EEG-based Authentication with Machine Learning

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Abstract

Authentication is a vital part of security in computer systems. As an alternative for biometrics, EEG-based authentication presents advantages compared to other biological characteristics. Brainwaves are hard to replicate, and different mental tasks produce different brainwaves. This study investigates the aspects of performance and time-invariance of EEG-based authentication. Two sets of experiments are done to record EEG of different individuals. We implement the use of machine learning such as SVM and deep neural network to classify EEG of subjects. The comparison between EEG features, electrodes position and mental task are made. We achieve 97% classification accuracy using three types of features from 4 electrodes. To test time-invariance, we record EEG in 2 different sessions. Data from earlier session is used as machine learning training data and data from later session are classified. We found out that classification accuracy decreases over time, and passive tasks performs better than active tasks.

Keywords:

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Finally I want to thank other researchers who pursue the EEG and biometrics field. Because of their achievements and publications, I can obtain enough knowledge to start this research and finally finishing this thesis.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1. Background

Authentication is a vital part of computer system security to prevent unauthorized access from non-legitimate users. It is a process of matching the credentials provided by a potential user to the credentials stored in the system. If the credentials match then the user is granted access to the system. Without authentication process, determining if a user is who he/she claims to be is not possible and there are risks of malicious attackers accessing the system. When the system is compromised, harm may come to the system or other user's assets.

Nowadays, the most prevalent authentication system used is the password-based authentication. The potential user presents a secret phrase to the system to prove his/her identity. The secret phrase should be only known to that user. However, in practice this is not always the case. Other people may find out about the password and impersonate the user. Also, the strength of a password is determined by its length and complexity so users need to remember difficult phrases to use a strong password.

An alternative to the password-based authentication is biometric authentication. It uses the unique biological characteristics of each person to identify and recognize a user. So it is difficult for malicious attackers to reproduce the biological characteristics of another user. Examples of biometric authentication are fingerprint authentication which uses fingerprint patterns and iris recognition which uses the patterns of iris in human eyes. In this research, another type of biometric that uses brainwave patterns called EEG-based authentication is investigated.

Electroencephalogram (EEG) or brainwave is the electrical activity of the brain. EEG-based authentication has advantages compared to other biometrics. Human brainwave is changeable by performing different mental tasks, different from fingerprints and iris that are permanent. During authentication process, users need to be conscious and active because the brain needs to perform a mental task. This prevents unauthorized access using other people brain. Meanwhile in other biometrics, attackers might use the biological characteristics of an unconscious user to break into the system.

With the advantages that EEG-based authentication brings, it could become the next popular authentication method. However, there are still a lot of uncertainties for this method to be implemented in the real life applications. In this research, various issues of EEG-based authentication are investigated such as the factors that impact the identification accuracy and whether the passing of time affects the performance.

1.2. Research Objective

The main objective of this research is to apply Electroencephalogram (EEG) as a base for an authentication system. To achieve this objective, it needs to fulfill the requirements of a strong authentication system including a high identification accuracy and resistance against time changes.

Firstly, as an authentication system is vital in the security of a computer system, it needs to perform with high accuracy either in accepting the correct credentials and rejecting the wrong credentials. There are unique patterns within the EEG of different people but some brainwave patterns are also similar when people are performing certain activities. Because of this, suitable factors and conditions of the authentication process needs to be found. Factors include EEG features, mental task and electrode positions of the EEG recording device. As this research uses machine learning as the classification method, the suitable machine learning type and settings are also tested.

An authentication system also needs the resistance against time. In real life practice, authentication is used to gain access to a system, so it is repeated often and in long period of time. The performance must not decrease over time so that users can still use the system even if the user doesn’t use the system after a while. A time resistant authentication also reduces the frequency of the need for users to re-update their credentials. In this thesis, the tasks and machine learning used for the classification process are compared to find out which one produces the best performance.

By investigating EEG-based authentication in terms of the different requirements for a good authentication, we hope to achieve the research objective of implementing EEG as a base for an authentication system.

1.3. Structure of Thesis

This thesis is consisted of 4 chapters. The scope of each chapter is:

1. Chapter 1 Introduction

   This chapter introduces the issue of current authentication system and EEG-based authentication as an alternative. Also written is the objective of this research.

2. Chapter 2 Review of Related Literature and Studies

   Literatures about EEG, authentication and machine learning are presented in this chapter. Some studies done by other researches about EEG-based Authentication are also included.

3. Chapter 3 Experiments and Results

   Methodology of two set of experiments (improving classification accuracy and about time-invariance) are written in this chapter. Also includes details of data processing, EEG features classification, results and discussion.

4. Chapter 4 Conclusion and Future Works

   The conclusion of this research and improvements to include in future works are written in this chapter.

Chapter 2

Review of Related Literature and Studies

2.1. Electroencephalogram

2.1.1. Introduction to EEG

Electroencephalogram, or shortened EEG, is the electrical activity of the human brain. Human nervous system, including the brain, is consisted of nerve cells called neurons. These neurons transmit signals to other neurons using electrical current. The voltage fluctuations resulting from the electrical current are then measured by recording electrodes. EEG is mostly used for medical purposes but it has the potential to be used in other areas, such as in computer security area.

EEG patterns form waves that are sinusoidal. They are classified into several categories based on their frequency bandwidth. Each category of waves appears when humans are doing different activities. There are multiple versions of classifications but five types of waves are commonly present. They are:

- Delta waves
  They are waves with frequency between 0.5 Hz to 4 Hz. They have low frequency but high amplitude. Delta waves can be observed when a person is sleeping, particularly on the third stage of NREM (Non-rapid eye movement sleep).
- Theta waves
  They are waves with frequency between 5 Hz to 7 Hz. They are found in humans when they are drowsy, meditating and sleeping.

- Alpha waves

  They are waves with frequency between 8 Hz to 15 Hz. They appear during relaxation, and more can be observed when eyes are closed.

- Beta waves

  They are waves with frequency between 16 Hz to 31 Hz. They are low amplitude waves and can commonly be observed while humans are awake. Beta waves are involved during active thinking, concentration and arousal states.

- Gamma waves

  They are waves with frequency higher than 32 Hz. They are involved in cognitive functioning such as sight and sound perception and higher processing tasks. It has been found that people with learning disabilities has lower gamma wave occurrences than average.

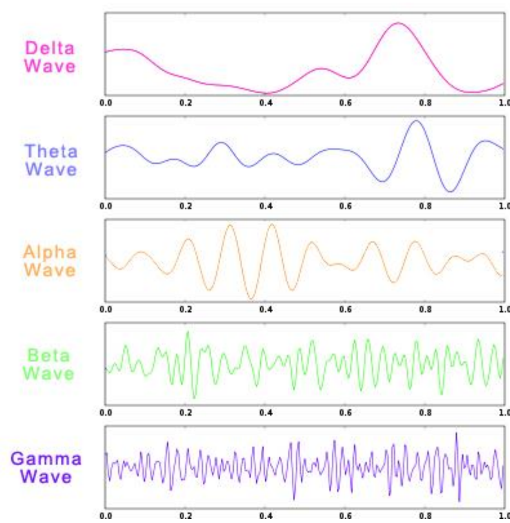

Figure 2.1 Classifications of Brainwaves [4]

2.1.2. Practical Uses of EEG

In medical and clinical field, EEG has the function of checking brain condition of patients. An example is to check the alertness, coma, or brain death status of a patient. For an injured patient, EEG can be used to investigate and locate damaged brain areas, as abnormal EEG readings shows that there is a problem near the measured area. EEG can also be used to monitor certain procedures, such as measuring the depth of anesthesia during operations. The calmness of the brainwave shows the relaxed condition of patients. Other uses include investigating seizures and epilepsies and test drug use for convulsive effects.

The use of EEG in medical field is driven by the advantages compared to other brain function monitoring methods. EEG measuring devices generally have lower costs and size, so it can be deployed in more hospitals and certain clinical rooms. It also has higher sampling rate, with clinical settings commonly use between 250 and 2,000 Hz sampling rate. However there are also devices that can record with above 20,000 Hz sampling rate. EEG also doesn’t cause side effects to patients such as claustrophobia.

Another common field for EEG implementation is BCI (Brain-Computer Interface). EEG is used as a media for communication between users and computer devices, providing an interface that enables users to control machines by using their brainwaves. Other than facilitating the input of commands to computer software and games, EEG BCI has been implemented in remote controlled toys. An example is Puzzlebox Orbit, a remote controlled helicopter that lets users fly it by concentrating and relaxing their minds. [7]

Figure 2.2 EEG-controlled Helicopter Toy [7]

EEG is also used in research fields, for studying medicinal methods, human psychology and physiology. In multiple studies, EEG is used as a measure to check the effects of various things, such as medicine, commercial products, music and others.

