DESIGN, IMPLEMENTATION AND ANALYSIS OF DEEP LEARNING BASED DECEPTION DETECTION

A Thesis
Presented to the
Academic Faculty

By

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Under the Guidance of
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CERTIFICATE OF APPROVAL

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This is to certify that the thesis titled **"Design, Implementation and Analysis of Deep learning based Deception Detection"**, submitted by **Abhijith V Nair**, to the Indian Institute of Technology Patna, is a record of bonafide research work under my supervision and I consider it worthy of consideration for the degree **Master of Technology in Mechatronics Engineering**. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree/diploma.

Dr. Jimson Mathew
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Date: May 24, 2019

Dedicated to my
parents and my beloved ones...

DECLARATION

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Abhijith V Nair

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ABSTRACT

Polygraph is the conventional technology used for the judgment of whether a convict is telling the truth or is lying on the criminal case he/she is accused. Controversies on polygraph led the way to use brain signals as a better explication for deception detection. The emotional state of a human can be better estimated by analyzing brain signals, specifically electroencephalograph(EEG) signals. Also, EEG is using for various other applications, including Brain-Computer Interface (BCI). There were some researches did in this domain for using the EEG as a tool for the deception detection, and the reliability & robustness of this method has been getting attention among the related researchers. Recent advancements in the using of neural networks (generally called as deep learning) show how much it more superior than the traditional machine learning methods. The deep learning models have the ability of automatic feature extraction and used them to classify the given input based on the respective application. With the combined help of unsupervised training and successive tunings increases the reliability of using deep learning methods. Because of this specific characteristic of neural networks over the traditional machine learning methods helped to use it for the classification of bio-signals like EEG.

This project aims to set up a deception detection experiment which has very much similarity with the real-life criminal trial and to implement a classification model which can easily classify the EEG signal related to lie from the truth one. We performed a visual stimulus based experiments where it will be elementary to analyze the brain responses to the known and unknown images with the help of the memory ability of the human brain. We used this as our base for the classification. In this project, we tried to analyze how effectively neural networks worked better than the currently existing models based on traditional machine learning. Our work reduced the overburden of feature extraction and selecting the right combinations of features for the recommended classification models. We first tried to build a familiarity detector were we used [1] as the reference paper, and we implemented an autoencoder based model with better classification accuracy. Further, we conducted a deception detection test and built different neural networks for the classification purpose. Our Stateful LSTM based model outnumbered all the other models with a significant accuracy rate.

Keywords : Electroencephalography (EEG), Independent Component Analysis (ICA), Deception, Deep Learning, Autoencoder, Stateful Long Short Term Memory (LSTM)

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List of Acronyms/Abbreviations

EEG	Electroencephalograph
ICA	Independent Components Analysis
PCA	Principal Component Analysis
GKT	Guilty Knowledge Test
CQT	Control Question Test
MLP	Multi Layer Perceptron
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
SVM	State Vector Machine
RNN	Recurrent Neural Network
LSTM	Long Short Term Memory

Chapter 1

Introduction

1.1 Background

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. It is one of the significant brain signal using in Brain-Computer Interface (BCI) applications and in many others which had been come up in the early 1930s after 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 [2]. 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.

EEG signals used for clinical as well as research purposes. In the research domain, EEG signals are used mostly in cognitive science, cognitive psychology, detection of seizures, neurolinguistics, etc. EEG signal analysis for the study of the brain function has more advantages than other existing methods. Like, the hardware cost for EEG signal acquisition devices is significantly lesser 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. 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. 1.1 shows a recorded EEG signal during a cognitive experiment. Usually, electrodes were placed on the scalp based on the International 10-20 electrode system.

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. Therefore there are a lot of applications where uses the EEG as the tool and some of them are listed below [3] -

- Detection of Epileptic seizures
- Study of sleep and its related disorders in humans
- Brain Computer Interface
- Cognitive performance analysis

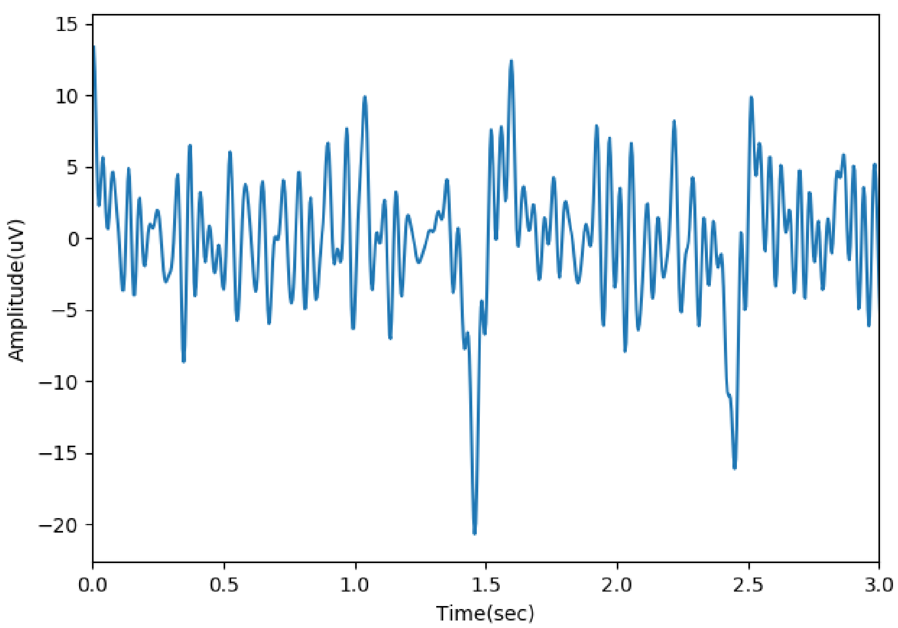


Figure 1.1: Figure shows the EEG signal recorded during a cognitive experiment

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 the 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 [4]. In early stages, not only for forensic analysis but also polygraph test was used in employment screening to check how much trustworthy the candidate to the company. But in later time the use of the polygraph by the companies were banned. 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. Fig. 1.3 shows the polygraph test setup where the sensors were connected on the subject.

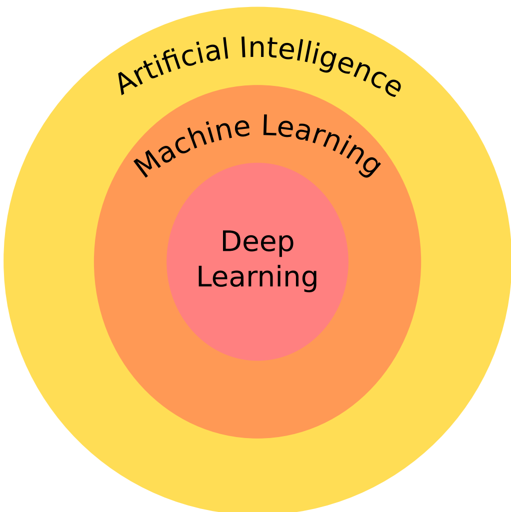


Figure 1.2: Venn Diagram of Artificial Intelligence

Always among the researchers, the reliability and trustworthy of polygraph was a big question. Thus some researches put forward the idea of analyzing the brain signals as a tool for detecting deception. The Silent Talker Psychological Profiler is used for the analysis of non- verbal behavior in the form of micro-gestures during the interrogation with the subject, and it is a camera-based method. It is mainly used for the purpose of credibility assessment. But the polygraph measurement has many limitations and it cannot get a direct view of the complex underlying brain processes [3]. Recent developments that allow the non-invasive monitoring using functional transcranial Doppler (fTCD) method gave very better problem- solving that employs a discrete knowledge strategy which selects neural pathways in one part of the brain. This model has a discrete knowledge based on the important components needed for completing the task. Based on this, a lie-detector system was designed and patented. There were some eye tracking technologies considered a polygraph alternative developed by professors from the University of Utah. 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 in Fig. 1.2. Still, deep learning posses so many advantages over the traditional machine learning techniques. Always machine learning depends on the feature extracted from the input data, and most of the times, this feature extraction is a manual job. Thus there is a high chance of intervention of errors into the final output, where on the other hand, deep learning techniques are a completely automated process and no need for manual feature extraction, which helps the user a lot.

Figure 1.3: Setup of a polygraph test [5]

1.2 Motivation

'Let a hundred guilty be acquitted, but one innocent should not be convicted'

The famous quote from Blackstone's formulation by William Blackstone in the Commentaries on the Laws of England, published in the 1760s reflects how much we should aware while trialing a person and to conclude whether that person is a criminal or an innocent. The conventional deception detection techniques always face so many questions on its reliability and how efficiently it works. Even though in the polygraph test, we are analyzing different bio-signals to conclude that whether the convict was either committed the crime. But if an innocent person is under stress, then sometimes his signal also get misclassified, and this led to the punishment of the wrong person. These negative side of polygraph led to the start of research for finding and implementing a better alternative for this.

Based on this idea, we aimed to introduce new methods for the potent use of EEG for the analyses of deception and want to modify the existing EEG based techniques to a robust one. We conducted different experiments for the detection of deception. This approach will improvise the reliability of deception detection and also reduces the manual effort in analyzing the signals. In our work, we have implemented different deep learning models for the detection of a lie from the recorded EEG while conducting the experiments most similar to the real-life criminal trial.

1.3 Contributions

The major contributions of our work summed as follows:

- We evaluated how EEG signals responded to the familiar faces over the unfamiliar faces and analyzed using a correlated experiment.

- We introduced deep learning models for the classification of familiar and unfamiliar EEG signal classes.

- 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.

- We evaluated the effectiveness of Independent Component Analysis (ICA) for the processing of the EEG signals.

- Our work shows how effectively we can use the raw neuro-signals, instead of going for Event-Related Potentials (ERPs).
- We implemented a robust deception detector model efficaciously using the potential of the stateful LSTM network.

1.4 Organization of the thesis

The research work presented in the thesis is organized and structured in the form of seven chapters, which are briefly described as follows:

i) **Chapter 2** focuses on the literature survey related to the currently available methods for lie detection and works associated with EEG specific to this domain.

ii) **Chapter 3** discuss on the early experiment conducted to get knowledge on EEG and the classification methods.

iii) **Chapter 4** focuses on how we prepared our dataset for the implementation of deception detector.

iv) **Chapter 5** evaluates and discuss the processing methods did on the acquired data.

v) **Chapter 6** demonstrates the various classification models implemented for the deception detection.

vi) **Chapter 7** investigates the overall performance of our proposed methods and compares with the existing methods.

vii) **Chapter 8** concludes the thesis and also outlines the scope for future work.

Chapter 2

Literature Review

2.1 Background of EEG

Brain is one of the most magnificent mysterious and alluring organs in our human body. There are still many kinds of research going on the brain to understand its hidden abilities and how this is coordinating so nicely to control our whole human body. The brain controls all physiological activities and also have the decision making capability. These functions are done with the help of billions of interconnected neurons inside the brain, and these neurons are the building block of our central nervous system [6]. The brain neurons communicated by generating electrical pulses and for understanding the brain and brain functions researchers are focusing on studying these electric potentials and also analyzes using some other brain imaging techniques like Magnetoencephalography (MEG), Magnetic resonance imaging (MRI), etc. Among all this, Electroencephalograph (EEG) has more advantages in acquiring and analyzing [1].

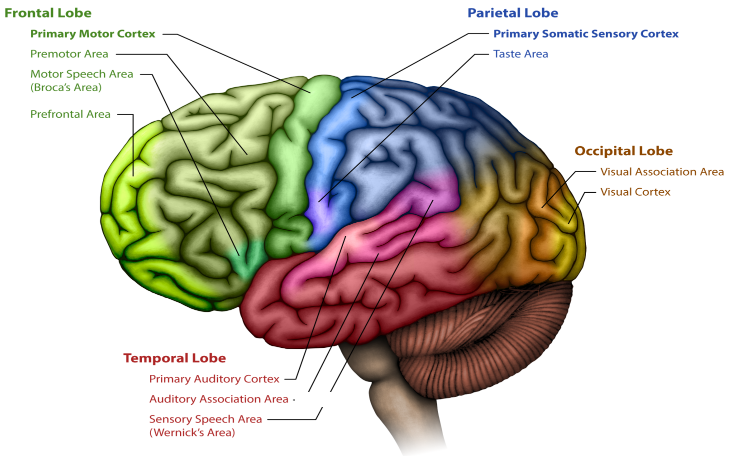


Figure 2.1: Major parts of the brain [7]

2.1.1 Brain Wave Components

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 [2]. Major brain wave components are (shown in Fig. 2.2) -

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

Delta Waves

Delta waves are mainly recorded while in deep sleep or deepest meditation and can use for understanding the sleep depth characteristics. Mostly these waves will start to appear in stage 3 sleep, and stage 4 is more dominated by delta wave components - combine both stages called N3-slow wave sleep. The dominance of delta wave activity can be seen in infants since their sleep mostly gets into N3 slow-wave stage sleep.

Theta Waves

Theta waves help us to understand the abilities like learning, memory, etc. It always shows the state of the hippocampus, i.e., this wave oscillations strongly seen near the hippocampus region. Since it helps to get a clear picture of the memory, the analysis of this wave can be used for understanding how much a person is familiar to a thing or another person. Thus, we can use this in the application of familiarity detection and eventually for deception detection.

Alpha Waves

Alpha waves are predominantly originated from the occipital region of the brain and related to the flowing thoughts, wakeful relaxation with closed eyes. Also, this wave component directly linked to the visual cortex region of our brain. So this wave intensity is high when it relates to focus, creative zone, concentration, etc.

Beta Waves

Beta waves are mainly associated with busy, anxiety, decision making, active concentration and also related to muscle contractions, i.e., before or during the movement.

