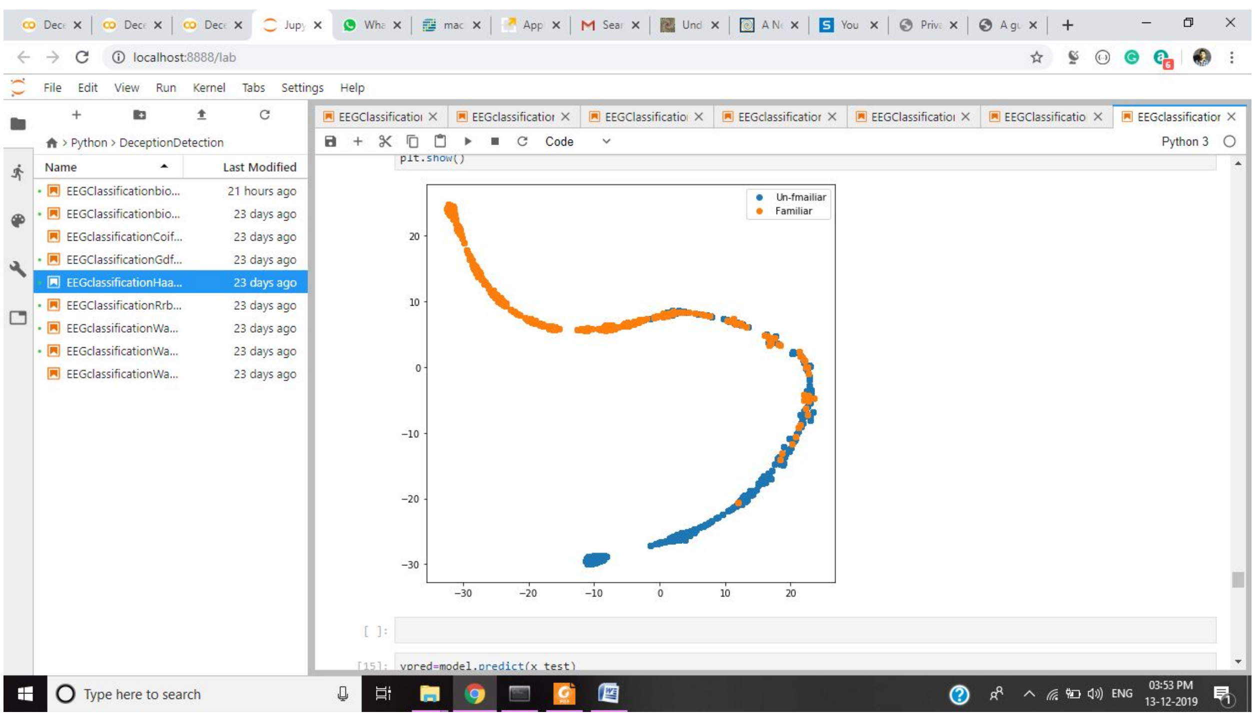
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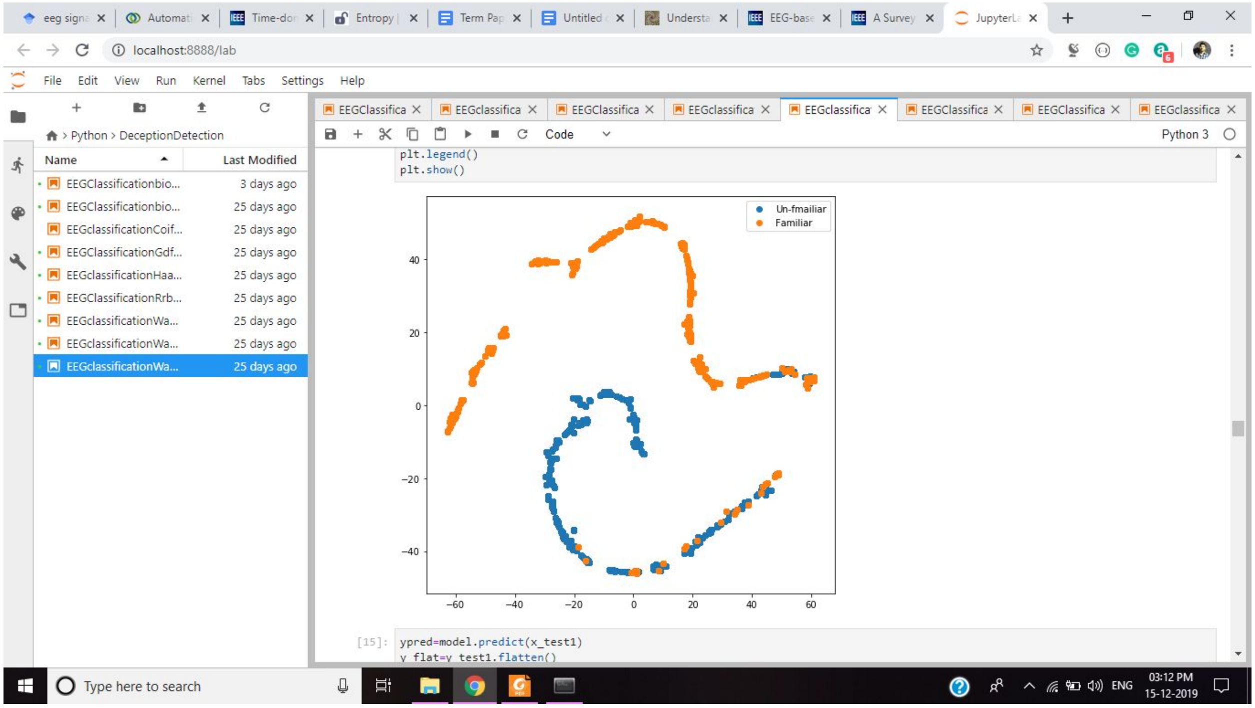