2.1.3. EEG Measurement

EEG can be measured by using EEG recording devices. EEG devices have electrodes which measures the electrical activity around them. The electrodes can be attached to several points on the head and they measure the EEG near the attached points. For medical purposes, the device is commonly shaped as a cap with electrodes attached around it. For BCI, the EEG recording device is usually more gadget-like.

Based on the measuring method, there are 2 categories of EEG recordings. They are invasive and non-invasive EEG recordings.

1. Invasive EEG recording

   In invasive EEG recording, the electrodes are directly implanted to the surface or the depth of the brain. This means that surgery is required for the electrodes placement onto the brain. Even though most modern EEG devices don't require direct contact with the brain, some epilepsy surgeries still require invasive EEG.
2. Non-invasive EEG recording

   Rather than directly attaching electrodes to the brain, non-invasive EEG attaches electrodes to head surface. However there are more noises compared to invasive EEG recordings so filtering and signal processing are required. Most modern EEG applications use wearable non-invasive EEG devices for practicality.

For non-invasive EEG, the electrodes of EEG measuring device can be attached to any part of the head surface, but there exist an international standard for electrode placement. The accepted international standard is named 10-20 system. It contains 21 points and names according to different lobes of the brain near the electrodes. For example the F alphabet is used for the electrodes near the frontal lobe, O for occipital lobe and T for temporal lobe. However as EEG devices with more electrodes appear, more detailed placement system became needed, and extensions to the 10-20 system appeared. They are the 10-10 system and the 10-5 system.

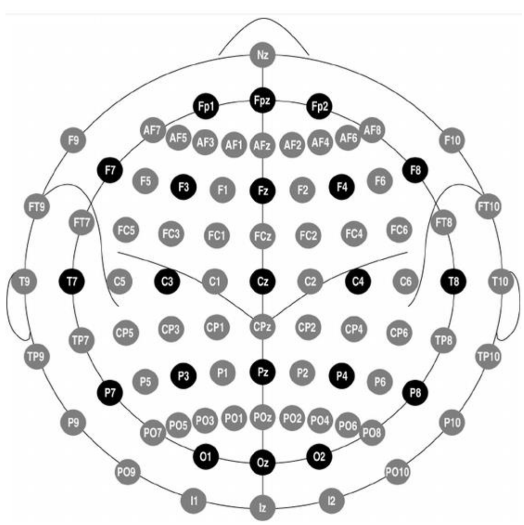

Figure 2.3 Electrode Positions and Labels in 10-10 System [8]

2.1.4. EEG Features

EEG Features are characteristics of an EEG recording. By processing a segment of an EEG recording, several EEG features can be extracted, or observed. Simplest features including statistical properties such as mean, standard deviation, variance, maximum and minimum amplitude. Other than those, there are more advanced EEG features that have been proposed, such as power spectral density and autoregression coefficients. In this research, 3 EEG features are used for classifying the experiment data. Those three features are discrete fourier transform (DFT), zero crossing rate (ZCR) and Hjorth parameters.

1. Discrete Fourier Transform (DFT)

   DFT is the frequency domain representation of a time domain signal. It can be obtained by applying Fast Fourier Transform (FFT) to a segment of EEG recording. When raw EEG is recorded, the recording consists of signals of multiple frequencies that are mixed together. FFT is a way of separating those signals into their respective frequencies. DFT is computed with the FFT formula:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N} \qquad k = 0, \dots, N-1.$$

   FFT converts the raw EEG segments into frequency domain, and the resulted DFT can be categorized into the brainwave categories. The DFT of frequencies 1 Hz to 4 Hz can be classified as delta wave, DFT of 5 Hz to 7 Hz as theta wave, DFT of 8 Hz to 15 Hz as alpha wave, and so on. However noises from electronic devices can be present in the EEG recording so frequencies of the electricity needs to be confirmed so that the DFT is not used for processing.

2. Zero Crossing Rate (ZCR)

   ZCR is the rate of positive-negative sign changes along a signal. In a sinusoidal signal, the signal goes up and down on the time axis and passes the zero sign. When this occur, the sign changes from positive to negative, or from negative to positive. The rate of this occurrence is calculated from an EEG segment and the result is ZCR. The formula for calculating ZCR is:

$$zcr = \frac{1}{T-1} \sum_{t=1}^{T-1} 1_{\mathbb{R}_{<0}}(s_t s_{t-1})$$

Where s is a signal of size T and $1_{\mathbb{R}_{<0}}$ is an indicator function

Before calculating ZCR using the formula, in real practice the zero axis is not always known. However since it is known that EEG signals are sinusoidal, the zero axis is the mean of the signal. To find out the mean as close as possible to the zero axis, large sample of data are needed so that the true mean can be found. Then the calculated mean can be used as a zero axis. ZCR is a signal feature that is used commonly for sound processing. Examples of use are for speech recognition and music processing to classify music instruments.

3. Hjorth Parameters

Hjorth parameters are statistical properties of time domain based signal. This feature is quite commonly used for EEG processing. There are 3 kinds of parameters: Activity, Mobility and Complexity.

a) Activity

This parameter represents the power of a signal. Can be calculated with the function:

$$Activity = var(y(t))$$

Where $(y(t))$ represents the signal

b) Mobility

This parameter represents the mean frequency of a signal. Can be calculated with the formula:

$$Mobility = \sqrt{\frac{var(\frac{dy(t)}{dt})}{var(y(t))}}$$

Where $(y(t))$ represents the signal

c) Complexity

This parameter represents the change in frequency. Can be calculated with the formula:

$$Complexity = \frac{Mobility(\frac{dy(t)}{dt})}{Mobility(y(t))}$$

Where $(y(t))$ represents the signal

2.2. Authentication

2.2.1. Introduction to Authentication

Authentication is a part of computer security which has the role of determining access to a computer system. Authentication process is the verification of potential user's identity using the credential provided by the user. The provided credential is matched with the list of credentials stored in a computer system's database to see which user the credential belongs to. If the matched user's identity is the same as the potential user then the potential user is granted access to the system. If not then the potential user's access is denied.

It is important to have strong authentication to prevent any potential attacks to the computer system. In the modern society, people use machines in their daily lives, to store work projects, personal information and other intellectual properties. With most of those machines connected to some kind of a computer network, another computer could potentially gain access to them. Without a strong authentication, an attacker may gain access and take valuable information from others. This doesn't apply only for network communications, but also for physical access to a device. If anyone can gain access to a device, when the physical device is lost or stolen, then the information stored in that device is at risk.

In authentication process, a potential user presents his/her credential to the system. There are three kinds of credentials and they are commonly called as factors. They are: what you know, what you have, and what you are.

1. What you know

   The idea of this factor is that only the potential user knows a certain knowledge that no other person knows. The authentication process uses this idea to distinguish the potential user from individuals by checking if he/she knows the secret knowledge. A simple example is the password protocol, or PIN number protocol. There are also authentication processes that need the user to present a pattern of button clicks or a certain ordering.

2. What you have

   This factor uses the idea that only the user is in possession of a certain object that cannot be replicated and should not be stolen by other people. An example of this factor is electronic ID cards.

In some offices, employees need to present a card to scanners to open a door or access a machine. This method is suitable for authenticating physical access, but is needs another factor so it can be used for network authentication.

3. What you are

   The next factor uses the idea that we should identify the potential user as a person him/herself. The method is by using biological characteristics of that person. As humans, we have unique biological traits, and that can be used as base to differentiate different individuals.

Beside the three single factors, some authentication systems combine one or more factors to make stronger authentication. A two-factor authentication (2FA) utilizes two or more factors. The most common application is the combination of what you know and what you have. An example is using your ATM card to withdraw money in ATM machines. You need to have your card and you need to know the secret PIN to access your account. By combining two factors, the disadvantages of one of them can be reduced. Rather than using the normal long and random password, short password such as 4 digit PIN number can be used. Even if an attacker found out about the PIN, without the card he/she can't access the system.

Currently the most used method of authentication is password authentication. The reason is because it is simple, inexpensive and convenient to deploy on systems. Only preparation in the software side to match and store usernames and passwords are needed to use this authentication. Since it can be applied for client server architecture, websites and network systems use this authentication form.