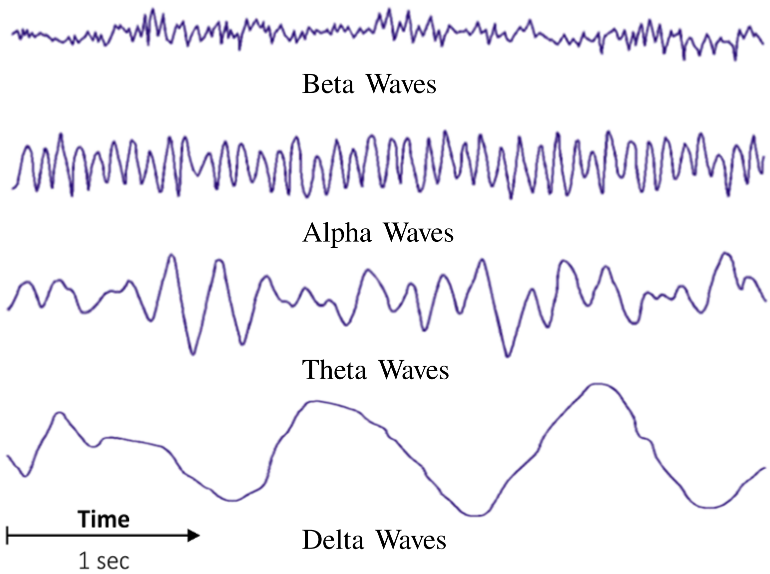


Figure 2.2: Different Brain Wave Components [8]

Along with this waves brain response can be analyzed by using Event-Related Potentials (ERPs).

2.1.2 Event-Related Potentials(ERP)

Event-Related Potentials are the electrical voltage generated inside the brain related to the response given by the brain based on the stimuli presented. The EEG signal will change concerning the cognitive, motor, visual events, etc. and analyze in the order of tens of milliseconds. Because of its small amplitude(1 - 30μV) compared to the standard EEG components, it is complicated to analyze ERP from raw EEG signals. Therefore, recording of ERP is entirely different, which contains epochs of data at a different time interval. So, for the better analysis of the effect of stimuli given to the brain, ERPs is the best choice. This signal can be represented in two forms - P, positive(e.g., P300, P200) or N, negative(N170, N100). The numeric indicates the time after the stimuli in milliseconds. The researches on Brain-Computer Interface is mostly based on ERPs (mainly P300) because there are always many correlations between the evoked ERP potentials and cognitive process. In humans, ERPs can be of two groups - one is the early waves that give maximum response during the initial time, i.e., starting 100 milliseconds after the stimuli presented termed as 'sensory' and the second category occurred at the later time which gives how the subject is responding to the stimulus which termed as ‘cognitive’.

2.2 Deception Detection

Lie Detectors are a prevalent device using in many criminal investigations all over the world. Most modern polygraph devices were patented, where Scott *et al.,* [9] 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 [10]. Modern polygraphs test use digital devices to record the physiological signals in Fig. 2.3 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

The researches related to deception detection mostly contains essential features from most of the psychologys diverse sub-disciplines. Podlesny *et al.,* describes the method of Psychophysiological Detection of Deception (PDD) which analyzes the physiological activity of the subject concerning the stimuli, either some set of questions or any other stimuli to find the subjects truthfulness [12]. It explains various test paradigms which can be used for the detection of deception. Also, the work explains the general considerations while conducting the deception experiments and the different mode of tests (deception tests and information tests) for deception detection that are mainly on differential responsivity. The effectiveness of using brain signal in the area of deception detection was found in the late 20th century. There is a relationship between deceptive signal and frontal lobe, which can analyze by mapping the EEG signal acquired from the subject who was asked to do some important task. The scope of using ERPs in Interrogative Polygraphy was tested by Farwell *et al.,* by

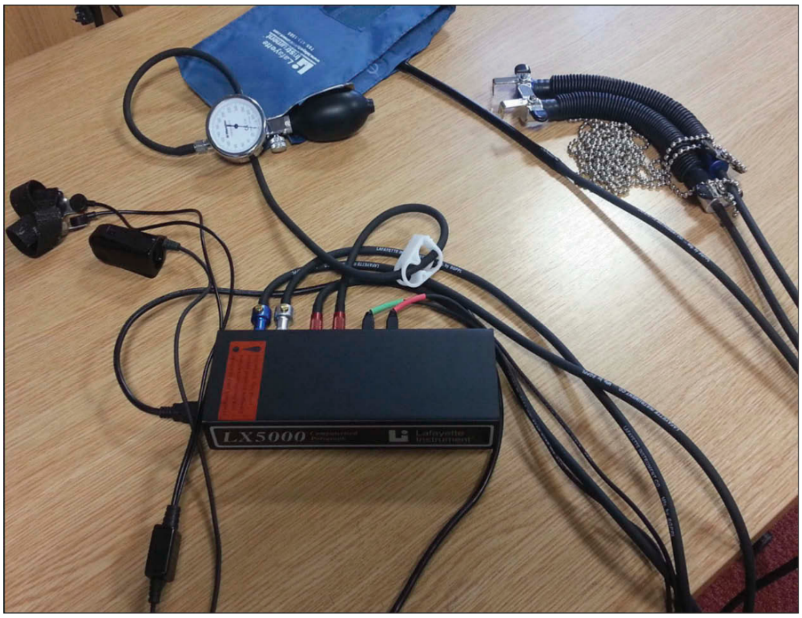


Figure 2.3: Equipment using for Polygraph Test [11]

using the Guilty Knowledge Test to understand the effectiveness of lie detection [13]. Here they did some a mode of experiments to discriminate the target and non-target stimuli. They found that targets elicited largest P300s in all subjects. But the system follows only the traditional ways for designing the GKT and also they only refer the P300 elicitation. P300 ERPs were recorded to evaluate human cognition. Wang *et al.,* [14] discussed techniques which can be used for detecting criminal identity deception. The author proposed an adaptive algorithm that helps to find the identities from incomplete data, which helps to find the deception in partial identities.

Traditional polygraph technique for the lie detection usually relies on Guilty Knowledge Test (GKT) and Control Question Test (CQT) to differentiate how the response of the convict varies with the relevant questions than to the irrelevant by real-time analyzing the recorded physiological signals. The fundamental assumption that the examiner took at the time of using the GKT is that the suspect had a better awareness of the crime-relevant knowledge that would reflect the questions which have a significant relation to the crime. But sometimes the variation in signals for relevant questions can be misclassified that paves the wrong judgment. The review by Ben-Shakar *et al.,* [15] on GKT described that it consists of a set of questions which some questions have functional relevance to the particular crime in which the suspects shows differentiable response and rest consists of neutral questions which commonly called as irrelevant questions. The subjects who were taking the GKT were exposed to a group of diagnostic items - named probes - consist of relevant and irrelevant stimuli. For determining the decision quality, the authors used bootstrapping method in the experiment. In [16], the authors did a detailed review of CQT. CQT consist of different stages where the examiner should have a better knowledge of the case and also regarding the relevant background of the suspect. After all the pre-examination scenes, a set of questions were asked to the examinee, and similar physiological reactions were recorded and analyzed by the examiner. But all of this process is not automatic, always require the help of a well trained human analyzer. D. D. Langleben *et al.,* discussed regarding an relationship between the event-related potentials by brain and lying based on the GKT which suggests that deception can also be related to the changes in other brain activity measures such as flow of blood regionally that could be anatomically localized with the brain evoked functional magnetic resonance imaging (fMRI) [17].

Brain waves usage in deception detection is increased in recent times. An authentication system based on EEG [18], there is a high concurrence between the reaction of subjects and behavior of EEG signal while the subject is exposed to visual stimuli, it represents that the effect of visual stimulus on EEG signals. Some researches show the efficiency of using EEG as a tool for biometrics [19]. The authors used autoregressive (AR) models for analyzing the EEG signal characteristics for using it for biometric applications. Palaniappan *et al.,* introduced the use of visual evoked potentials in the domain of biometrics. The authors recorded the VEP signals from subjects by showing some pictures set mentioned in [20]. Analyzing the Event-Related Potentials (ERPs) triggered while the subject is exposed to different faces [21], the N170 and P2 waves gave the degree of familiarity effects with small amplitude signals after 170ms and 250ms, respectively. The mentioned experiment indicates the face recognition at the perceptual and non-semantic level encoding of the given stimuli. Yeom *et al.,* [22] proposed a stimulus paradigm which they confirm that there was always a subject-specific brain- wave pattern to his face image and other face images. A difference in ERPs of familiarity level of the subjects face and other faces is distinguished at 250ms time by N250 analysis. EEG signals always show a more significant negative brain potential in right posterior recording sites 170msec (N170) after face stimuli onset relative to other faces stimuli. But repeated experiments show that repeated exposure of own faces elicits a more considerable negative brain potential (N250) at inferior temporal sites compared to non-target faces [23]. In [13] shown how the P300 component varies for target stimuli from the irrelevant stimuli. This experiment demonstrated how an interrogator could effectively use ERP analysis along with the Guilty Knowledge Test. The data acquisition was made using Ag/AgCl electrodes, which were placed on F_z, C_z, and P_z. Analysis of P300 Event-Related Potentials (ERPs) helped to find out the response of the subject to relevant and irrelevant stimuli.

2.3 EEG Signal Processing

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. Baseline drift is one of the significant artifacts in EEG, which reduces its signal to noise ratio. It is mainly because of the reduced contact between the electrodes and scalp skin, the effect of temperature and electrical powerline noise affects the EEG recorded. In [24] Reddy *et al.,* put forward techniques for removing the mentioned noises from EEG using methods like Adaptive Filtering, LMS Algorithm, etc. Elimination of artifacts is one of the major roles in EEG signal processing. Ngoc *et al.,* [25] proposed the role of wavelet components in removing the artifacts in the EEG signal. The author used the wavelet transform to detect and remove the artifacts due to eye blink.

The work by A.Mishra *et al.,* in [26] used the combination SWT-ICA (Stationary Wavelet Transform-3 Independent Component Analysis) for EEG processing. The authors used SWT for the decomposition of the EEG signals and applied soft thresholding to get a better approximation. It later used fast ICA for the blind source separation. The review in [27] compared different available techniques in time and frequency domain for the feature extraction of EEG and concluded that each method have distinct advantages and disadvantages over the other and also the methods varies based on which type of EEG signals have to measure and its application. Pierre *et al.,* in [28] proposed a method for determining the unwanted signals in EEG recordings from clinical data. They formulate the method based on the assumption that artifacts were shown themselves as outliers in more than one EEG-derived parameters. In this, the author determined the threshold for detection of an outlier by analyzing the experimental cumulative distribution function in the training set of clinical EEG recordings. But the system only trained for clinical data and they didnt use any statistical methodology towards the multivariate data, which can help much more improvement in the system.

The techniques of Independent Component Analysis (ICA) and Principal Component Analysis (PCA) are also used for the efficient elimination of the noises in EEG. Proposed work by Akwei *et al.,* [29] explained about the rejection of powerline noise included in the biomedical signals. They used the advantages of blind source separation and wavelet analysis to increase the quality of the recorded signal. The work did by Turnip *et al.,* [30] discussed the artifact removal from EEG using some feature extraction methods. They discussed various noises in EEG signals and used band-pass filtering along with ICA and PCA for remove artifact. The work showed the effectiveness of ICA over PCA, where PCA didn't reduce the amplitude level, and noises like EOG were not removed. For artifacts due to eye blink or of its movement are in large amplitude compare to the electric potentials from the brain. We always instruct our subjects to reduce body movements or facial expressions; otherwise, we have to take care of the removal of artifacts carefully. Otherwise, this affects the informative signal included in the recorded EEG. Carrie *et al.,* [31] presented the Blind Source Separation (BSS) which is a part of ICA for the effective artifact removal. The results reported by the author shows that the introduced method gave a high degree of accuracy for the removal of unwanted components in the EEG.

2.4 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 thatgot while the subjects are shown to the visual stimuli (familiar and unfamiliar). Using the Continuous Wavelet transform the time-frequency features were extracted [1] from the EEG band of 4-8Hz. CWT used for finding the sudden transitions in the signal. The feature combinations were fed to the SVM classifier and obtained better accuracy. The work in [32] proposed a autoencoder based model for the better classification of famliar non-familiar stimuli uing the EEG signals. Also in [33], extracting features from EEG by using discrete wavelet transform used for classifying the epileptic seizure and they employed the support vector machine model for classification. Shiu *et al.,* [34] implemented a CSP-DNN framework for getting better results for the classification of MI-BCI signals. Common Spatial Pattern (CSP) were used for the extraction of variance based CSP features and the EEG signals were classified using Deep Neural Networks.

For the epilepsy detection, EEG signals are represented by wavelet packet coefficients and the feature extraction is done by using the wavelet packet entropy method in combination with cross-validation [35]. k-Nearest Neighbor (k-NN) classifier is used for the construction of Hierarchical Knowledge Base (HKB). While testing the data, for the computation of classification accuracy and rejection rate used the top-ranked discriminative rules from the HKB. Auto-regressive linear models are also used for extracting the temporal fluctuations of a given EEG data, which work in an unsupervised manner [36]. For calculating the score for the anomalies mainly uses an appropriate threshold value to achieve a scalable decision making for the epilepsy detection and prediction.