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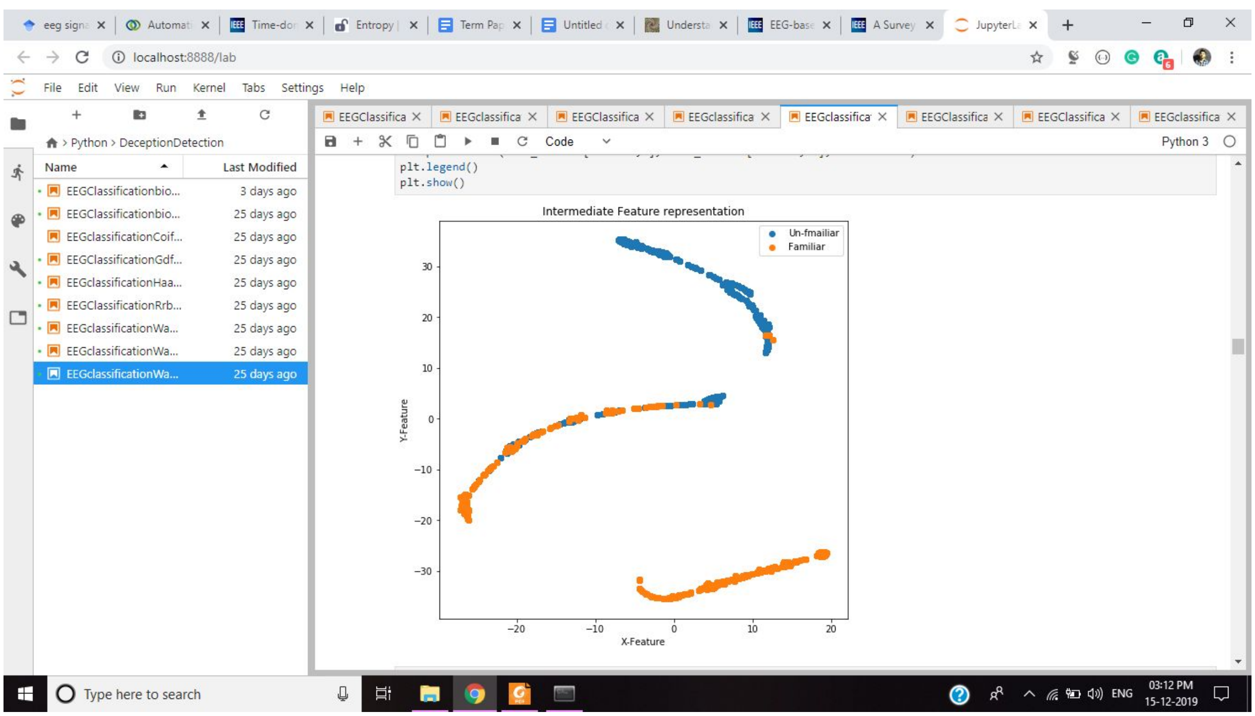