However there are also disadvantages. The strength of a password is determined by three things. They are the length, character set and randomness. The longer the password, the stronger it is since attackers need to guess more characters. Character set is the possible characters that can be used to make a password. Larger character set increases the number of possible combinations of passwords. The randomness of password is the chance of a character being used next to a certain character. For example, using phrases from English words is less random than using a phrase that is randomly generated and has no meaning. Attackers can guess passwords by using words from dictionary; this is called a dictionary attack. The more random a password is, the stronger it is.

The disadvantages of using password authentication come from the effort to fulfill the requirements of making a strong password. A strong password is long and random. As humans, it is difficult for us to remember such difficult phrases so we tend to use phrases which are easy to remember. But usually they are weak passwords. With so many simple passwords, attackers can guess them and break into computer systems easily. Some people also write down their password but if another person managed to take a look at it then the password is compromised and attacker may gain access to the system.

2.2.2. Biometrics System

Different from password authentication, biometric authentication uses the unique biological traits of individuals to check if a potential user is who he/she claimed to be. It uses the "what you are" factor. In biometrics, the credentials are taken from the body parts of users. Since the biological trait itself is the credential, users doesn't need to put any effort to remember a password or bringing an ID card. Some examples of biometrics are:

- Retinal scan: utilizes the pattern of retina of human eyes
- Fingerprint scan: utilizes the arch, loop and whorl patterns of fingerprints
- Handprint scan: scans the whole hand patterns
- Voice recognition: uses the different voice characteristics of humans as a base
- Vein matching: analyzes the blood vessel patterns visible from the surface of skin

But not all traits can be used for an authentication system. There are some requirements that need to be fulfilled so that it can be applied for real-world applications. There are seven measures for assessment which are:

1. Universality: the trait should be a biological characteristic that is possessed by most people so that it can be used by all of users of a system.
2. Uniqueness: the trait should be unique and different from one individual to another so during authentication each person can be distinguished.
3. Permanence: the trait should not change much over time. Even after a long time has passed, the trait should not vary from the start so the trait can be used for long period authentication.
4. Measurability: the trait should be easy to record, or extract. The process of authentication must not take a long time because it is done every time users want to access a system.
5. Performance: the trait should produce high accuracy, high processing speed, and utilizes effective technology choices.

6. Acceptability: the trait should be accepted by the population. It means that users should be willing for their biological trait to be recorded and used by the system.
7. Circumvention: a trait should be hard to be replicated. If it is easy to replicate or forged, then many attackers could exploit this weakness and the authentication produced is not a strong one.

Brainwaves of individuals have unique patterns between each other so EEG has the potential to be used as a biological trait for biometric authentication. When talking about the factors of authentication, EEG-based authentication is classified into the “what you are” factor. However the brainwaves of humans change when they are doing different activities or thinking about different things. If these tasks generate different brainwave patterns that are still unique between people, then mental tasks can also be counted as a factor, which is “what you know”. By combining a secret mental task to replace a passphrase and using the biometric EEG, EEG-based authentication has the potential to be used as a two-factor authentication in one system.

Other than the multi-factor property, EEG-based authentication also has other advantages compared to other biometrics. Brainwave itself is a way of communication between nerve cells, so as long as a human is alive, EEG can always be used. However with biometric such as fingerprints, injuries may make the patterns unclear, and there are people who can’t use fingerprints because of disabilities. EEG-based authentication also needs the user to perform a mental task. So if the user is unconscious, malicious people can’t use his/her EEG to access the system. With fingerprints, accessing a system still can be done using an unconscious person’s finger. EEG is also hard to be stolen and forged, unlike fingerprints.

However the current state of EEG-based authentication is not ready to be applied in real life practice, unlike the fingerprints identification and other biometrics. The performance and permanence aspect are still on research and various researches have tried to propose different kind of systems. Another disadvantage is that current EEG measuring devices are also prone to noises. Regarding measuring time and ease of use, EEG measuring devices with many electrodes needs time and effort to be attached correctly to the head surface. But easy to wear EEG devices with fewer electrodes also exist.

2.3. Machine Learning

2.3.1. Introduction to Machine Learning

Machine learning is a field of computer science that provides computers the ability to learn by itself without explicit programming. The algorithms of machine learning create models which learn from data and also make predictions. Machine learning can be applied to solve various problems such as classification, regression, clustering and more. In this research, machine learning is applied to classify the EEG features of subjects.

Based on the learning process, machine learning can be categorized into three types:

- Supervised learning: the learning data are given labels that explicitly state which categories they belong to. In this case, the model is taught to learn patterns from an already classified data so it can classify new data.
- Unsupervised Learning: the learning data are unclassified and don't have labels attached on them. The model is asked to find patterns and classify the data by itself.
- Reinforced Learning: the model interacts with dynamic environment and always updates to improve itself. After the model took an action, it is given reward or punishment as feedbacks for learning.

In this research, two types of machine learning are applied for data analysis. They are support vector machine (SVM) and deep learning. In both, the learning process used is supervised learning. Since the owners of brainwaves are known, we can feed the subject id as label together with EEG features data.

2.3.2. Support Vector Machine

Support Vector Machine, or SVM, is a machine learning that is often used in classification problems. SVM algorithm builds a model that treats data as points in a multi-dimensional space. The dimension is the number of features contained in each row of data. In our research's case, it's the number of EEG features. Learning the clusters of data points, SVM classify them into groups by constructing a set of hyperplanes. To classify the data, more than one hyperplanes might be found. However finding out the best hyperplane is also one of the goals. The best hyperplane is generally the one that produces the highest margin, or distance between each group of data points. After deciding on the hyperplanes, new data can be classified into groups based on them.

An example of SVM model is as follows:

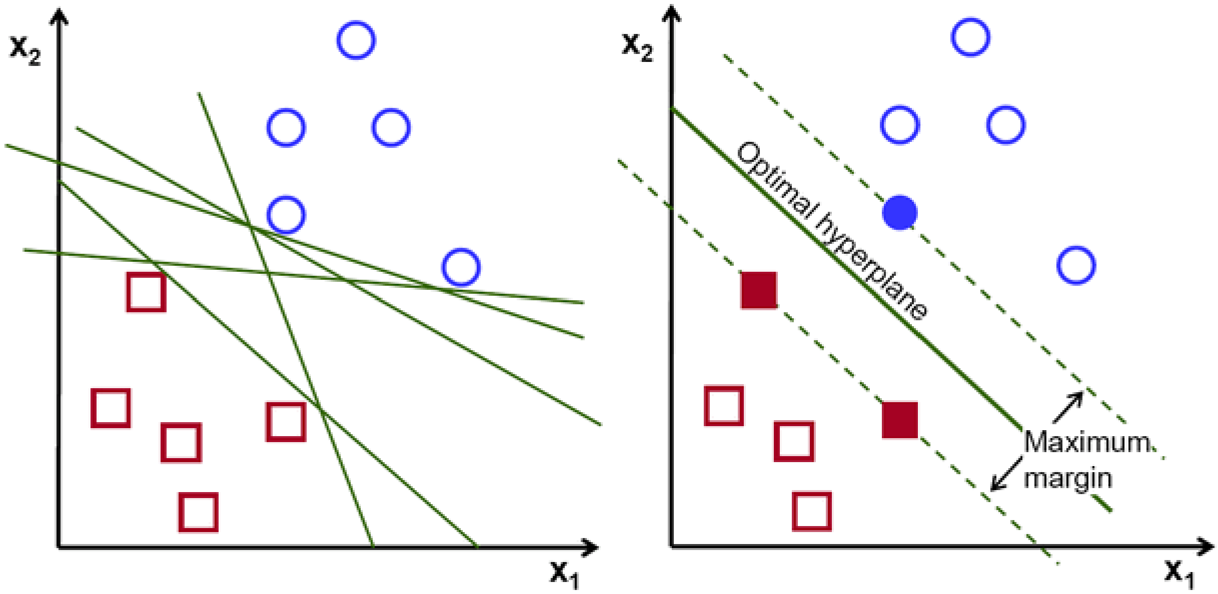

Figure 2.4 Examples of SVM Hyperplanes [16]

The example shows a two dimensional space with two groups of data. Circle and square data belong to different classification group so SVM needs to find the best hyperplane to separate them. In the figure on the left, the lines show possible hyperplanes that can be used to divide the groups. To find the optimal hyperplane to split the groups, the margin, or distance between the nearest points of the two groups to the hyperplane is calculated, and the hyperplane that produces the largest margin is selected as the optimal hyperplane. This is illustrated in the right figure. After finding the optimal hyperplane, SVM can make predictions of data classification. If a new data is entered on the left bottom side of the optimal hyperplane, SVM classifies it into the square data group and new data on the right upper side of the optimal hyperplane is classified into the circle group.