Understanding the emotions using EEG was a milestone, and this paved the way to use the EEG for deception detection. The work by Bos *et al.,* [37] shows the efficiency of EEG to vary with the emotions and author classified the emotions using binary linear FDA (Fishers Discriminant Analysis) classifier. The work by Smitha *et al.,* [38] also used Continuous Wavelet and Linear Discriminant Analysis (LDA) classifier for the classification, where LDA showed good accuracy than the compared SVM method. In [39] explained various feature extraction techniques for EEG. The author compares Hilbert-Huang transform, Principal Component Analysis, Independent Component Analysis, and Local Discriminant Bases methods and shows how each technique is varying and how efficient are these for the better classification of EEG.

The work by Cakmak *et al.,* [40] recorded the alpha waves from the electrodes placed on the frontal region, and the Short Time Fourier Transform (STFT) was used for the feature extraction. In [40], the result achieved by the model after the classification showed that a persons lie behavior has a direct relation to the alpha waves from the frontal region. Work by the Turnip *et al.,* [41] shown an abnormal change in amplitude when a person is telling a lie. To analyze the mentioned component, it requires three types of stimuli - probe, target, and irrelevant. Adaptive neuro-fuzzy inference system (ANFIS) - the combination of the fuzzy and neural networks - had used in the classification stage and Independent Component Analysis (ICA) was used in the signal processing stage [41]. Since EEG/ERP data is non-linear multi-dimensional signal using of neural networks for the analysis can be more advantageous because it doesnt require manual feature extraction techniques.

The work mentioned in [42] evaluated the effectiveness of the neural network than the conventional machine learning models for the detection of the P300 component. The whole classification was done by training the model using the data from 4 subjects and tested the data of 11 subjects without any further training. The authors tried to compare the effectiveness between classifiers like Linear Discriminant Analysis (LDA), Multi-Layer Perceptron (MLP) and Stacked Autoencoders (SAEs) in which SAE gave the best classification performance with an accuracy of 69.2%. Bias-variance error trade-off is always a big problem for classifiers. Neural networks and a combination of dynamic classifiers are efficient in synchronous experiments. Some works based on the combination of both CNN and LSTM. In [43] Baloglu *et al.,* proposed a Convolutional long-short-term memory (CLSTM) for the classification of EEG signals. They used a nine-layer CLSTM neural network for automatic classification of both EEG and seizure detection, where the model directly using the raw EEG data acquired without even doing simple filtering techniques.

2.5 Research Gap

Based on literature review, we find that

1. Currently, there is no general system with greater reliability and robustness which can work as a alternative for the polygraph method. Thus designing a new mode of deception detector is totally a research objective.

2. The models using brain signals for the deception detection purpose still suffers a significant less accuracy and rely on the traditional learning methods which makes the process more complex.

3. The some of the current methods using ERPs for the analysis purpose and which can make it more time consuming.

4. Many researchers have done work in deep learning for various EEG based applications but a few have its use in deception domain. Thus the advantages of deep learning can fully utilize in this domain which can help to implement more robust and optimized algorithms for finding the deception.

Chapter 3

Basic Building Block

3.1 Overview

In this chapter, we discussed the work that we started as the basic block for the implementation of the deception detector. The work comprises how we understand the EEG signals for the particular use and the introduction of the deep learning models for the analysis of bio-signals.

3.2 Approach

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 showing in 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.

3.3 Technical Details

We used Biosignalplux EEG setup for the measurement of EEG [44]. It is a three-electrode sensor, which is a single channel differential sensor was shown in Fig. 3.1. The red indicated electrode is for a positive connection. The black color indicated electrode for the negative connection and the remaining white color one is for the reference function. We connected the red one in $O1$ electrode position, the black one

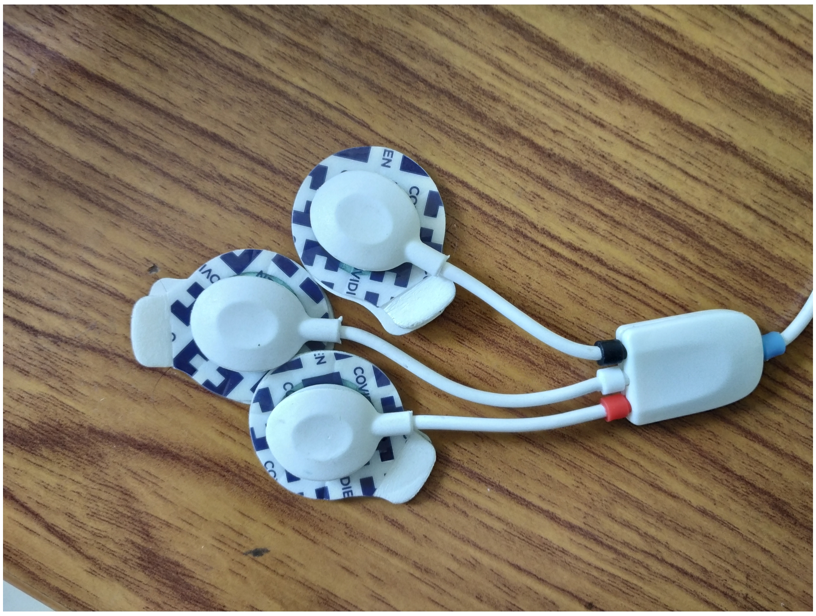


Figure 3.1: Biosignalplux EEG electrode sensors used for the recording purpose

to the $O2$ electrode position based on the International 10-20 electrode system and the reference electrode was stick on the back of the ear, which used as the reference signal because comparing to the other parts of the brain this location has only fewer muscle activities. We used $O1$ and $O2$ because this portion of the brain consists of the visual cortex region. Thus the response of the brain to the visual stimuli will be higher in this portion. The electrodes were connected to the biosignalplux Hub, which is an eight-channel device shown in Fig. 3.2. It consists of 8 channels, and we used the third channel for acquiring the signal with a sampling rate of 1000Hz. It is directly connected to the device software through Bluetooth channel, and we can real-time visualize the signal. The interfacing software is shown in Fig. 3.3. From the software, we have the option to change the sampling rate and offset the & gain of the recording signal.

3.4 Processing and Analysis of the Signal

The recorded EEG signal is free from DC offset, and the key feature of the device is it records data with high signal to noise ratio. Thus we get the signal with less noisy and later we did the bandpass filtering for filtering signal within the range of 0.5-30Hz. We used a 6^{th} order Butterworth Bandpass filter. The frequency response of the implemented filter is shown in Fig. 3.4 and we can see that the filter has almost a flat response in its passband. Here we tried to find the anomaly while seeing a familiar image and how it differs from the unfamiliar image. The filtered signal thus passed to a Recurrent Neural Network (RNN) based Long Short Term Memory (LSTM) model

Figure 3.2: Biosignalplux HUB used for connecting the sensors

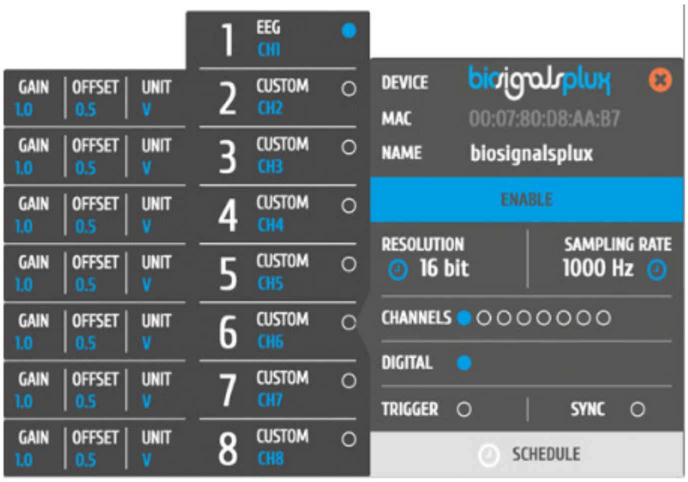


Figure 3.3: Biosignalplux Interfacing Software for the acquisition of data

for the anomaly detection. We gave the input as 128 features per batch, and the size of the input feature of the RNN is 32 and used 32 hidden units per layer with two hidden layers. Also, we introduced a 20% dropouts between the layers and used Adam as the optimizer. The recall, precision and f_1 score of the final output are calculated directly from the code, and the trend is shown in Fig. 3.5. The final accuracy given by the model was abysmal and it is of about 45%. We used 70% of the data for the training purpose and rest for the testing purpose.

The primary reason for the unfortunate result was because we only used a single channel data, and it is not sufficient for functional analysis. The individual electrode signal can't represent all the changes in the brain related to the visual stimuli we provided. This can be a significant reason for reduced classification accuracy. Also,

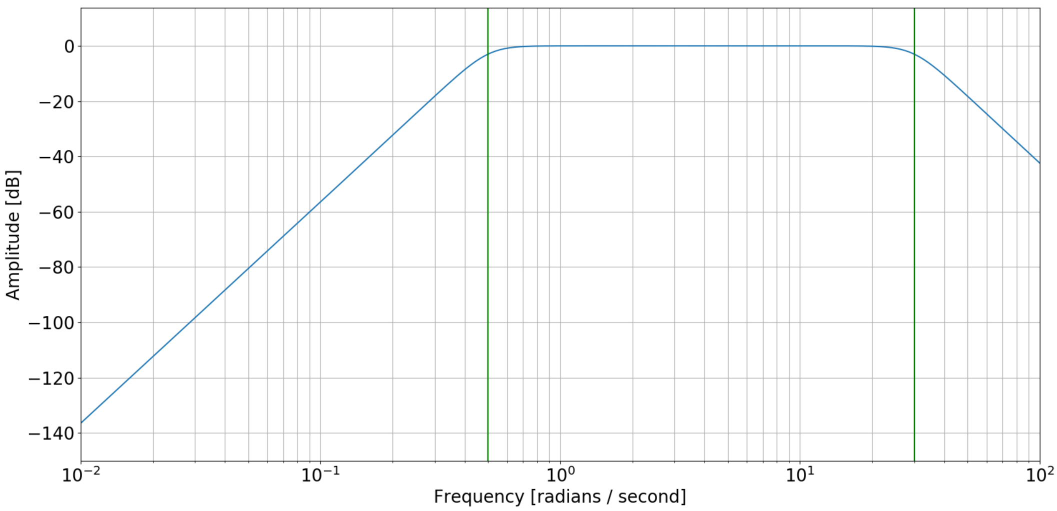


Figure 3.4: Frequency response of the 6^{th} order Butterworth bandpass filter. The green vertical line represents the cutoff frequencies - 0.5 Hz & 30 Hz

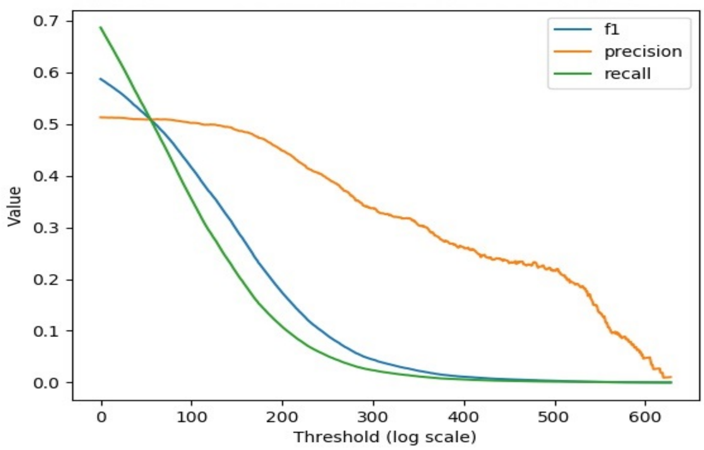


Figure 3.5: Final Evaluation matrix of the final model

the data is not sufficient for a deep learning tool to extract enough features for the classification purpose. The experiment shows the limitation of the used EEG signal acquiring device for the particular application which motivates us to choose a compatible device at low cost for this application. Thus we used our new equipment for the further stages of our project, and its detailed description is given in the coming chapters.

Chapter 4

Dataset Preparation

4.1 Overview

In this chapter, we will give a detailed knowledge of the dataset we prepared and used for the effective implementation of deception detection. The collected data get preprocessed later and used for the final classification.

4.2 Familiarity Detection - Dataset I

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.

4.2.1 Experimental Setup

For the collection of data, we chose ten 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 effect in the recorded signals. Since EEG have very less signal to noise ratio, we took care to minimize artifacts as maximum as possible. A two-step process completed data collection. In the first step, we collected data for training purpose, which was the training phase, and the second step of the process was the testing phase. In both phases, we have shown different visual stimuli to the subjects. The subject was asked to sit on a chair in a comforting manner, and the LCD monitor was placed on a distance of 65cm from the subjects. Thus they will get a clear vision of each stimulus. We maximum tried to make the room used for setting up the experiment was of noise free and also taken care of the overexposure of light.

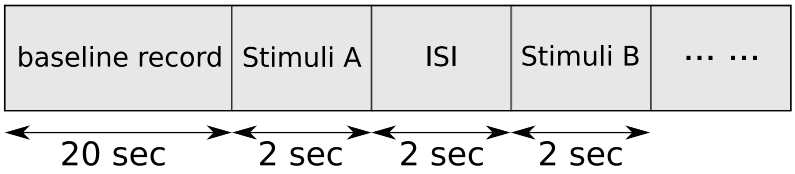


Figure 4.1: Timing Graph

We have two sets of images - familiar and unfamiliar - for the subjects. Each set consists of a total of nine images. In the familiar set, we used the photos of prominent personalities in different domain of the world, and why because we chose them, they are very familiar to every people. So the subjects can easily distinguish them. In unfamiliar set, we carefully chose nine photos of people who have no relation with the subjects each image of the dimension of 768*432. In the training phase, we first showed the set of familiar images to the subject, and after that, the set of unfamiliar images. There were 5 minutes relax time between two sets for each subject. EEG recording was done separately for two sets. After the training phase, we took the EEG data of subjects with testing phase images. In the testing phase, we randomly showed familiar and unfamiliar images and used a total of 18 images. Each image showed for the 2sec duration, and in between every image, there will be a 2sec Inter-Stimuli Interval time, where the subject got relaxed and got ready for the next image. The timing diagram is shown in Fig. 4.1. Both phases follow the same timing. First 20 seconds we used as the baseline signal, where the subjects were in a relaxed condition which used as a reference signal. We did three trials of the experiment and in each trial comprises a testing and training phase. In between each trial, there was a time gap of 20 minutes to make the subject relax and refresh. Finally, we took data from one trial with data having less noise interference.