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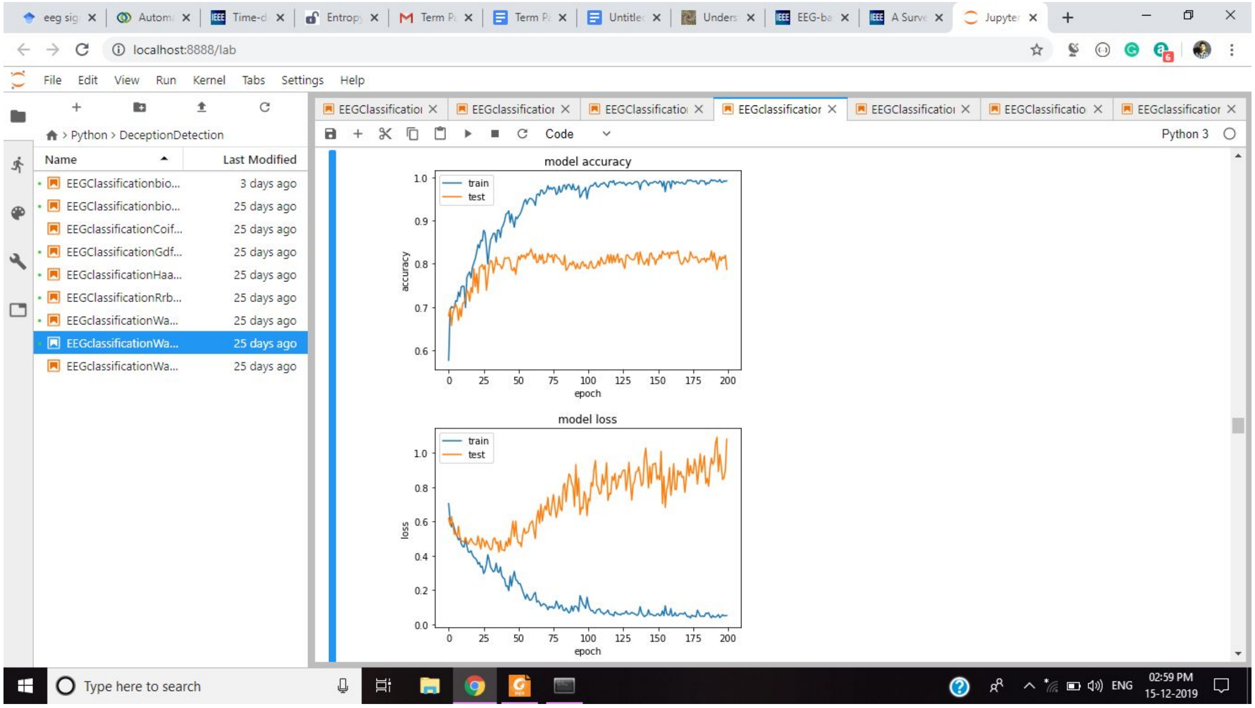