Even though the example above shows two dimensional data, in practice the data can have more than two dimensions. For our experiment data, we have 3 kinds of EEG features with total of 196 dimensions. In the example, the classification performed is linear classification where SVM divides the points into 2 groups. However SVM can classify more than 2 groups with the help of kernel functions. Several kernel functions exist such as polynomial function kernel and hyperbolic tangent function kernel but for our research we use Gaussian radial basis kernel in every SVM classification.

2.3.3. Deep Learning

Based on neural networks, deep learning is a machine learning area that tries to model high level abstractions contained in data. Compared to older learning algorithms, deep learning can be used to process a very large numbers of data using many layers with many processing units. The structure of deep learning is inspired by the human nervous system. There are layers of nonlinear processing units and each layer processes the output from the previous layer. The layers have hierarchical relationship, from low-level features to high-level features. In each layer, there are a number of processing units (nodes) similar to an artificial neuron. These units change their parameters during learning process.

Examples of deep learning models are deep neural networks, convolutional neural networks, and recursive neural networks. For our classification of EEG features, deep neural network is applied.

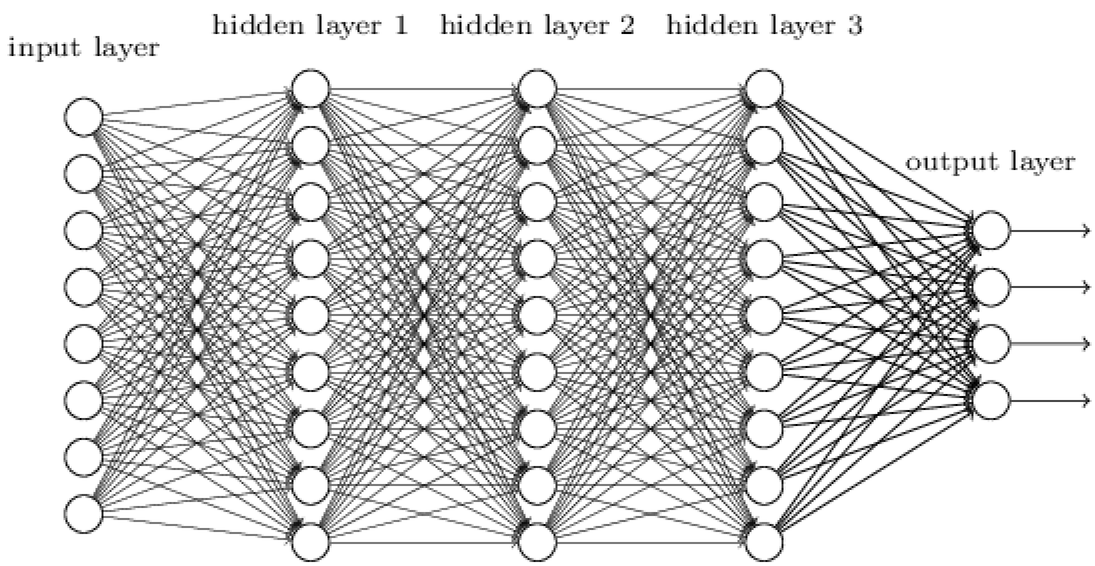

Figure 2.5 Structure of Deep Neural Network [18]

A deep neural network consists of an input layer, output layer and multiple hidden layers between them. Each layer has a number of nodes where computation takes place. The number of hidden layers and number of nodes inside each layer depends on the designer of the network. In order to find the best network, many variation of hidden layer configurations need to be explored. Each hidden layer processes data features of different levels. A hidden layer takes the output of the previous layer as input. So the further into the network, the more complex features are recognized.

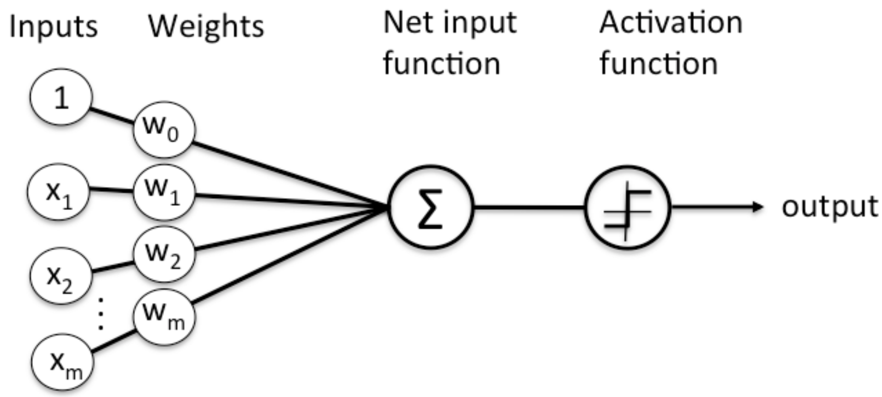

Figure 2.6 Structure of a Processing Node [19]

In processing data, every node in a layer acts like a switch that either turns ON or OFF. The decision is based on the input, weight vector and the activation function used in the layer. Many types of activation function exist, making it another parameter to be considered during the creation of a deep neural network. Examples of activation functions are ReLU (Rectified Linear Unit), Logistic, TanH, and SoftExponential. The output layer for classification of multiple classes normally uses softmax function as the activator. The weight vector is coefficients that affect the impact of each input. In learning process, these weights are modified to find the best values.

During training process of deep neural network, a training dataset is fed into the network multiple times. After each time, the weight parameters inside the nodes are modified. The function that learns the weight vector is called the optimizer function. A popular optimizer is SGD (Stochastic Gradient Descent). We also applied it in our deep neural network. The training dataset is fed into the network in batches. The passing of each data in the training dataset is called an epoch. In training a deep neural network, the optimizer, number of epochs, and batch size are parameters to be considered.

2.4. Related Studies

To realize EEG-based authentication, multiple studies have been done over the past years. There are a number of researches that propose factors and conditions for the authentication process. The factors include the mental task, EEG features, electrode positions and classification method.

There are studies that utilize machine learning for the classification method. The study by Ashby et al. uses SVM to classify the EEG features of 5 subjects [20]. In the experiment, the device used has 14 electrodes and the subjects are asked to perform 4 different tasks; staying still, imagining limb movement, visualize and count numbers, and visualize geometric rotation.

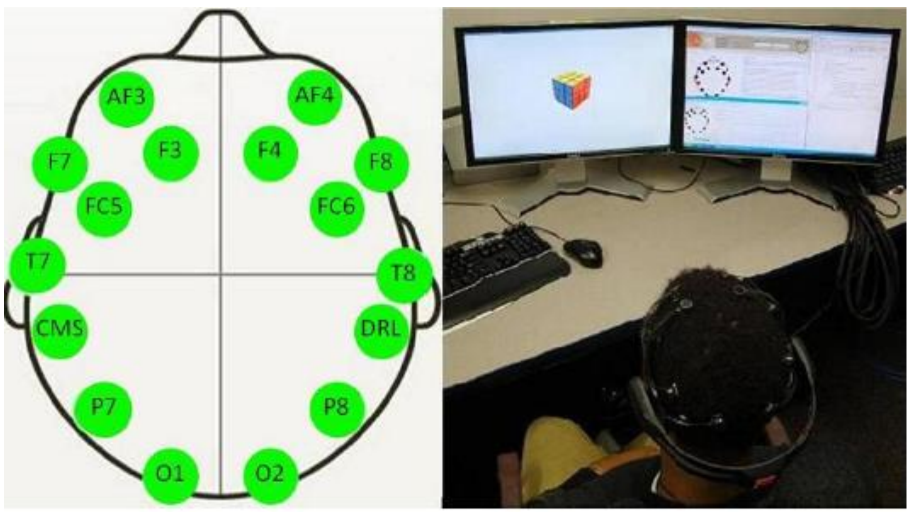

Figure 2.7 Electrodes Position (Left) & Experiment Condition (Right) of Study by Ashby et al. [20]

The pictures above shows the electrodes position of the EEG recording device and also the experiment condition. From EEG recordings, four EEG features are extracted, which are autoregressive coefficients, power spectral density, spectral power and interhemispheric power difference. Using SVM classification, the results are promising, the classifications produce in average 97.69% accuracy across 4 tasks.