4.2.2 Technical and Dataset Format Information

Each set in training phase run for a total duration of 56 seconds, and in the testing phase, it was for 94 seconds. We used eight electrodes 'OpenBCI Ultracortex Mark IV' EEG cap for recording the EEG data. The Fig. 4.2 shows the EEG cap and the electrode positions [45]. It uses eight electrodes with 10-20 International Electrode

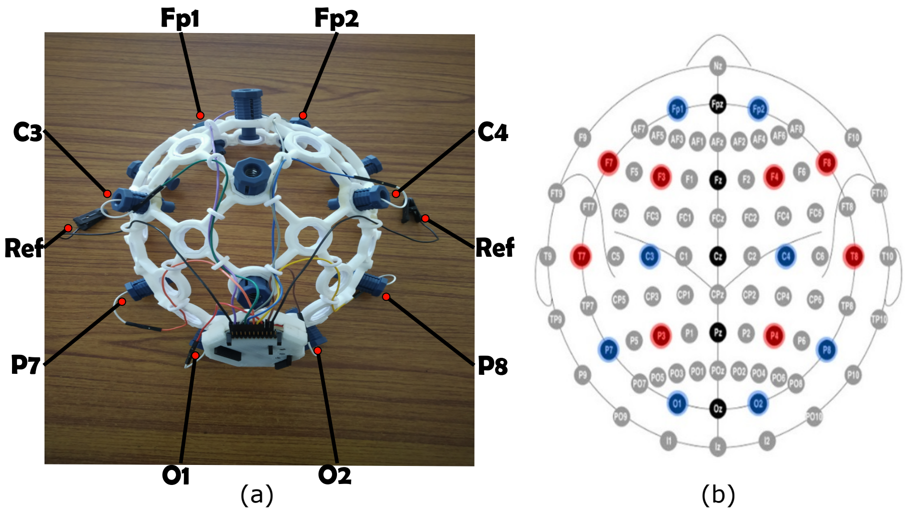


Figure 4.2: OpenBCI Ultracortex Mark IV used for the data collection. It is of 8 electrode type shown in left image and uses a 32 bit ADC for transferring the acquired signal to the PC with the help of serial wireless receiver connected to the computer.

System - Fp1, Fp2, C3, C4, P7, P8, O1, and O2. Also, have one reference electrode and one bias electrode that can connect to each ear lobules where the disturbance is very low. The cap is using ADS1299 32-bit ADC chip for recording the analog EEG voltage and convert it to digital EEG which can be visualized in OpenBCI GUI Fig. 4.3. The tools in GUI help to visualize the signal and have some simple signal pre-processing tools like applying notch filter, bandpass filters, provision for viewing the real-time FFT plots, etc., which helps to see the signal more clearly and can see even some changes concerning the stimuli. But these changes can't be saved. It has only the provision to store raw data. So we need to do all the pre-processing techniques from the initial step onwards. The data recorded by OpenBCI at a sampling rate of 256 Hz. For this particular experiment, we focussed on only four electrodes - P7, P8, O1, and O2. It is because these four electrode positions cover the visual cortex region of the brain, which showed in the related works section. Thus we can analyze how the visual region is responding to the familiar and unfamiliar images separately.

The data set contains recorded signals from the four electrodes saved in μV along with channel names and also the EEG cap have an incorporated accelerometer module. So the data also contains the data of head movement in X, Y, Z directions (in G). Along with this, it consists the timestamp and saves the sampling index with the data. We collected the real-time data of subjects in each CSV file, which was used for further analysis and classification. So for each subject, we have three files of data: two training data and one testing data.

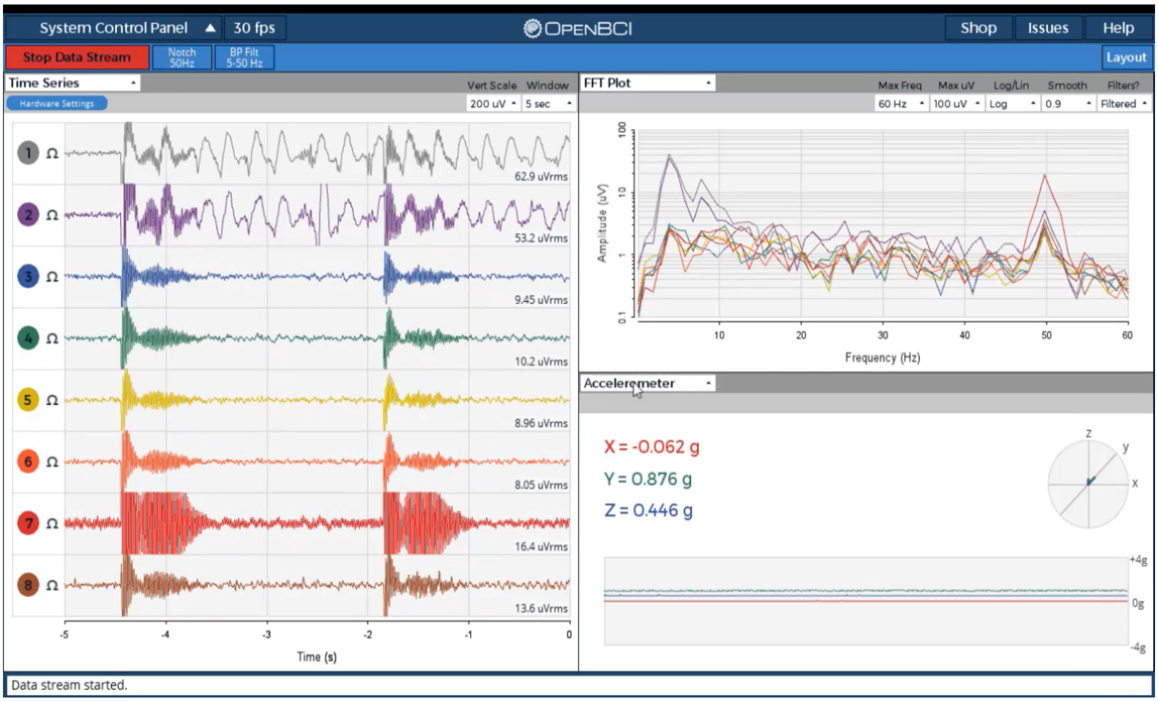


Figure 4.3: OpenBCI GUI used for the visualisation of the EEG signal recorded by the device. It has various signal processing tools inorder to see more artifact free signal.

4.3 Dataset for Deception Detection - Dataset II

Implementation of deception detector is the final target of our project. So we first designed an experiment which can suit better and replicate the original lie detection trials. Thus we designed visual based stimuli and exposed it to subjects to get the corresponding responses. Based on this, we used different models and techniques to detect whether the subject is telling a lie or not.

4.3.1 Experimental setup

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 14 subjects for the completion of this work. For all we named them from A to N. They have a normal or normal-to-corrected vision, and no subject has any records of any neurological disorders or mental illness. They were given the essential guidelines regarding the experiment beforehand and were instructed to reduce unnecessary facial expressions and body movements, which can decrease the overall effect of noise in the EEG signal. The visual stimuli were shown on a monitor which was placed almost 70cm from the subjects position, and they were asked to concentrate on the monitor while the stimuli were shown. The experiment was tried to conduct in the noise-free environment and made it isolate from other disturbances.

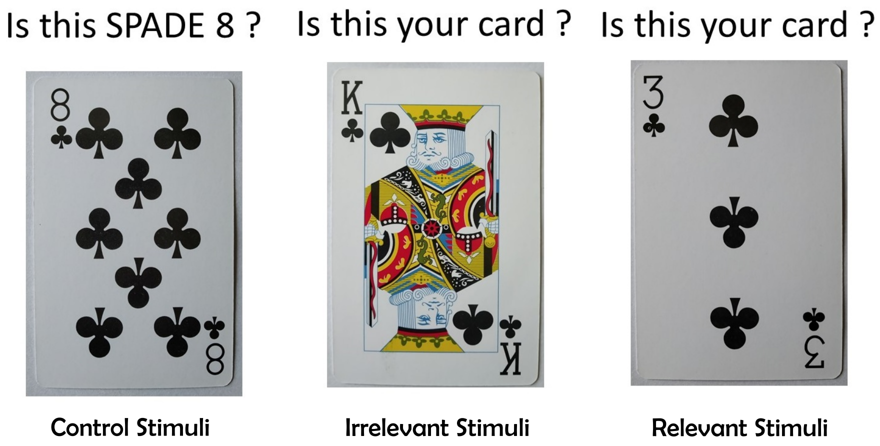


Figure 4.4: CQT based visual stimuli - Control, Relevant and Irrelevant stimuli - for deception detection.

Conventional CQT consist of 3 types of questions - control, relevant & irrelevant. Thus our main aim was to design this 3 type of questions as corresponding visual stimuli to the subjects. It is because brain signals always show considerable changes in the images or visual scenes. We used playing cards as our stimuli element, and we divided them into three groups, as mentioned. The three stimuli are shown in Fig. 4.4, which shows the three stimuli gave to the subject B. In Control stimuli, the subjects had the knowledge of all cards in the set of which can relate precisely to the questions based on the past of the convict in traditional CQT. The subject had to choose any two playing cards from a set of 10 cards, and those two cards acted as the relevant stimuli for the subject. Thus for all subjects, the relevant stimuli were different, which depended on their selection of the cards from the relevant set. This relevant visual stimulus accurately replicates the questions based on the particular crime that convict was trialing for the crime. Irrelevant stimuli acted as a disturbance in between the relevant and control stimuli for making a distraction in the subjects mind. So it is easy to catch when the subject tries to deceive. Here the subject had no prior knowledge on this stimuli. Among 14 subjects, seven subjects were told to tell an intentional lie (guilty group) while their card was shown and the remaining seven subjects were instructed to tell the truth to their relevant card stimuli (innocent group). For all stimuli, the subject should respond by saying either yes or no. Control stimuli were exposed first to each subject to get a better baseline signal which can use it to classify the deceive one from the relevant stimuli. All stimuli except control were shown to the subject three times, and randomly thus the subject cant predict the upcoming stimuli. The block diagram of the proposed model is shown in Fig. 4.5

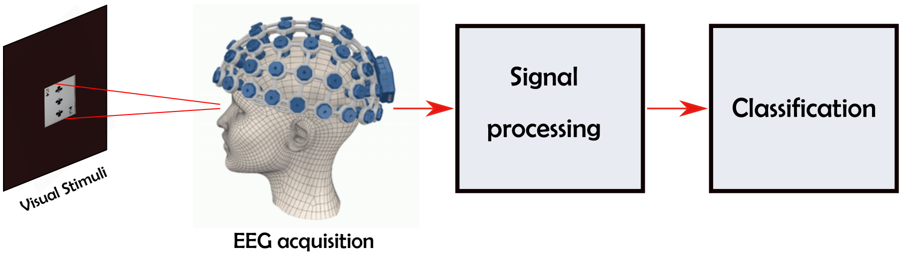


Figure 4.5: Block Diagram of the Proposed Deception Detector

4.3.2 Technical and Dataset Format Information

The same OpenBCI 'Ultracortex Mark IV' EEG cap was used for the data acquisition, and EEG data were recorded with a sampling rate of 256Hz. For this particular experiment, we used all eight electrodes of the OpenBCI EEG cap shown in Fig. 4.2. Each stimulus was shown for 1.5 seconds, and in between, there is 1 second rest time. The dataset is of a total duration of 172 seconds and saved in a CSV file format. The saved file contains the data of all the eight electrodes with channel names along with the timestamp, sample index, and the accelerometer readings.

Chapter 5

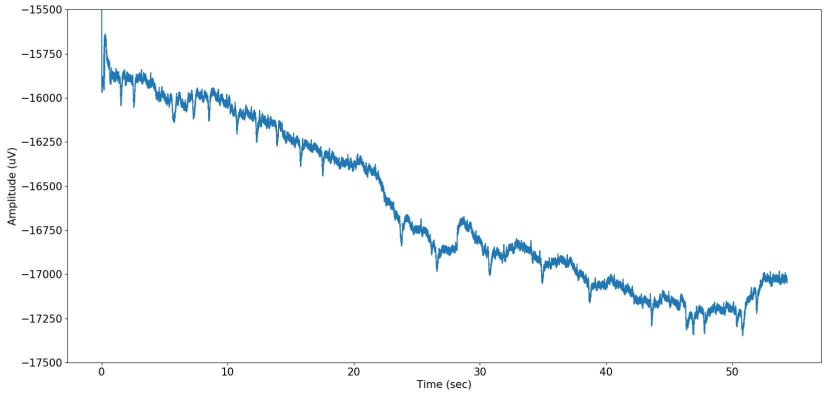
EEG Processing

5.1 Overview

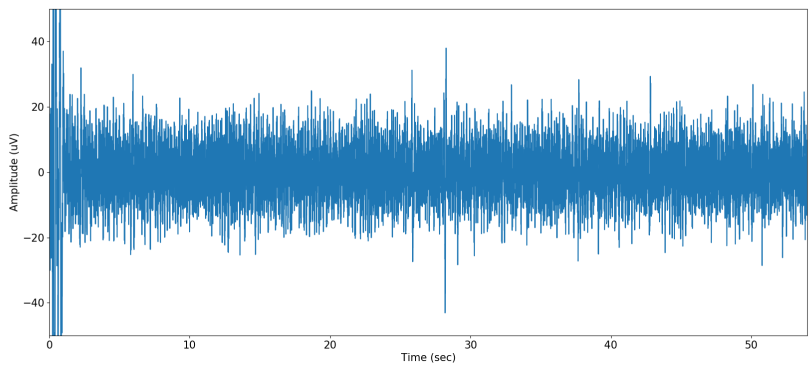
In this chapter, we will give a detailed knowledge of the pre-processing and further stage of EEG signal noise removal methods which can quickly help to obtain a better classification rate for the final deception detection model.