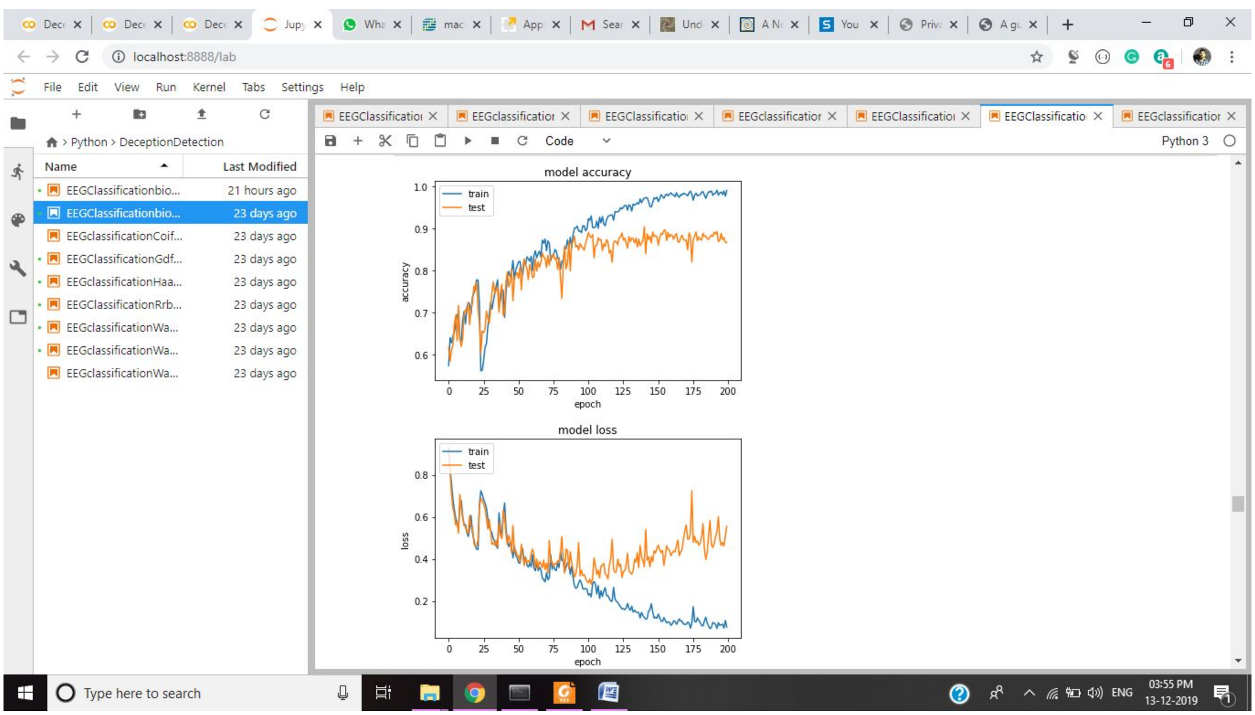
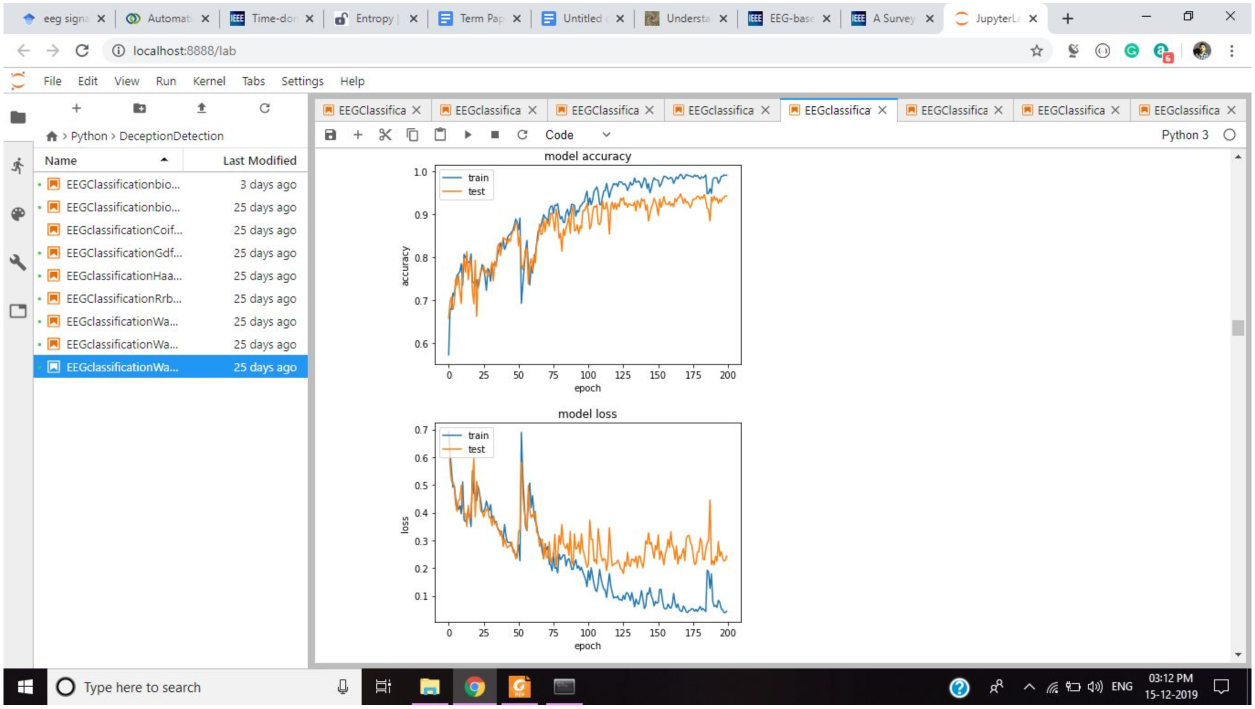
Accuracy-83% :