Another study by Hu et al. focuses on EEG-based authentication in pervasive environment [21]. For real life implementation, it is essential to have short measuring time and ease of use for the EEG measuring device. The device for recording is a cap with a single electrode located on the center of the head.

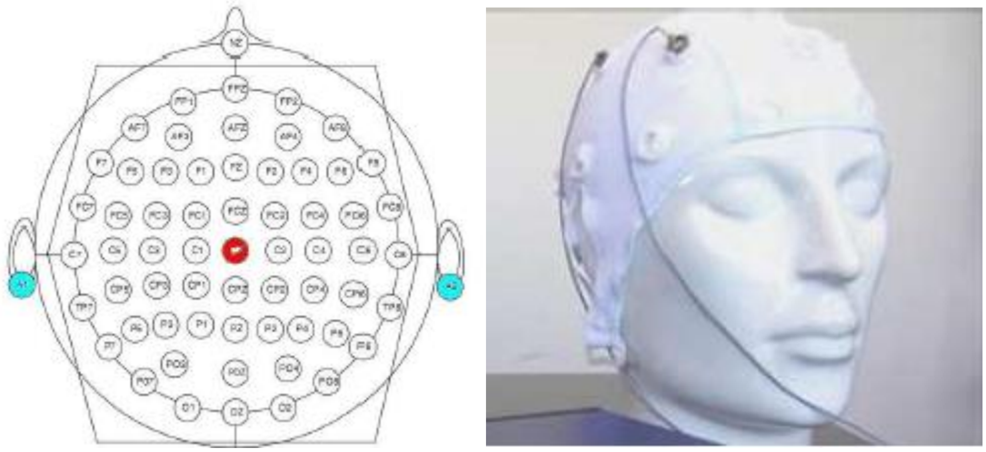

Figure 2.8 Electrodes Position (Left) & Electrode Cap (Right) of Study by Hu et al. [21]

In the experiment, 11 subjects participated. The subjects are asked to stay idle during the EEG recording. After filtering and noise removing, EEG features of autoregressive model coefficients are extracted. In this study, features classification doesn’t use machine learning but instead they use naive Bayes classifier. The results of the classification show that classification accuracy varies with EEG recording time. Longer recording time produces higher accuracy. The lowest accuracy being 66.02% using 4 seconds sample time and highest being 100% with 56 seconds sample time.

Both studies show classification results for one single session of recording, so the effect of time to the classification performance is not known. Another study by Blondet et al. tackles the issue of permanence of EEG-based Authentication [22]. Experiment is held over 5 months and consists of three sessions recorded in different times. Number of subjects participated on all 3 sessions are 9 subjects. The EEG feature considered is Event Related Potential (ERP) from middle occipital electrode. Classification method used is cross-correlation.

The results of the experiment show that relatively high accuracy is kept between sessions. Second session averages about 90% and third session averages about 80%. However not all subjects has high accuracy. Few of the subjects produce less 70% accuracy for some sessions and one of the subjects produce only 10% accuracy in a certain session. This shows that the performance is also affected by subject individual factors. For some people, their brainwave might not change much over time but brainwave of certain people might change.

Chapter 3

Experiments and Results

3.1. Introduction

In order to achieve the research objective of realizing an EEG-based Authentication system, two important aspects of a biometrics authentication need to be fulfilled. They are performance and permanence. In performance aspect, we focus on raising the classification accuracy of different individuals. In permanence aspect, the effect of time to the classification accuracy is investigated. We held experiments to gather data and test our proposed EEG features and methodology.

In the experiments, we ask subjects to perform mental tasks while EEG is recorded. Then we preprocess the raw EEG and extract EEG features. The EEG features are used for machine learning training and classification. We compare different mental tasks, combination of EEG features, combination of electrodes and machine learning conditions.

3.2. Experimental Design

We held two sets of experiments with different number of subjects and mental tasks. The first experiment has the goal of comparing factors to find the best combination for classification accuracy. In this experiment, subjects participated in one session of recording. The second set has the goal of investigating the time-invariance property of EEG-based Authentication. Subjects participated in more than one session of recording with time interval. Even though they are separate experiments, some experiment conditions are applied to both experiments. They include the EEG measuring device used, EEG recording conditions, and experiment flow.

3.2.1. EEG Measuring Device

We use a wearable 4 electrodes EEG measuring device called Muse, the brain sensing headband made by company Interaxon. It has the form a headband and does not require the use of conductive gel during recording process. Muse records EEG and transmits the data to the computer via Bluetooth. Here are the specifications of the device:

Figure 3.1 Muse, the Brain Sensing Headband [23]

Wireless Connection:	Bluetooth 2.1 + EDR
Sample Rate:	220 Hz or 500 Hz
Reference Electrode:	FPz (CMS/DRL)
Channel Electrodes:	TP9, FP1, FP2, and TP10 (dry)
Electrode materials:	Silver (FP1, FP2), Conductive silicone-rubber (TP9, TP10)
Battery Life:	Maximum 5 hours

The device has 4 recording electrodes which are two electrodes on the forehead and two electrodes on the back of both ears. The electrodes are named according to the 10-10 system of electrode placement. They are FP1 (left forehead), FP2 (right forehead), Tp9 (back of left ear) and TP10 (back of right ear). During the experiments, raw EEG with 500 Hz sampling rate are recorded by all 4 electrodes and transmitted to a computer.

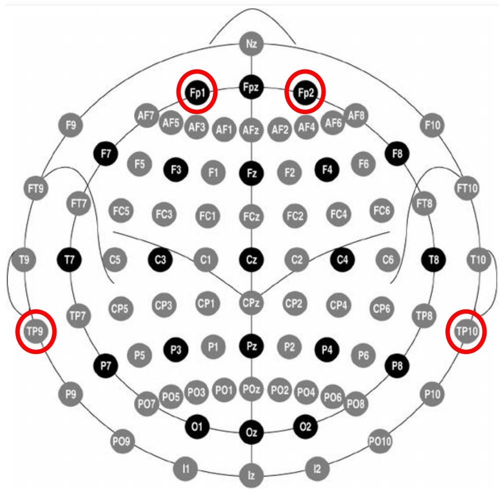

Figure 3.2 Electrode Positions of Muse (circled in red)

3.2.2. EEG Measuring Condition

When recording the brainwave of humans, the signals of every ongoing brain activities are recorded. So to get the brainwave of only the mental task given is very difficult. Other brain activities can be mixed up in the EEG recording. To minimize the amount of other brain signals, during the experiments subjects are given instructions of what not to do during EEG recording session.

To reduce the brain signals caused by muscles activity, subjects are asked to make their body movement as minimum as possible. For example subjects should not move their arms, feet or head. But vital body movements such as breathing are required by humans so they are not prohibited. Before the recording session starts, subjects are asked to sit down in a comfortable position.

The mental tasks of our experiments don't require the subjects to observe any image or videos so they are asked to close their eyes during recording. This is to reduce the effect of brain signal caused by brain processing of vision from sense of sight.

During the recordings, noises and sounds from surrounding area are also taken account. The experiment room is kept as quiet as possible. The people inside the room are requested to not talk and make loud noises during the EEG recording process. One of the mental tasks is for subjects to listen to music from headphones so in this case sounds from the room don't make much impact.

3.2.3. Flow of Experiment Session

Here are the steps and general flow of a session of experiment:

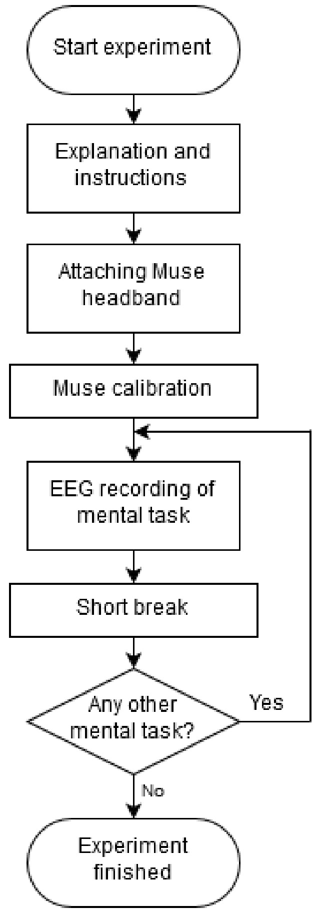

Figure 3.3 Flow of an Experiment Session

In a session of experiment, raw EEG data of a subject while performing separate mental tasks are recorded. The session starts by us explaining and giving instructions to the subject. The flow of experiment and different mental tasks are explained. Instructions about the device and what to do and not to do during EEG recording are also told to the subject.