5.2 Filtering

Signal acquired by the EEG device always contain powerline noise of high frequency and other unwanted physiological artifacts due to the effect of eye movements (EOG), muscle movements (EMG), etc. Also, the recorded signal contained DC offset. It is due to sometimes in time series signals the mean amplitude of the signal will not be equal to zero, and this offsetting is known as DC offset or DC bias. Cause for the DC offset is of a fixed voltage offset which occurred while the analog signal is converted to digital by the Analog-to-Digital Converter(ADC). Also, we had done the baseline correction of the recorded EEG signal to remove the unwanted drifts/offset. All of these noises and drifts were mainly due to change in skin conductance or sweat. Baseline correction can be done either in single trials and after that, we can average the trials or can do the averaging first and later the correction is done in the average one and also these noises have to remove before starting the processing of EEG signal. In the baseline model, for removing the baseline drift and dc offset, we took the mean of the signal and subtracted from the whole signal. In Fig 5.1, the Fig. 5.1a shows the raw EEG signal recorded from Dataset I and the Fig. 5.1b shows the baseline corrected, and DC offset removed the EEG signal. Powerline noise from the recorded device affects the signal quality. The powerline signal was of frequency range 50-60 Hz. Since it is not exactly on any of this frequency, using of band-stop filter can't give considerable effect in reducing this noise. Thus we implemented a band-pass filter because always EEG is of the low-frequency signal. We were only focusing on the alpha and theta bands of recorded EEG in the baseline model (using dataset I). Thus we used a band-pass filter of the range 4-13 Hz. But no bandpass filter is ideal. Thus it will reject all the outer frequencies, but there is a region just outside the passband of the filter where those frequencies get attenuated which is called as roll off. We need to always keep this roll off very narrow. So by using a single bandpass, we can't achieve it. Therefore, we achieved it by using a combination of lowpass and highpass instead of a single bandpass.



(a) EEG signal before removing DC offset removal/baseline correction



(b) Baseline corrected EEG signal

Figure 5.1: EEG signal from Dataset I

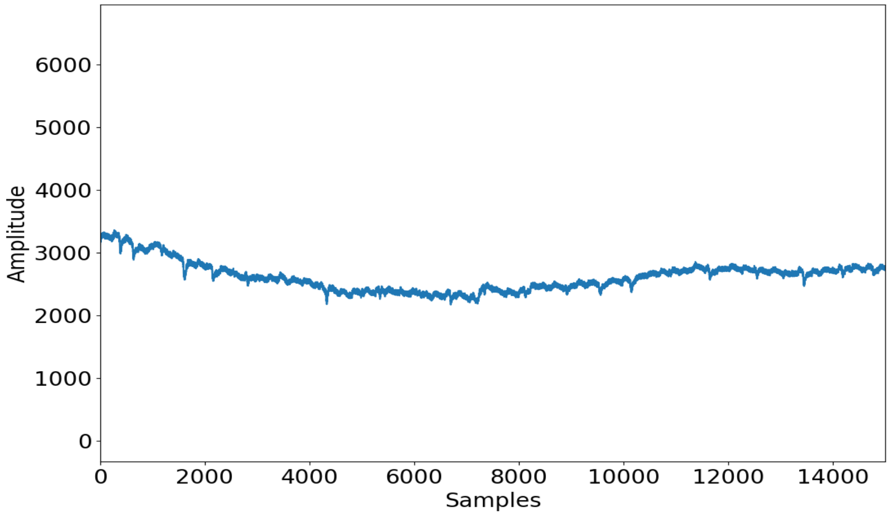
For the deception detection EEG data (from dataset II), we performed the detrending process of the signal to remove a trend over time. This technique helped us to understand the fluctuations in the data, which helped the deep learning model to do a better classification. This organized shift can occur because of the sensor drift. Detrending was done by using the first difference - $final\_value(t) = original\_data(t) - original\_data(t-1)$ - which is used related to the process ARIMA

(Autoregressive-Integrated-Moving-Average) [46]. Fig. 5.2 shows the EEG signal before and after detrending. After this process, we need to remove the powerline noise, which was in between the 50 - 60Hz range. Also, we are concentrating on the frequency range of 0.5 - 30 Hz. Thus we implemented a digital filter for getting the wanted region of the signal along with eliminating the noise of high frequency, powerline noise, etc. Digital filters had an important part in the filtering process of the signals like EEG, ECG at low frequency. Thus we used Finite Impulse Response(FIR) filters for the filtering operation. We used a 50^{th} order FIR Bandpass filter and its response is shown in Fig. 5.3 and Fig. 5.4 shows the step and impulse response of the implemented FIR bandpass filter. We used the Kaiser window for the smoothening of filter coefficients. Kaiser window is used because the change in length of the window doesnt affect the size of passband and stopband ripple size. The equation 5.2.1 gives the Kaiser window [47] [48] implemented where α was set to 5.2. Fig. 5.6 shows filtered EEG signal and the different brain wave components - Delta, Theta, Alpha, and Beta.

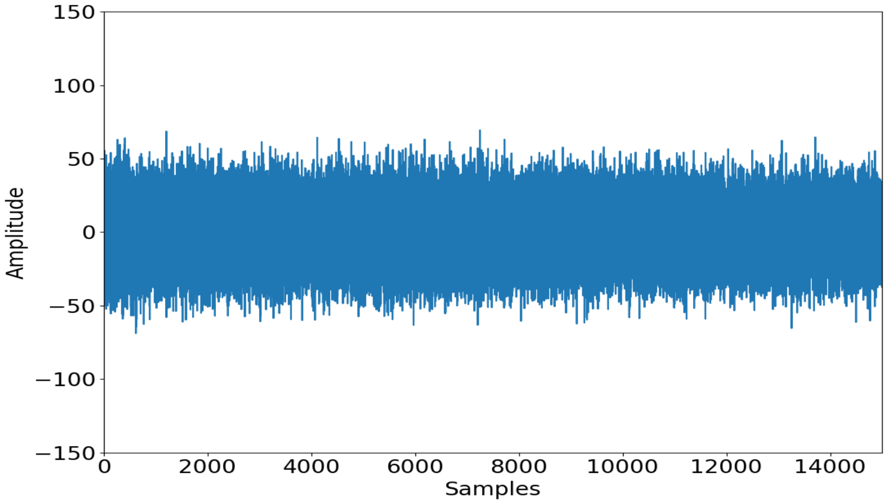
$$w_k(n) = \begin{cases} \frac{I_0\left[\alpha\sqrt{1-\left[\frac{2n}{N-1}\right]^2}\right]}{I_0(\alpha)} & \text{for } |n| \leqslant \frac{N-1}{2} \\ 0 & \text{otherwise} \end{cases} \tag{5.2.1}$$

5.3 Independent Component Analysis

Independent Component Analysis (ICA) was used to remove the artifacts present in the filtered signal. ICA is very different from Principal Component Analysis (PCA) because PCA is based on uncorrelated components, but ICA is on statistical independence. Always there were difficulties for the proper representation of multivariate data like EEG until Independent Component Analysis (ICA) came. Finding the direct representation of non-gaussian data to convert it into statistically independent components, that will helps the fast computation and conceptual simplicity. ICA is a type of blind source separation method which can be used for better artifact removal from signals like EEG, ECG, etc. The main function of ICA is to introduce different measures of non-gaussianity [49]. It is the statistical method of uncovering the hidden information (based on the application) in some signals or set of some random variables. ICA generates a model in which the variables are some linear combination of the unknown variables. We take the assumption that these variables would be nongaussian and also independent mutually. ICA is trying to reduce the mutual information and maximize the non-gaussianity. The base equation for ICA



(a) EEG signal from Fp2 electrode before detrending



(b) EEG signal from Fp2 electrode after detrending

Figure 5.2: EEG signal before and after removing the unwanted trend (Dataset II)

is starting with the equation 5.3.1 [50], where X is a random vector with elements $= [X_1, X_2, .., X_n]^T$ or we can say it as the mixed matrix/ mixed signal and S is the matrix of independent source signals $= [S_1, S_2, ..S_n]^T$. Our final target is to find the S matrix using the equation 5.3.2. After getting the A matrix, we can calculate the W matrix, which is the inverse of the A.

$$X = AS \tag{5.3.1}$$

$$S = WX \tag{5.3.2}$$

For familiarity detection, we were using the EEG signal from the four electrodes,

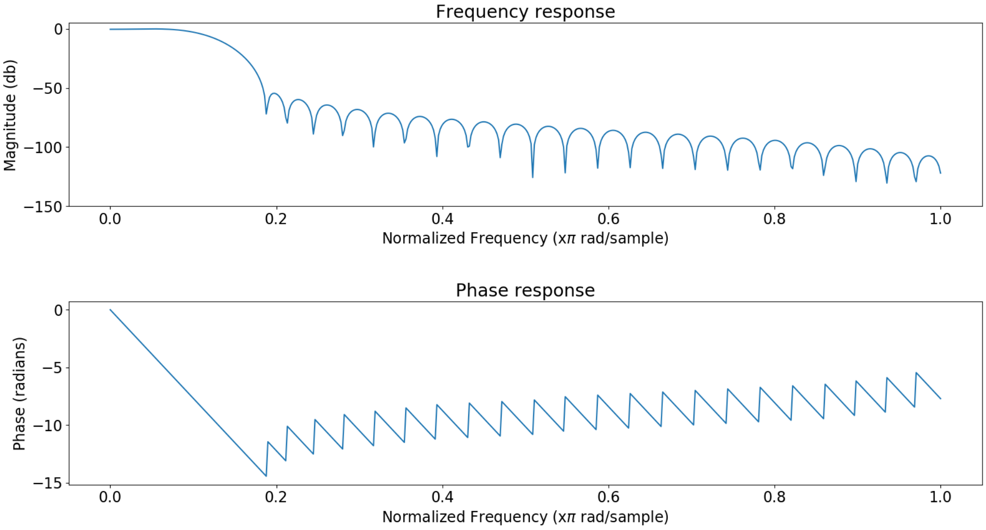


Figure 5.3: Response of the FIR bandpass filter used

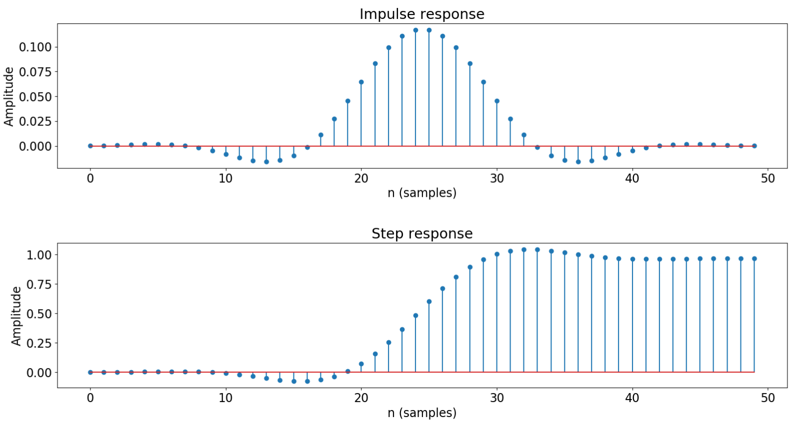


Figure 5.4: Impulse and Step response of the FIR Bandpass Filter

as mentioned in the previous chapter. We did the ICA of this signal and got four mutually independent components, as shown in Fig. 5.7 and the raw signal in Fig. 5.5. For deception detection, we used all the eight electrode signals, and after doing the ICA, the components are shown in Fig. 5.8. Out of the eight independent components by analyzing the signal, we chose six components from it for the further classification process.