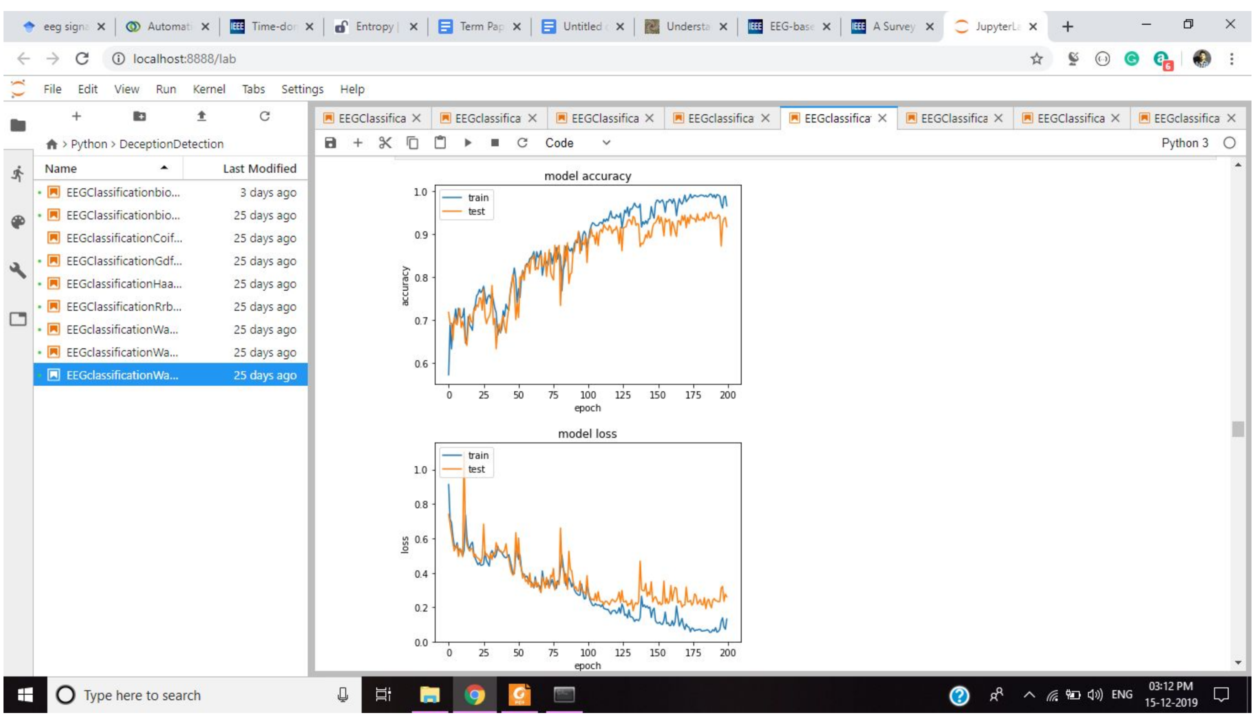
Accuracy-88% :