Next, subject is asked to wear the Muse headband. Since Muse has dry electrodes, subject can just wear it without any conductive gels. The position of Muse is checked so that the electrodes are on the correct position on subject’s head. Hair of subject must not block the electrodes. For subjects with glasses, they are instructed to remove the glasses since it will block the electrodes behind ears. The measured EEG is displayed on the computer so in case of a lot of noises, the position of Muse can be adjusted.

After correct attachment of Muse, subject is asked to stay still for a while. Muse needs time for calibration of brainwave measurement. Time taken is about 1 minute. The calibration reduces noises and artefacts recorded by the device. However not all noises are blocked so during preprocessing of raw EEG, filtering is applied.

In the experiments, number of mental tasks in the session varies between experiment 1 and experiment 2. The EEG recording steps are repeated until all the mental tasks are finished. Subject is asked to perform a mental task while Muse records the EEG. Recording time for every mental task is 4 minutes. In data processing, the first and last 30 seconds are removed so there are 3 minutes worth of data for every recording. After each mental task recording, subject takes 1 minute short break. While subject is resting, the EEG recording is confirmed. If the recording has no errors, then we move on to recording of next task. If there are problems in the recording, then the EEG recording is done once more. After the entire mental task recordings are finished and no problems are found then the session ends.

3.3. Improving Classification Accuracy

In our research we try to investigate EEG-based Authentication by using machine learning. By training a model using subject's brainwave, the model recognizes unique patterns of each subject. In authentication process, subject's presented credential (in the form of brainwave) is classified by the model into the multiple subject classes. To improve classification accuracy, there are a lot of factors that can be considered. We evaluate different combinations of mental task, EEG features, electrodes, and type of machine learning.

To test the different factors and get the classification accuracy, first of all raw EEG data of subjects are collected from the experiment. Then those raw EEG data are preprocessed to remove noises and artefacts. Next, EEG features are extracted from the EEG. Obtained EEG features data are divided into 2 datasets. The first one is training dataset which is used to train machine learning model. The second is prediction test dataset which is the input for the machine learning classification. After machine learning training, the trained model is used for classification process. Prediction test dataset is classified into the subject classes. From the resulted classification, we can calculate the percentage of data which are classified into the correct classes. This is the classification accuracy.

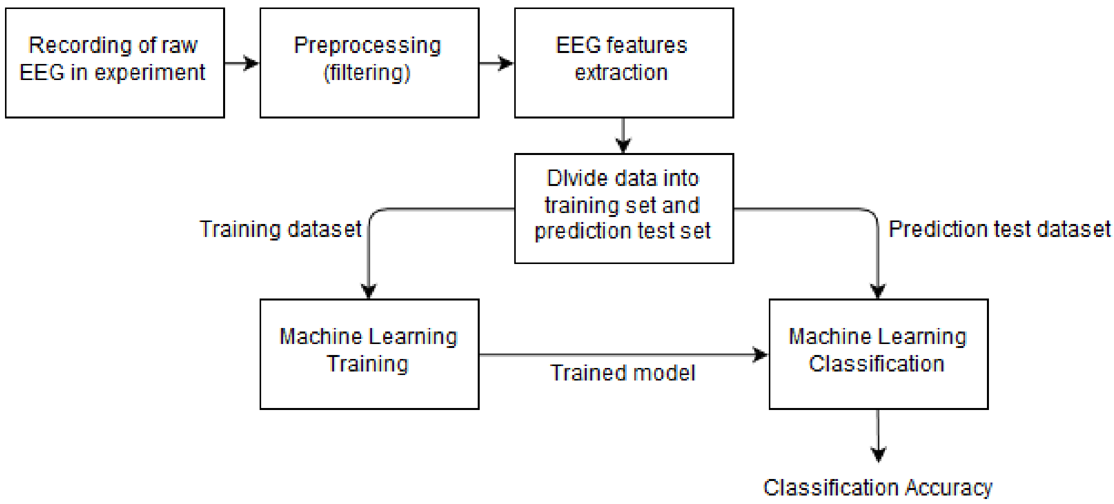

Figure 3.4 Data Processing of First Experiment Set

3.3.1. Raw EEG Data Collection

Two kinds of mental task are performed by subjects in this set of experiment. For each task, 3 minutes worth of EEG recording data are collected. The two tasks are relax task and music task.

1. Relax Task

   Subjects are asked to close their eyes and try to relax as much as possible. They are instructed to focus on their breathing and not to think hard. Body movements are also kept on minimal. Room condition is quiet so outer interferences are minimized. This task is meant to get the brainwaves during calm state.

2. Music Task

   Subjects wear earphones and listen to music that is played. The music is instrumental classical music where violin is the main instrument. In this task subjects are also asked to close their eyes and make minimal body movement. This task is meant to record the brainwave of subjects when they are responding to music stimuli.

We choose the two mental tasks because they are easy to do and replicate even after time had passed. Since authentication is performed in a long period of time, users should be able to be in a similar state in every authentication process. These two tasks are natural and users don't need to remember any instructions. If we use complicated tasks, users may not remember the feeling when they performed the task before.

Each subject participated in one session of experiment. There are 20 subjects, consisted of 15 males and 5 females. The average age of all subjects is 23.3 years old with standard deviation of 1.89. Data are collected from 4 electrodes. From all 20 subjects, a total of 40 separate 3 minutes EEG recording of two mental tasks are collected in the experiment.

3.3.2. Data Processing

For each mental task, 3 minutes of raw EEG data are collected. Before EEG features extraction, preprocessing is done to remove noises and artefacts. The experiment room has electronic devices such as computers, air conditioner and lights which produce interferences in the EEG recording. To remove the interferences, recorded signals of frequencies other than the EEG frequencies are removed.

The method of noise removal is by applying passband filter to the raw EEG recording. FFT (Fast Fourier Transform) filter with passband frequencies of 1 Hz to 45 Hz is used. Signals with frequencies lower than 1 Hz and higher than 46 Hz are removed from the recording. Remaining signals in the recording are the brainwaves which are put through EEG features extraction process.

Each 3 minutes EEG recording is divided into 1 second segments of data and EEG features are calculated based on that window size. It results in 180 data rows being collected from each EEG recording. There are 3 types of EEG features that are extracted from each segment. They are:

1. Discrete Fourier Transform (DFT)
   DFT of frequencies between 1 Hz to 45 Hz are calculated from each segment. Calculation is done using fft() function in R environment. 45 DFT features are collected for each electrode. Since there are 4 electrodes, 180 DFT features are available for one second EEG segment.
2. Zero Crossing Rate (ZCR)
   One ZCR feature is computed for each segment. In calculating ZCR, knowing the zero axis is needed. However since it is not known in real life practice, mean of EEG signal is assumed to be the zero axis. The function zcr() from R package seewave [24] is utilized. From all 4 electrodes there are 4 ZCR features.
3. Hjorth Parameters (Hjorth)
   There are 3 Hjorth parameters: Activity, Mobility and Complexity. They are calculated using each of the respective formulas. Three Hjorth parameters features are extracted from each segment for a total of 12 Hjorth parameters features from 4 electrodes.

From EEG features extraction, two datasets of relax task and music task are obtained. Each dataset consists of 3600 rows of data from all 20 subjects. The dimension of each row is 196 columns from all EEG features of 4 electrodes.