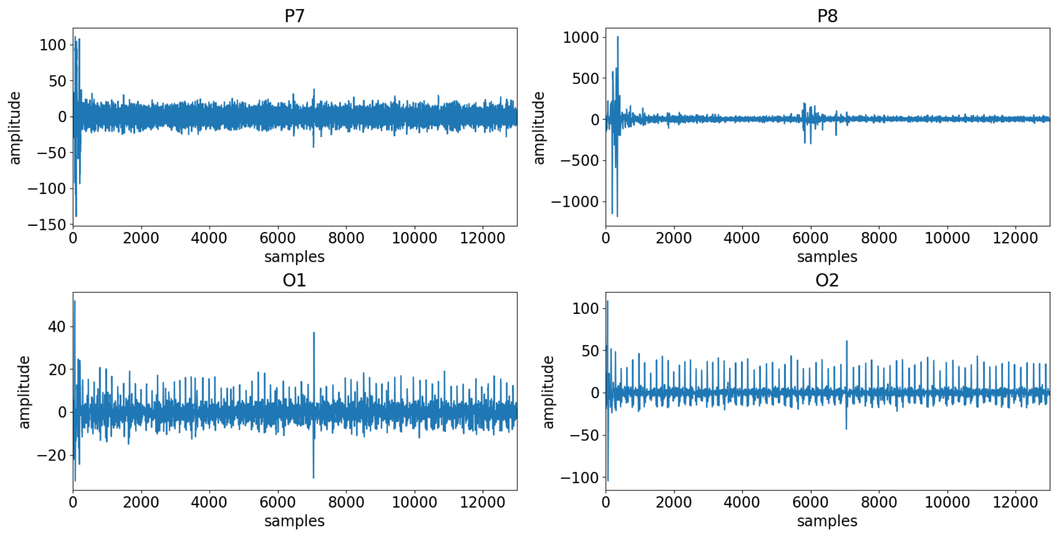


Figure 5.5: Raw EEG signal from the four electrodes - P7, P8, O1, O2 - for familiarity detection

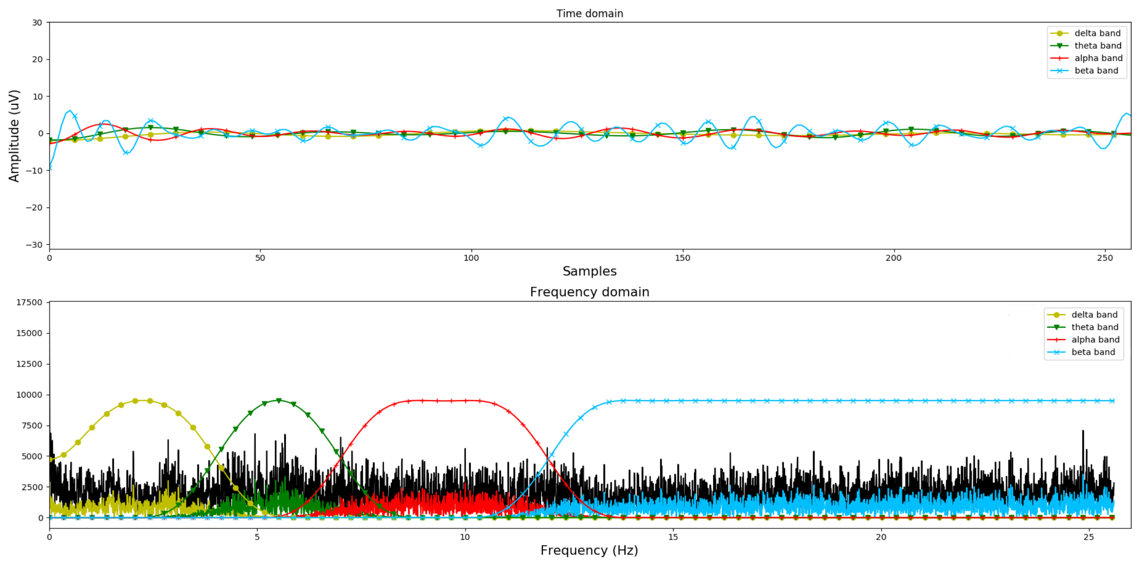


Figure 5.6: EEG Component Signals: The filtered EEG signal is in the range of 0.5Hz-30Hz. The diagram shows the plot of brain waves in both the time domain and the frequency domain separately - Delta waves(0.5 to 4Hz), Theta waves(4 to 8Hz), Alpha waves(8 to 12Hz) and Beta waves (12 to 30Hz). The yellow, green, the red and blue line in the frequency plot represents the amplitude of the filters used for getting each wave and for each filter the outside signal portions were rejected

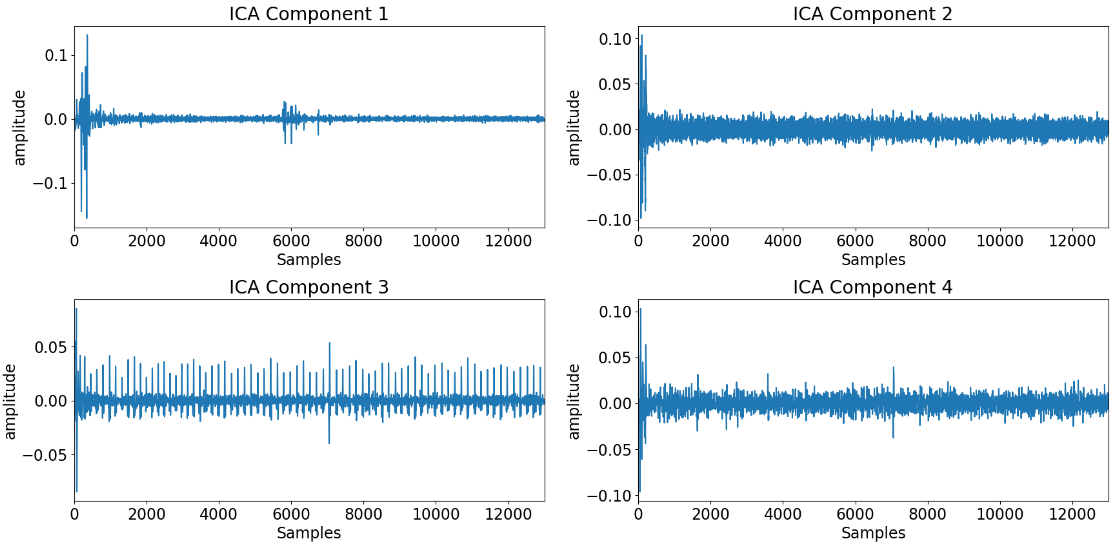


Figure 5.7: ICA components of the Familiarity detection system

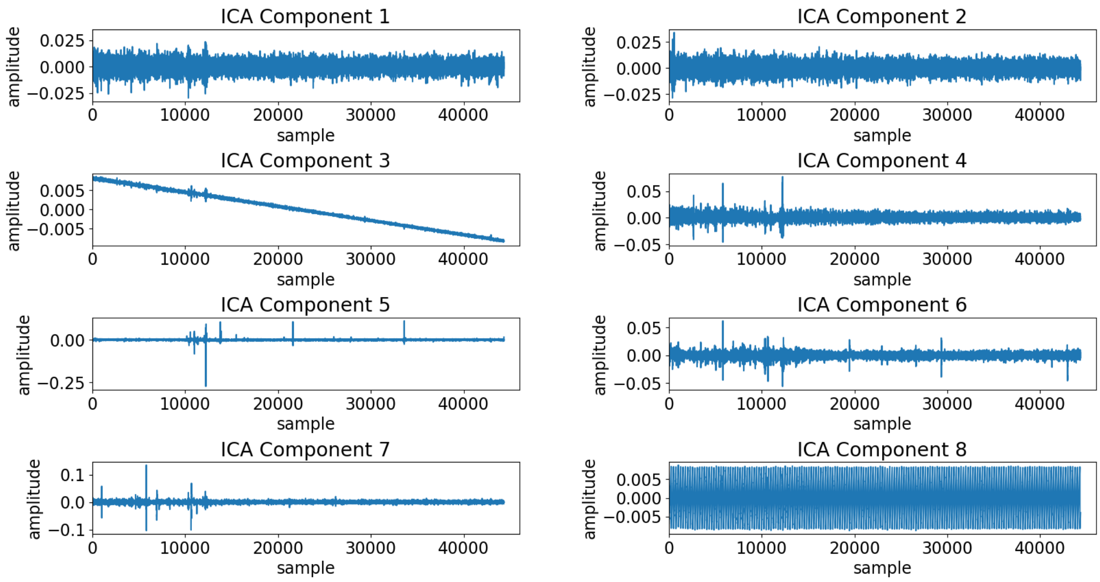


Figure 5.8: ICA components of deception detection experiment signals

Chapter 6

Classification

6.1 Overview

In this chapter, we give a detailed knowledge regarding the different classification techniques used for the familiarity recognition and our final deception detection. Also, we showed how each model varies in its properties and its architecture.

6.2 Baseline Model

The task of the baseline model is to classify the EEG signal based on the familiar and unfamiliar image stimuli. There was some research carried out regarding the familiarity detection and one that mentioned in related works section done by [21] used ERPs recorded from the subjects while showing different images (unfamiliar faces, familiar faces, subject's faces) and the authors used traditional statistical analysis to classify the effect of this given stimuli. While the work did in [1], which was our reference work used traditional machine learning techniques for the classification of familiar and unfamiliar image stimuli based EEG signals. The author extracted various time-frequency domain features. State Vector Machine (SVM) was used by the author to classify the features to finally conclude whether the corresponding signal related to familiar or unfamiliar images. Traditional machine learning algorithms deal with very limitations. One of the problems of the machine learning algorithms are most of them are very open to significant errors, and it is tough to correct those errors because of the complexity in the algorithms. We were aimed to introduce the deep learning techniques over the traditional machine learning to decrease the complexity in feature extraction.

We first tried with a simple multi-perceptron network (MLP) with 128 input neurons and single neuron as the output because we have to classify the output to only two classes - familiar or unfamiliar. 128 represents to samples in 0.5 seconds. The MLP consists of four hidden layers with neurons 64, 32, 16, and eight, respectively.

The implemented MLP is shown in Fig. 6.1. Then we tried with an autoencoder model for the classification. Autoencoder networks are used for reducing the unwanted artifacts/noises inside the given input with the help of non-linear feature extraction. The network will try to reconstruct the original input signal by retaining only the prominent features of the input. The implemented autoencoder network structure is shown in Table 7.1. In this autoencoder network, we have all the independent components of ICA, i.e., four. Both encoder and decoder have three hidden layers of neurons, and we store each 128 chunk data output from the decoder output and give it to a single neuron for the classification. Rectified Linear Unit was the activation used for the particular classification along with Root Mean Squared Logarithmic Error (RMSLE) as the loss function. We labeled the data as 0 for familiar stimuli signal and 1 for unfamiliar image stimuli signal - these are the two classes used for the classification.

Layer	I/0	Input	Output
Encoder			
fc_1	4/36	Processed data	fc1_o
fc_2	36/18	fc1_o	fc2_o
fc_3	18/9	fc2_o	fc3_o
Decoder			
fc_4	9/9	fc3_o	fc4_o
fc_5	9/18	fc4_o	fc5_o
fc_6	18/36	fc5_o	fc6_o
fc_7	36/1	fc6_o	fc7_o
relu	-	fc7_o	cfd_out

Table 6.1: Network architecture of the Autoencoder for familiarity detection

6.3 Deception Detection Model

As we mentioned in the earlier section, our focus was mainly ineffective classification of the recorded EEG using the deep learning methods. Modeling of deception detection model was our final target, where we implemented different models for getting a good classification result. After removing the artifacts using ICA, we fed the data to different classifier models to find whether the subject is telling a lie or not. We tried to classify the input into three - irrelevant classes, the non-taken card in the relevant set and take the card in the relevant set. And from this, we resolved to detect which cards were accepted by the subject and whether he/she belongs to the innocent or

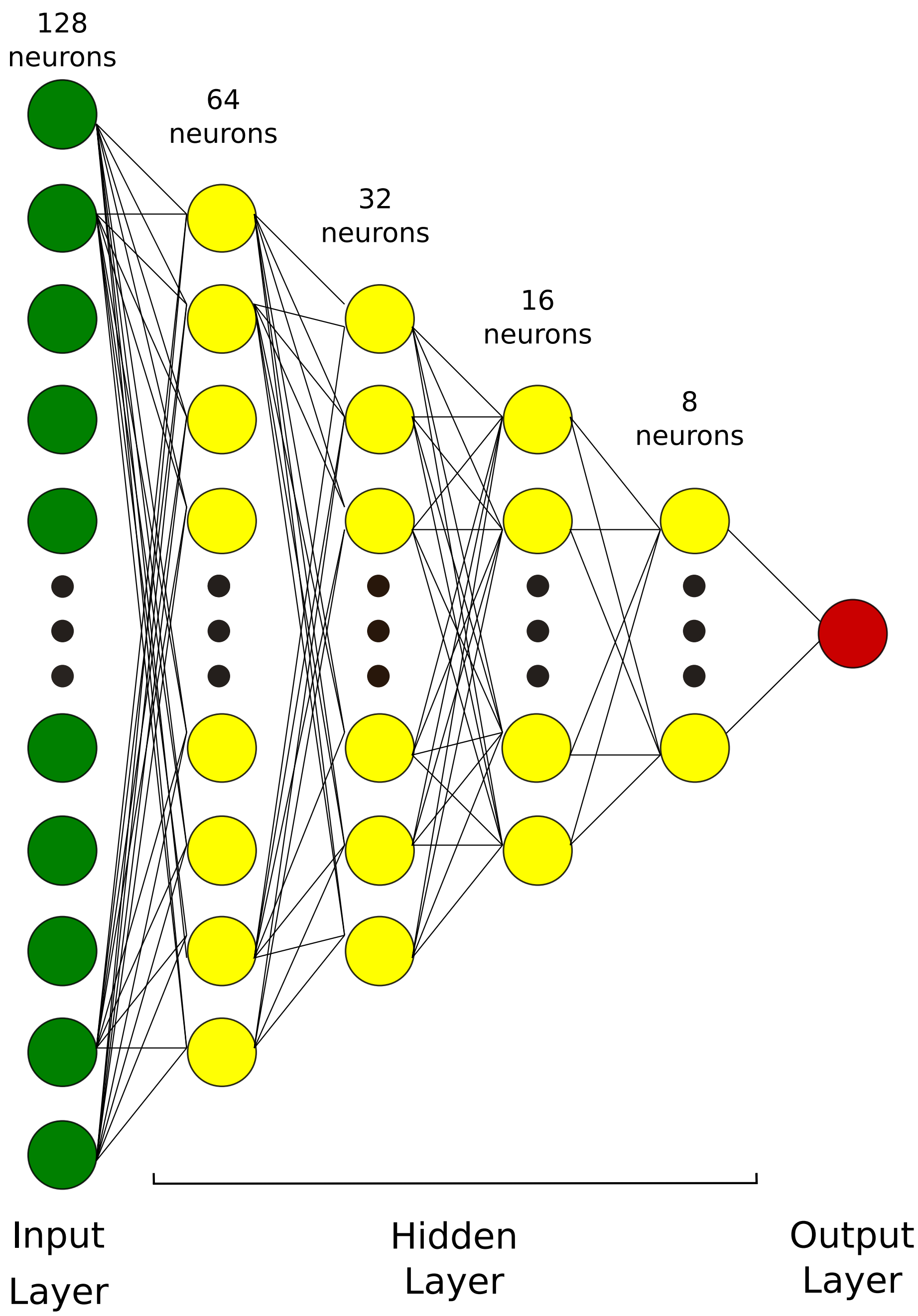


Figure 6.1: Multi-Layer Perceptron network used for familiarity classification

guilty group. The initial model we tried was the simple MLP model as the same one (in Fig. 6.1) implemented for the baseline model with some changes in the hidden layer neurons. The first hidden layer have 72 neurons; the second one has 36 neurons, and the output layer consists of 3 neurons. Then we implemented an Autoencoder network with the structure shown in Table 7.2. The autoencoder network took six inputs samples and after the decoder network a chunk of 128 samples saved in a fully connected layer and tried to classify whether the subject was told a lie or not.