Accuracy-94% :



Accuracy-95% :



Chapter 5
Testing

5.1 Testing Plan

The experiment was based on visual Control Question Test (CQT) for the deception detection, and the final target was to detect whether the subject is telling a lie or not.
We selected a total of 13 subjects for the completion of this work.

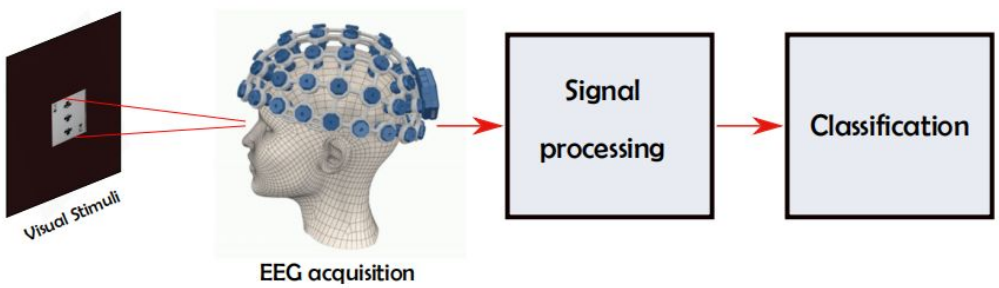


Fig 5.1 Testing Block diagram

5.2 Limitations of the solutions:

In some research paper they use Independent Component Analysis(ICA) and Event Related Potential(ERP) analysis in which subject can manipulate the model by performing some uneven activities before the experiment in which model predict wrong results so before applying this experiment we need to cross examine the subjects and their state of mind.

Chapter 6
Findings, Conclusion and Future Work

6.1 Findings :

Dataset Preparation:Our whole project focused on the practical application of EEG for human use. Thus the recording of EEG has to done very carefully. Familiarity detection is one of the vital features of the brain. We utilized this feature as our baseline to build up the deception detector system using EEG. The primary aim of this system is to classify the familiar and unfamiliar images. Prime care should take to try recording the EEG signal with minimal noise.

Data Collection: The experiment is used for understanding much about the EEG signals and how can we use the deep learning tools for its classification. This work is the building block of the later implemented deception detection. In the conducted experiment, we tried to implement a simple familiarity detector by showing different familiar images and unfamiliar images to the subject.

We chose seven healthy subjects for experimenting. Subjects were only told to look on the images shown on the screen and didn't give any clue regarding the type of images that will show. We showed nine different familiar and nine unfamiliar images to the subject in randomly. We exposed each image for two seconds, and in between the images, we gave one second rest time by showing a blank screen. Subjects were instructed to minimize their body movement to record a better signal.

6.2 Conclusion :

In this work, we present an improved version of a new deception detection model using stateful LSTM for the classification of EEG signals.

Our main objective is to increase the accuracy in result by using the advantages of EEG over the other physiological signals in the conventional deep learning tool. We were trying to overcome the reliability issues facing by the current lie detection technologies by utilizing the brain signals,which is more reliable than other signals. Also, deceiving/altering the brain signal is a somewhat difficult task. We implemented visual based questions in our project for analyzing the truth. For this, we designed two experiments - one is the familiarity detector which is used as a baseline model, and the other is the deception detector model. We used different familiar and unfamiliar images of persons were used as the visual stimuli and acquired EEG signal while showing these stimuli to the subjects. We introduced a deep learning model for the classification purpose,Our proposed model gave an accuracy rate of 95% than the reference model which got only 70.71%.