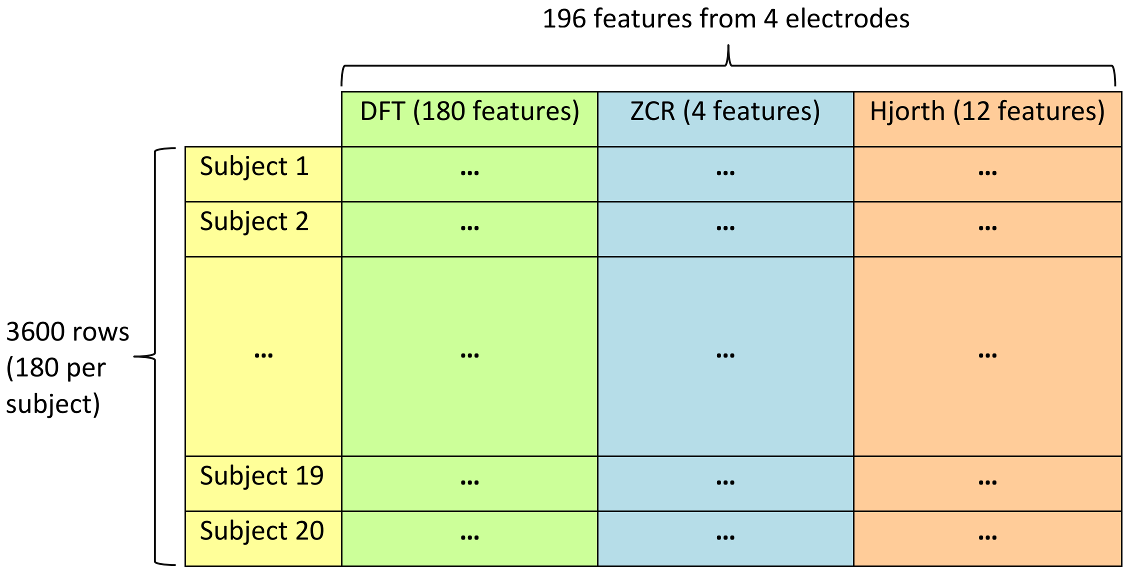

Figure 3.5 Structure of EEG Features Dataset

An illustration of the whole dataset is shown above. Relax task and music task has the same composition of data. In machine learning training and classification process, we pick subsets of data to compare different features, electrodes and tasks.

3.3.3. Machine Learning Training and Classification

Machine learning is applied to EEG-based Authentication in recognizing individual characteristics of each user’s EEG features. First, a machine learning model is trained using training data of EEG features. The model learns the characteristics of each user. During authentication process, EEG features are extracted from user provided EEG sample and those features are classified by the machine learning model. If the percentage of features that are classified into the correct user class reaches a certain threshold, then that user is authenticated and given access to the system.

In this experiment, we obtain dataset of EEG features from 20 subjects. The dataset is divided into 2 sets for machine learning training data and machine learning classification prediction test data. Before dividing, we normalize the data using Gaussian normalization. From the 3600 rows, 80% of them are selected as training dataset and 20% as prediction test dataset. The selection is done randomly.

Two kinds of machine learning are used in this research, support vector machine and deep neural network. The following are the configurations for both machine learning:

1. Support Vector Machine (SVM)

   We use SVM algorithm implementation of ksvm() function from kernlab package [25] in R environment. The parameters for the model are:

   - Type = C classification
   - Kernel = Gaussian radial basis function kernel
   - Cost = 1
   - Cross validation = 10

   As shown above, 10-fold cross validation is performed for every training session. This is to ensure the reliability of the learning process.

   In classifying prediction test data, SVM outputs a table that shows the amounts of data of each subject class which are classified into other classes. A screenshot of the example output is the following:

result_predict	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20
S01	28	2	0	0	0	3	0	0	0	0	1	1	0	3	0	0	1	1	1	3
S02	0	33	1	0	0	0	1	1	3	1	0	0	0	1	0	0	0	0	4	0
S03	0	0	13	2	1	1	0	2	1	0	0	2	0	0	0	2	4	2	0	2
S04	0	0	1	21	2	1	0	0	0	0	0	1	0	0	1	2	1	1	4	0
S05	0	0	2	1	23	0	0	0	2	0	0	2	0	0	0	1	1	1	0	0
S06	0	0	5	3	1	23	1	1	1	0	0	0	0	0	4	0	3	1	0	3
S07	0	0	0	0	0	0	26	0	0	0	0	0	0	1	0	1	0	1	2	1
S08	0	1	0	1	0	0	0	26	0	0	1	0	0	0	0	1	1	0	0	0
S09	2	0	0	2	0	1	0	1	25	0	0	1	0	1	0	1	1	0	1	1
S10	0	0	0	0	0	0	0	2	0	30	0	0	5	0	0	0	0	2	0	0
S11	1	0	1	0	2	3	0	1	2	0	32	1	0	0	2	0	1	0	1	0
S12	0	0	1	0	2	0	0	0	0	1	0	16	2	0	2	2	1	4	0	0
S13	0	0	0	0	0	0	0	0	0	1	0	1	29	0	0	1	0	0	2	0
S14	0	0	0	0	0	0	2	0	0	0	0	0	0	29	1	1	0	0	1	0
S15	1	0	1	1	0	1	3	0	0	0	1	0	0	1	24	0	2	0	0	0
S16	1	0	2	0	0	0	1	1	2	0	0	1	0	0	0	19	4	1	3	2
S17	0	0	2	1	2	1	0	0	0	0	0	3	0	0	2	1	11	0	2	0
S18	0	0	5	3	0	0	0	1	0	3	0	3	0	0	0	0	2	22	0	0
S19	1	0	1	1	1	1	2	0	0	0	1	3	0	0	0	3	2	0	14	0
S20	2	0	1	0	2	1	0	0	0	0	0	1	0	0	0	1	1	0	1	24

Figure 3.6 Example of SVM Classification Output

- S01 until S20 indicates the id of subjects. S01 is subject 1, S02 is subject 2, etc.
- The columns indicate the real class of the data.
- The rows indicate the predicted (classified) class of the data.

- Example: The red circle shows a number 3. It means that 3 data units from subject 9 class are classified into subject 2 class.
- To calculate classification accuracy, total data that are classified into the correct subject classes is divided by the whole data size and then changed into percentage.

2. Deep Neural Network (DNN)

   The deep neural networks for our classifications are built using Deep Neural Network implementation in Keras neural networks library [26]. Environment for the program is Tensorflow architecture in Ubuntu OS. Parameters of the models are:

   - Layers = input layer, 3 hidden layers and output layer
   - Nodes in hidden layers: Hidden layer 1 = 250 nodes
     Hidden layer 2 = 300 nodes
     Hidden layer 3 = 100 nodes
   - Activation functions = ReLU function in hidden layers and softmax function in output layer
   - Optimization = stochastic gradient descent (SGD) optimizer with 0.01 learning rate
   - Fitting process = 100 epochs with batch size of 50, data chosen randomly

   When classifying prediction test data, the deep neural network automatically calculates how many percent of data are classified correctly. This is treated as the classification accuracy.

By using the two machine learning algorithms, we calculate classification accuracies of prediction test data. To find out the best combination of EEG features, electrodes and other factors, we select subsets of data dimensions and feed them into the machine learning models.

The results for machine learning classification:

1. Classification Accuracies by Combination of EEG Features

The results of classification by combination of EEG features are shown. Classifications are made using only each feature type, combination of 2 feature types, and combination of all 3 feature types. For the classifications, we use data from all 4 electrodes. In each combination, the results of using data from relax task and music task are both shown in the same table. Results from SVM and DNN are shown in separate tables.

- Single EEG Feature Classification Accuracies

Table 3.1 SVM Results for Single EEG Features

Task	EEG Feature		
	DFT	ZCR	Hjorth
Relax Task	91.71%	41.01%	63.03%
Music Task	86.18%	38.37%	59.62%

Table 3.2 DNN Results for Single EEG Features

Task	EEG Feature		
	DFT	ZCR	Hjorth
Relax Task	93.47%	36.95%	60.91%
Music Task	86.08%	37.59%	59.49%

- Combination of 2 EEG Features Classification Accuracies

Table 3.3 SVM Results for Combination of 2 EEG Features

Task	EEG Features		
	DFT & ZCR	DFT & Hjorth	ZCR & Hjorth
Relax Task	92.36%	92.19%	69.02%
Music Task	86.72%	87.36%	64.02%

Table 3.4 DNN Results for Combination of 2 EEG Features

Task	EEG Features		
	DFT & ZCR	DFT & Hjorth	ZCR & Hjorth
Relax Task	95.14%	95.58%	68.07%
Music Task	91.03%	92.41%	64.18%

- Combination of 3 EEG Features Classification Accuracies

Table 3.5 SVM Result for Combination of 3 EEG Features

Task	EEG Features
	DFT, ZCR, Hjorth
Relax Task	93.13%
Music Task	88.44%

Table 3.6 DNN Result for Combination of 3 EEG Features

Task	EEG Features
	DFT, ZCR, Hjorth
Relax Task	97.00%
Music Task	94.80%

2. Classification Accuracies by Combination of Electrodes

Next, we use subsets of data from different electrode sources. There are 4 electrodes which are TP9 (left ear), FP1 (left forehead), FP2 (right forehead) and TP10 (right ear). We compare the classification accuracies from different electrodes and combination of them. For all classifications, we use all 3 EEG features (DFT, ZCR, Hjorth). Results from Relax Task and Music Task data are shown in the same table and results from SVM and DNN shown in separate tables.