Then we implemented a vanilla Long Short Term Memory (LSTM) network, which is the type of Recurrent Neural Network (RNN). The input layer comprises six neurons where we fed processed data. We used LSTM cell vanilla architecture is shown in Fig. 6.2. It consists of 3 gates, which are the input gate, forget gate, and an output gate. It has a cell state which is the central part of the LSTM cell. All the equations related to gate and cell state is mentioned in equations 6.3.2 - 6.3.6 [51]. Equation 6.3.1 take the inputs and previous output which gives the ability that what to forget or remember by the network with the help of a Sigmoid activation function, where b_f is the bias and W_f is the weight vector. New input along with the candidate layer output ($\tilde{C}_t$) and add this to the previous cell state(C_{t-1}). Then the cell state will be updated using the C_{t-1} and $\tilde{C}_t$. Finally, the cell will give the new output(o_t) and passing it through a *tanh* activation layer, thus decides the final output.

Layer	I/0	Input	Output
Encoder			
fc_1	6/36	input ICA data	fc1_o
fc_2	36/18	fc1_o	fc2_o
fc_3	18/9	fc2_o	fc3_o
Decoder			
fc_4	9/9	fc3_o	fc4_o
fc_5	9/18	fc4_o	fc5_o
fc_6	18/36	fc5_o	fc6_o

Table 6.2: Network architecture of the Autoencoder for deception detection

The main advantage of using LSTM over an RNN is its ability for handling long dependencies. A combination of Autoencoder - LSTM network also implemented for a better detection accuracy rate. A stateful LSTM network model was also used for the classification purpose, which is shown in Fig. 6.3. LSTMs are sometimes unreliable for longer sequences. At this time we can try by using stateful LSTMs. Comparing to the stateless model, the stateful model always transfers all the states of the previous batch to the next batch [52] which gave an advantage to the stateful model over stateless.LSTMs are sometimes unreliable for longer sequences. At this time we can try by using stateful LSTMs. Comparing to the stateless model, the stateful model always transfers all the states of the previous batch to the next batch [52] which gave an advantage to the stateful model over stateless. From the complete data (i.e., dataset II), we used 70% of the data from each subject used for the training purpose of the models implemented and the rest 30% was used for the testing purpose. We tested data of each subject separately using each model.

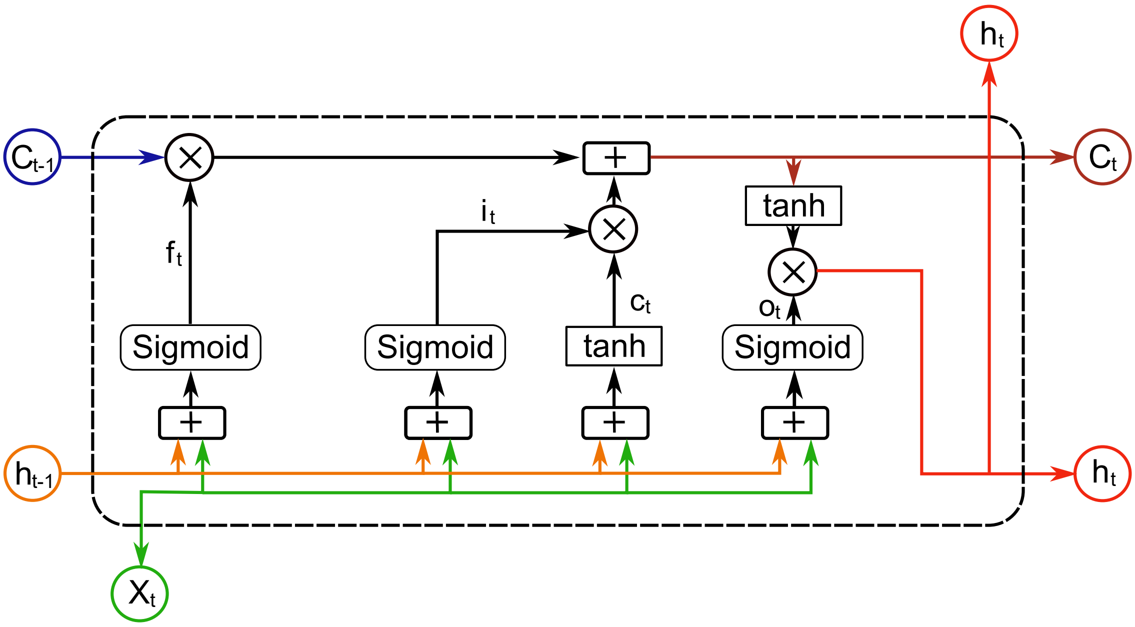


Figure 6.2: LSTM Cell Architecture

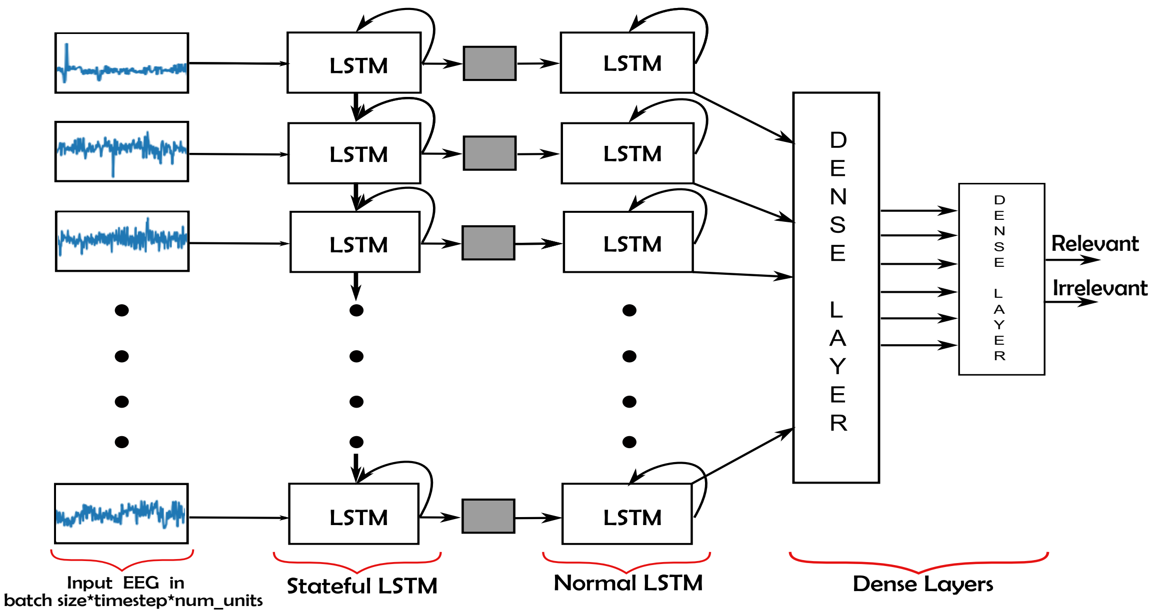


Figure 6.3: Implemented Stateful LSTM Model

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{6.3.1}$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{6.3.2}$$

$$\tilde{C}_t = tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{6.3.3}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C} \tag{6.3.4}$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{6.3.5}$$

$$h_t = o_t * tanh(C_t) \tag{6.3.6}$$

Chapter 7

Results and Discussions

7.1 Overview

In this chapter, we discussed the analysis done on the final classification results and how successfully we implemented the deception detection model. Also, we will discuss the advantages of the applied models/techniques over traditional lie detection techniques.

7.2 Analysis on Familiarity Detection Model

EEG signal analysis for the human face recognition was started from the late 90s of the twentieth century. Our works were based on the methods proposed in [1]. The author used SVM based classification using the time-frequency features extracted from the recorded EEG signal while showing different familiar and unfamiliar image stimuli to the subjects chosen. We also conducted the same experiment with ten subjects that we chose. We aimed to introduce effective deep learning techniques for the efficient classification of the signal data, which can pave a way to use the implemented methods further for deception detection. We mentioned the models implemented in the last chapter - the MLP and Autoencoder network. The confusion matrix of the MLP is shown in Fig 7.1a - we can see that out of 180 images MLP classified 95 images accurately with an accuracy rate of approx 52%. Comparing to the reference model in [1] the classification accuracy of MLP got relatively less. Moving on to the Autoencoder network, the model tried to find the relevant features using the encoder, and with those features, the decoder reconstructs the signal. We used a single neuron for the final classification, as shown in the network architecture from the last chapter. The 128 samples points which replicate 0.5-sec data were stored in the last fully connected layer with 128 neurons, and after that, we go for the classification output neuron.

Autoencoder network gave a better result compared to the reference model [1]. The

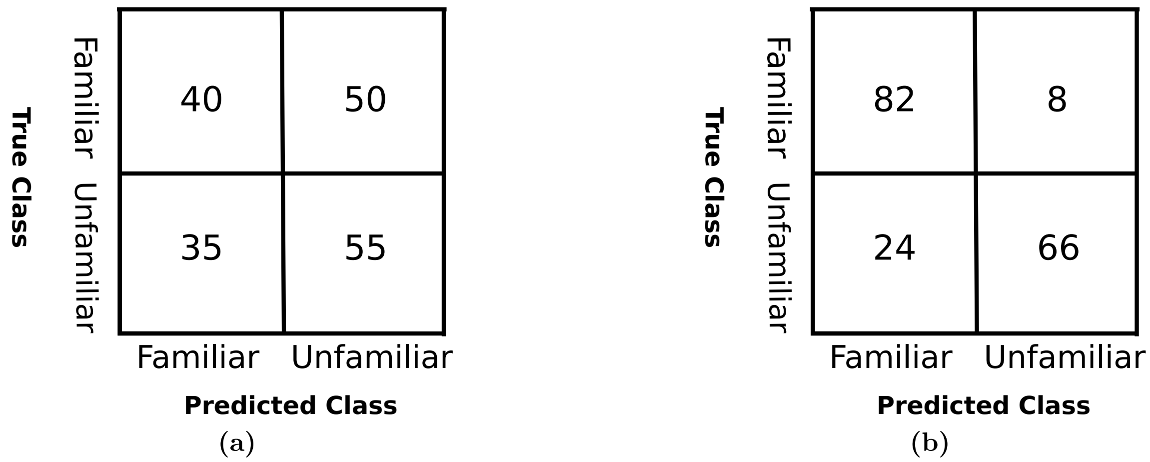


Figure 7.1: Confusion Matrix of MLP model and Autoencoder model

Method	**No.of Subjects**	**Peak Value** (familiar,unfamiliar)	**Peak-Peak Value** (familiar, unfamiliar)	**Band Power** (familiar,unfamiliar)	**Classifier Accuracy**
SVM Method [1]	7	17.1762, 17.7488	1.1472, 1.1250	6.25E-06, 6.10E-06	70.71%
Proposed Method [32]	10	15.839, 16.396	4.0016, 3.5521	1.68E-03, 1.2038E-03	**82.21%**

Table 7.1: Comparison of Proposed and Existing method

Model	**Precision(%)**	**Recall(%)**	f_1 **score(%)**	**Accuracy Rate(%)**
MLP	40.44	53.33	45.99	52.78
Autoencoder	91.11	77.35	83.66	82.21

Table 7.2: Evaluation Matrix Parameter comparison of MLP and Autoencoder models for Familiarity detection.

confusion matrix of the autoencoder network is shown in Fig. 7.1a, where 148 images accurately classified from 10 subjects data. Also, for the representation of the familiar and unfamiliar stimuli signal, we extracted some time-frequency domain features like