The acquired EEG signals were processed using the FIR filters and ICA process. Using the selected components, we tried to detect which subject told a lie and which one not with the help of some implemented deep learning models. Among the built models and the currently existing methods, the stateful LSTM gave an exceptional result of an accuracy rate of 78%. All the proposed deep learning models gave a state of the art results compared to current methods, which shows the superior characteristics of this over the traditional learning methods. Using visual stimuli as the CQT and the realtime data EEG recording helps to get the instantaneous changes in the brain signal.

The reliability of EEG is higher compared to other signals used in the polygraph method. We are focusing on the raw neuro-signal rather than going for ERP analysis. Also, our techniques reduced the burden of manual feature extraction done for traditional learning methods. Thus no need to rely on specific features for the final detection because we can’t generalize the feature combination for the classification every time with different models but by using deep learning the model only take cares regarding the features automatically.

6.3 Future Work :

Complete elimination of signal processing techniques and using the raw signal as the input to the detection model.

• Real-time deception detection model with much more better accuracy rate.

• Hardware based implementation with a more optimized neural network.

• Combining the other physiological signals to increase reliability.

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EDUCATION

JAYPEE INSTITUTE OF INFORMATION TECHNOLOGY
B.TECH IN COMPUTER SCIENCE
CGPA: 7.0/ 10.0

NATIONAL INSTITUTE OF OPEN SCHOOLING
HIGHER SECONDARY SCHOOL
Percentage: 90%

INFANT JESUS' SCHOOL
HIGH SCHOOL
CGPA: 9.2/10.0

LINKS

Github:// akashgupta2612
LinkedIn:// akashgupta
Skype:// akashguptastar

COURSEWORK

UNDERGRADUATE
Data Structures and Algorithms
Artificial Intelligence
Computer Architecture
Computer Graphics
Operating Systems

SKILLS

PROGRAMMING
Python • C++ • C

WEB DEVELOPMENT
HTML • CSS • MySQL • Asp.NET

BLOCKCHAIN
Bitcoin • Smart Contract • IOTA

EXTRA-CURRICULAR

- Coordinator of Training and Placement Cell, JIIT
- Head of Training and Placement Newsletter
- Coordinator of JIIT's Photography Hub - JPEG

PROJECTS

WASTE CLASSIFIER USING CONVOLUTIONAL NEURAL NETWORK
Aug 2018 – Nov 2018 | Minor-I

- Classify waste objects into Biodegradable or Non-biodegradable waste on the basis of it's class with the model trained by the Convolutional Neural Network and is separated using a robotic platform controlled by Arduino Uno ATMEGA 328P.

AMBULANCE CENTRE ALLOCATION AND ACCIDENT ANALYSIS
Jan 2019 – April 2019 | Minor-II

- Identification and allocation of ambulance centre by interpreting the accidental data and forming clusters and predicting the most evident attribute that contribute to the accident in particular cluster.

SEARCH ENGINE OPTIMIZATION AND WORD RECOMMENDATION
Aug 2017 – Nov 2017 | Mini-Project

- Word recommendation system searches and displays all the recommended words with currently typed prefix. Search Engine Optimization searches for the frequency of the word searched from the list of available files and displays the one with highest word frequency.

SMART FARMING
Aug 2017 - Sep 2017 | IC3 Conference

- A miniature version of an automated farming technology that can irrigate the farm using harvested rainwater and can detect soil's moisture. It also consisted of a sun-tracking Solar Panel and could notify the farmer about the farm's health via SMS.

INTERNSHIP

ERNST AND YOUNG | AUTOMATED GST COMPLIANCE
May 2019 – July 2019

- A solution that automates the complete end-to-end process of GST Compliance which is the primary form of Indirect Taxation in India. It assisted the complete process, from taking up the monthly return of a client to finally uploading it onto the Indian Government GST Filing Portal. Our solution provides a Web Portal for the same.