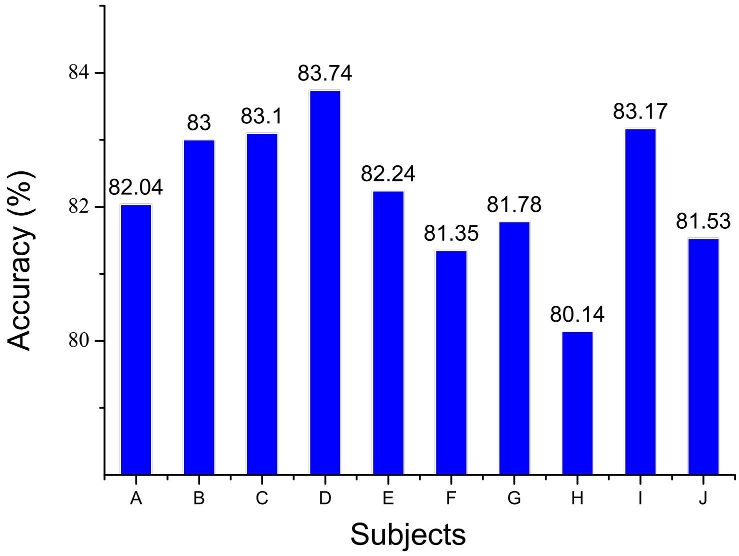


Figure 7.2: Subject wise Classification Accuracy

- Peak to Peak, Mean, and the Band power. This feature varies with the effect of N170 and P200 potentials in the recorded data. Both these features changed with the familiarity effects of the image to the subject. The table 7.1 shows the comparison with the extracted features and the reference model along with the accuracy [1]. The proposed model get an accuracy of 82.21%, which is far better than the accuracy rate of the SVM method in reference work, which got only 70.71%, where Fig. 7.2 shows the subject wise accuracy classification. Also, we calculated the precision, recall, and f-score of the implemented models shown in Table 7.2. The equations related to the evaluation matrix were given in equations 7.2.1, 7.2.2 & 7.2.3. The features extracted for the classification in the reference model was not a generalized one. If we perform the same experiment once it is not sure that the same combinations of features will give the same or more classification accuracy using SVM. But our proposed model [32] is completely independent of manual feature extraction where the autoencoder model itself take the needed features from the signal and give the classification accuracy. Thus we showed how deep learning model is dominated over the traditional machine learning methods for the classification of familiarity detection. We used this model as a base for developing the final deception detection model.

$$Precision \ = \ \frac{True\ Positives}{True\ Positives\ +\ False\ Positives} \tag{7.2.1}$$

$$Recall \ = \ \frac{True\ Positives}{True\ Positives\ +\ False\ Negatives} \tag{7.2.2}$$

$$F1\ Score = 2 * \frac{Precision\ *\ Recall}{Precision\ +\ Recall} \tag{7.2.3}$$

7.3 Analysis of Deception Detector

Implementation of the deception detector is the final target of our work. For this, we made a baseline model used for familiarity detection. We are only focussing on providing visual stimuli based CQT instead of conventional CQT which was using along with polygraph test. For getting better classification results, we performed experiments using different deep learning models. We also focussed in best signal processing techniques because EEG has a very less signal to noise ratio. Most of the noises were in high frequency; therefore, we used the bandpass filter to extract the useful information included in EEG and pre-processed the data using detrending and reference subtraction for removing the DC offset. Wavelet approach is not much optimal, which led us to use the FIR filters. For eliminating the artifacts inside the filtered signals, we did ICA and removed the artifact components. The ICA components are shown in Fig. 5.8 were extracted from the dataset II and we got eight components. But while analyzing the components, we can see that some of them are pure noise. So we used six independent components from the ICA components for the final classification.

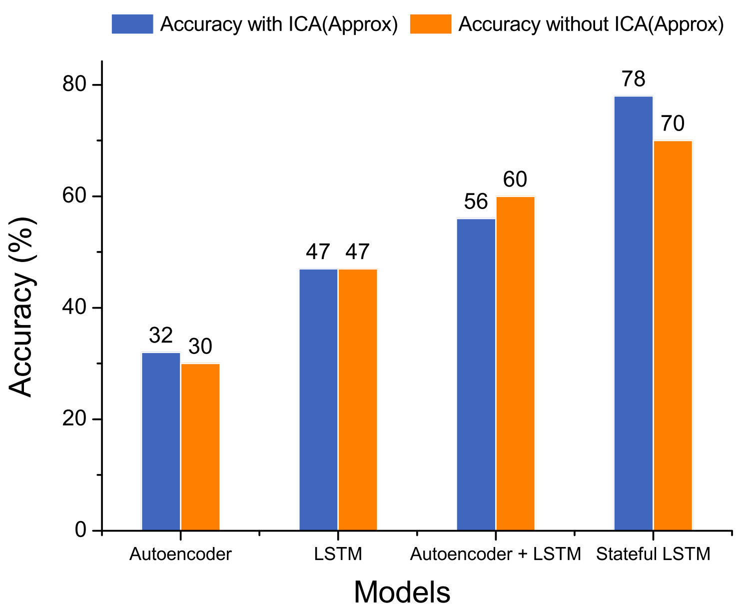


Figure 7.3: Accuracy Comparison between the implemented models with and without doing ICA

We implemented five deep learning model for the better analysis of deception from the recorded signal from the dataset II - MLP, Autoencoder, LSTM, LSTM + Autoencoder & Stateful LSTM. The architecture of all the models was discussed in the previous chapter. All the models show different accuracy rate towards the dataset and shows in Fig. 7.3. Also, the figure shows how the effect of processing the signal with ICA on the EEG signal. Autoencoder network gave abysmal results. We used autoencoders for dimensionality reduction, and we used a Dense layer as an output layer with three neurons. One reason for the unfortunate result is because autoencoder eliminates some critical information from the input data. The implemented autoencoder model gave an accuracy of about 32%. Stateless LSTM and the combination of autoencoder-LSTM gave accuracy only of 47% and 56% respectively. Comparing all models, stateful LSTM model is providing the best result of almost 78% with using ICA processed components as the input. But by directly feeding the filtered signal, the model gave only a rate of accuracy 70%, which is a comparatively significant difference. Using stateful LSTM data accuracy level of some subjects went to more than 85%. As we tested the data of each subject separately, the table 7.3 shows the testing accuracy obtained for each subject. .

Subject ID	**Accuracy**	**Classification Result**
A	0.7264	Detected
B	0.5728	Undetected
C	0.745	Detected
D	0.6753	Undetected
E	0.76	Detected
F	0.91	Detected
G	0.84	Detected
H	0.702	Undetected
I	0.8771	Detected
J	0.6534	Undetected
K	0.8022	Detected
L	0.8754	Detected
M	0.8937	Detected
N	0.7943	Detected

Table 7.3: Subject wise classification result using Stateful LSTM

In the LSTM layer, we used 6 LSTM cell units in first LSTM layer, with Relu as the activation layer. Usually, in statefulLSTM, the inputs are checked on batches and output of one batch is given to the other and the output from this is given to a normal LSTM further given to a Dense layer of 6 neurons and then to 2 neurons Dense layer from where we got the final classified output as either relevant or irrelevant. Whole data is divided to n batches as $A = A_1, A_2, ..., A_n$,where A is the complete data and each batch is of the size $timestep * numberofunits$. i.e. for the stateful LSTM the input shape was $batchsize * timestep * numberofunits$. Dense layers used softmax as the activation function and Mean Squared Error as the loss function. Stateful property of LSTM networks can handle large sequential data, which leads to the usage of it in applications like audio, natural language, etc. [53]. The stateful LSTM network can retain the memory from the previous batch, which paved the way to give better efficiency for the proposed deception detection method. For all the implemented models classification of the data without doing ICA didn't show an excellent result. All the models and the proposed model was also showing poor test accuracy. Using of ICA can efficiently remove internal artifacts in the filtered EEG that make the models to extract the required features easily. Since the filtered EEG is of the small frequency range, the remaining artifacts also in the same frequency range only. So the proposed model failed to make better classification results using data without doing ICA. As in [30] experiments shown the effectiveness of ICA for artifact removal from EEG signal.

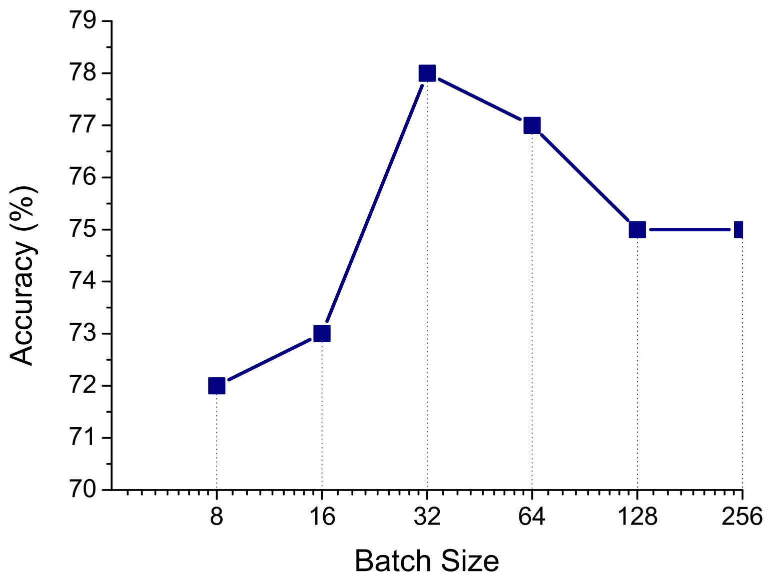


Figure 7.4: Accuracy Variation with Batch Size

Our proposed model gave better accuracy than the Stacked Autoencoder Model (SAE) proposed in [42], which provided only 69.2%. The classification accuracy of the SAE was very less compared to our proposed model. But SAE was used for detection of P300 waves in [42] where our proposed model using neuro-signal for the discovery of the lie. Also, the paper tried to compare SAE with other machine learning

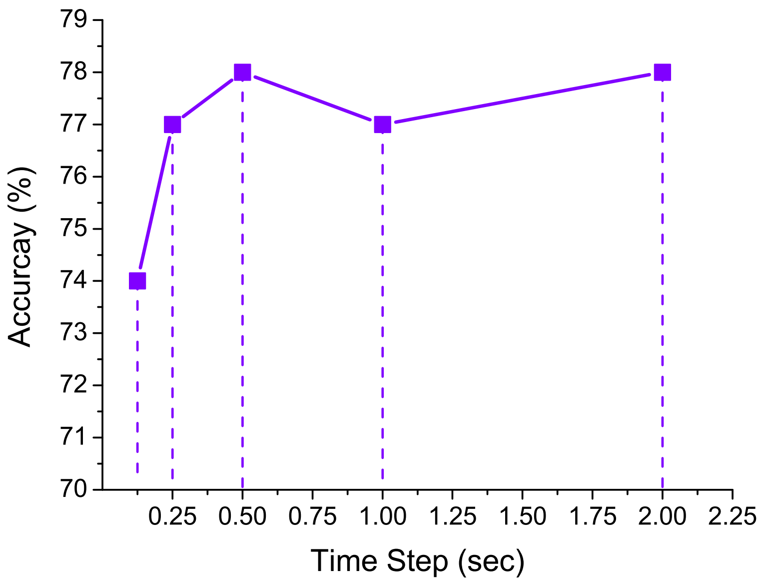


Figure 7.5: Influence of Timestep Variation in Input

techniques and regular multi-layer perceptron models where SAE dominated in classification accuracy. The work [54] for the detection of the lie by P300 classification done by using Sate Vector Machine (SVM) algorithm but the accuracy obtained is less (70.83%) and also requires different features for the classification, where our proposed algorithm can work better. The features used in [54] for the SVM model can't make as generalized features for better classification. This drawback can be eliminated by using our proposed model where it doesn't require any feature extraction step; the stateful LSTM model tries to find the useful features by its own. No need to rely on manual feature extraction techniques for the classification of long duration EEG signals.

The proposed model uses a timestep data as the input. Since the output given by the OpenBCI cap was of 256Hz sampling, we tried different sampling rate as input to the model. For the input with a time step of about 0.125 sec, the model gave almost good accuracy, as shown in Fig. 7.4. When we changed the timesteps of the input from 0.125sec to 2sec, the accuracy increased up to 78%(approx). Using fewer data as one of the prime concern, we chose 0.5sec (128 samples) as the optimized time step. We also analyzed the variation of the accuracy of classification concerning the change in the batch size of the input to our proposed model - stateful LSTM. Fig. 7.5 shows the accuracy variation of different batch size from 8 to 256. The batch size can govern the number of predictions that can make by the model. Data fed with a batch size of 32 gave the most optimized result comparing to other batch sizes. Batch size has a great effect on learning data automatically by the model. Reason for this good accuracy for the model in 32 batch size data is because the model Based on this, the input was provided with the dimension 32*128*6(optimized input dimension) which gave the best result. This study shows that how well we did the deception detection using deep learning models.

Chapter 8

Conclusion and Future Scope

8.1 Conclusion

In this works, we present visual stimuli based CQT along with an improved version of a new deception detection model using stateful LSTM for the classification of EEG.

Our main objective is to introduce a new mode of CQT which can easily expose to the convict and to use 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 used as a baseline model, and 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, where we use an autoencoder network. Our proposed model gave a accuracy rate of 82.21% [32] than the reference model in [1] which got only 70.71%.

We designed the visual based CQT and provided as stimuli to the subjects on an experiment which is very similar to the real-life criminal cases. The acquired EEG signals were processed using the FIR filters and ICA process. Using the selected ICA 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 real-time data EEG recording helps to get the instantaneous changes in the brain signal concerning the stimulus. This always helps to conduct an efficient criminal trialing and to conclude whether the convict is telling a lie or not. 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.

8.2 Future Scope

- 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.

Publications

Conference:

1. **Abhijith V Nair**, Kodidasu Murali Kumar, and Jimson Mathew, "An improved approach for EEG signal classification using Autoencoder," **8^{th}** ***International Symposium on Embedded Computing and System Design (ISED)***, 2018.

Journal:

1. **Abhijith V Nair**, Alwyn Mathew, Jimson Mathew, and A P Vinod "Deception Detection using Stateful Long Short Term Memory Model," ***Biomedical Signal Processing and Control Journal***, **(Under review)**

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