CERTIFICATIONS

PYTHON FOUNDATION
June 2018 – July 2018 | FOSSEE IIT Bombay

- Learned Python programming fundamentals such as data types, structures, variables, loops, functions, file handling, elementary image processing. Worked on NumPy, Pandas and Matplotlib to handle and manipulate data.

Ajay Kumar

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42 Shaheed Nagar, Near BBA University, Lucknow ,UP, India

04 July, 1996

Objective: To make positive contribution as part of your dynamic and well reputed organization in a position where my technical skill and decision making will be appreciated and enhanced.

EDUCATION

UG: B.Tech(Computer Science & Engineering)
Jaypee Institute Of Information Technology,Sector 62 Noida
08/2016 – Present *6.6*

XII(CBSE Board)
New Public Inter College,South City Lucknow
05/2014 *69.6*

X(CBSE Board)
Army Public School,Nehru Road Lucknow Cantt
05/2012 *6.4*

CERTIFICATION COURSES

Python Training
Digipodium Lucknow
05/2018

Android Training
Digipodium Lucknow
05/2018

Java Training
Trainedge Lucknow
05/2017

INTERNSHIP

Internship from (Indian Institute of Technology , Patna) (05/2019 – 07/2019)

-Work on Machine Learning EEG Classification

-Under Dr Jimson Mathew Sir

SKILLS

C / C++ Language | Java / OOPs Concept | Python/ Data Science(Pandas/Numpy) | App Developer(Android) | Machine Learning | Software Engineering | Logical Thinking

PERSONAL PROJECTS

EEG Classification(brain-computer interfaces) (06/2019 – Present)
- Python(Machine Learning)

Daily News(Recommendation System / Sentiment Analysis) (10/2018)
- Python(Machine Learning) with FrontEnd

Family Locator App (provide User interface and activities of Login/Signup/Map and Firebase (07/2018)
- Android Application

Learning Programming Hub(Using MY Eclipse IDE with sql database Login/Sign/Validation/Programming Languages Notes) (07/2017)
- Java

Hotel Management (Services Management/ File Handling) (08/2016)
- C

EXTRACURRICULAR ACTIVITIES

- Chess

- National Cadet Corps

INTERESTS

Travelling | Surfing Internet | Socializer | Providing Feedback

Saurabh Gupta

Objective: To succeed in an environment of growth and excellence and earn a job which provides me job satisfaction and self-development and help me achieve personal as well as organisational goals.

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37, Sector 8, Faridabad, Haryana

EDUCATION

Computer Science Engineering, B.Tech
Jaypee Institute of Information Technology, Noida, Uttar Pradesh
07/2016 - Present CGPA – 6.8

Science, Intermediate (CBSE)
Modern Vidya Niketan Sr. Sec. School,Sec-17 Faridabad, Haryana
2015 – 2016 Percentage – 88.6

High School (CBSE)
Modern Vidya Niketan Sr. Sec. School,Sec-17 Faridabad, Haryana
2013 – 2014 CGPA – 9.4

WORK EXPERIENCE

Web Developer
NHPC Lmtd. May 2019 – July 2019
Faridabad, Haryana

- Created a website for NHPC to provide a web based UI for organising quiz based on general knowledge and grammar.

TECHNICAL SKILLS

Programming Languages: C, C++

Web Technologies: CSS, PHP, HTML

Database: Mysql

TECHNICAL PROJECTS

Waste Segregation Bot
- A waste segregation bot that segregate waste into biodegradable and non-biodegradable through Image Classification using Arduino and CNN in Python.
- https://github.com/saurabhgupta0398/waste segregation

Metro Fare Calculator
- Used dijkstra algorithm to find minimum distance between nodes(stations) and give fare corresponding to it.

EXTRA CURRICULAR ACTIVITIES

Member of UBA Team:
- An active member of Unnat Bharat Abhiyan team.
- Surveyed different villages of Noida and created report on the problems faced by the villagers and submitted it to IIT Delhi with the solutions.