- Single Electrode Classification Accuracies

Table 3.7 SVM Results for Single Electrodes

Task	Electrode			
	TP9	FP1	FP2	TP10
Relax Task	61.22%	61.04%	56.01%	71.05%
Music Task	54.76%	42.61%	48.09%	69.48%

Table 3.8 DNN Results for Single Electrodes

Task	Electrode			
	TP9	FP1	FP2	TP10
Relax Task	58.88%	58.93%	55.29%	69.63%
Music Task	54.15%	39.71%	40.12%	69.44%

- Combination of 2 Electrodes Classification Accuracies

Table 3.9 SVM Results for Combination of 2 Electrodes

Task	Electrodes					
	TP9 & FP1	TP9 & FP2	TP9 & TP10	FP1 & FP2	FP1 & TP10	FP2 & TP10
Relax Task	78.61%	86.11%	80.83%	72.36%	85.83%	86.25%
Music Task	66.67%	78.05%	79.72%	63.47%	76.80%	85.69%

Table 3.10 DNN Results for Combination of 2 Electrodes

Task	Electrodes					
	TP9 & FP1	TP9 & FP2	TP9 & TP10	FP1 & FP2	FP1 & TP10	FP2 & TP10
Relax Task	86.94%	85.63%	82.63%	75.27%	90.30%	89.52%
Music Task	75.38%	77.97%	80.49%	62.96%	81.74%	87.05%

- Combination of 3 Electrodes Classification Accuracies

Table 3.11 SVM Results for Combination of 3 Electrodes

Task	Electrodes			
	TP9, FP1, FP2	TP9, FP1, TP10	TP9, FP2, TP10	FP1, FP2, TP10
Relax Task	88.33%	89.16%	91.38%	90.83%
Music Task	81.25%	80.27%	87.50%	85.83%

Table 3.12 DNN Results for Combination of 3 Electrodes

Task	Electrodes			
	TP9, FP1, FP2	TP9, FP1, TP10	TP9, FP2, TP10	FP1, FP2, TP10
Relax Task	91.91%	94.05%	94.30%	94.25%
Music Task	85.47%	88.08%	91.39%	89.86%

- Combination of 4 Electrodes Classification Accuracies

Table 3.13 SVM Result for Combination of 4 Electrodes

Task	Electrodes
	TP9, FP1, FP2, TP10
Relax Task	93.13%
Music Task	88.44%

Table 3.14 DNN Result for Combination of 4 Electrodes

Task	Electrodes
	TP9, FP1, FP2, TP10
Relax Task	97.00%
Music Task	94.80%

3.3.4. Discussion

Based on machine learning classification results, the best combination of factors can be observed. First, we compare different EEG features. The results are compiled in the graphs below:

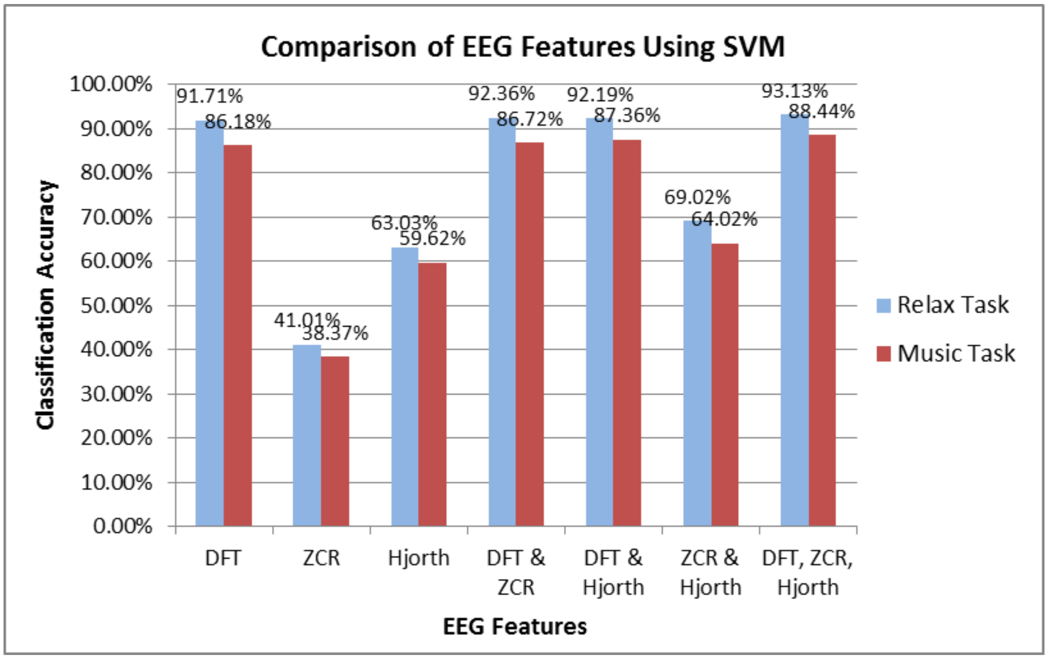

Figure 3.7 Comparison of EEG Features Using SVM

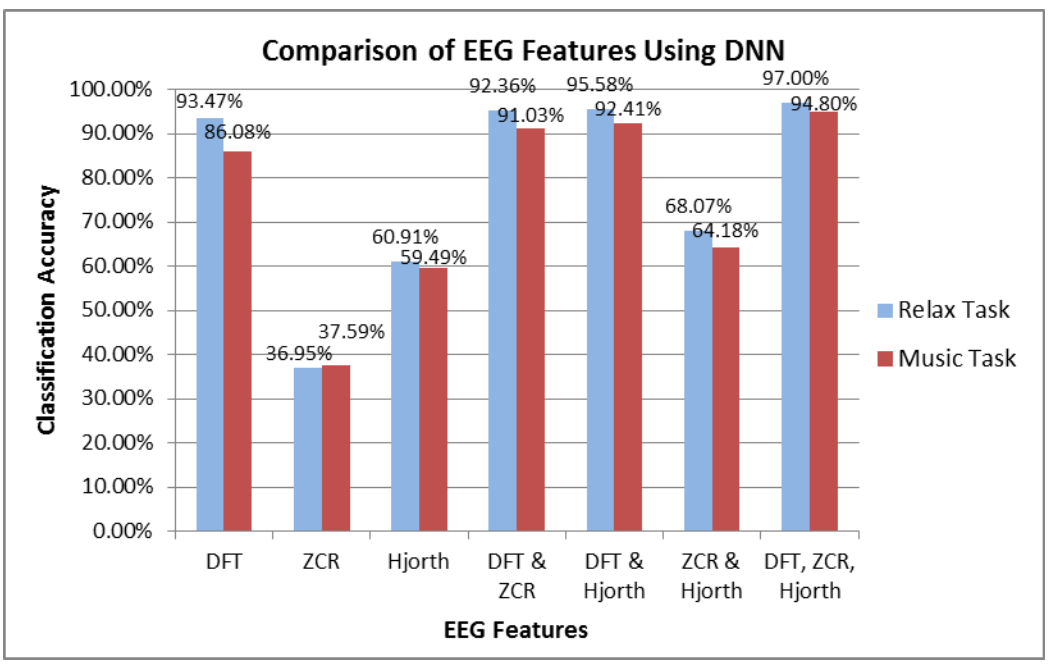

Figure 3.8 Comparison of EEG Features Using DNN

There are three type of EEG features; DFT, ZCR and Hjorth parameters. Comparing the results in using just each type of feature, DFT produces the highest classification accuracies, about 85% to 90% in both tasks and both machine learning. The second best one is Hjorth parameters with around 60% and third is ZCR with around 35% to 40% accuracies. A possible reason for the result is that the amount of features data in each type is different. DFT has 180 features, Hjorth has 12 features and ZCR has 4 features. With different amount of data, machine learning is able to learn more from data with higher dimensions. Compared to others, DFT has significantly higher performance. We extract DFT of frequencies 1 Hz to 45 Hz. In this range, the 5 type of brainwaves; delta, theta, alpha, beta and gamma waves are found in those frequencies. In brain activities from mental tasks of the experiment, ratio of the 5 waves and uniqueness of each wave might be learned by the machine learning models. With many factors contained in DFT feature, it is a possible reason that causes very high accuracy using just DFT.

In combination of 2 EEG features, combination of DFT and either ZCR or Hjorth parameters increases the accuracy slightly compared to single DFT. Using combination of ZCR and Hjorth parameters gives accuracy of about 64% to 69%. Although it is an improvement compared to just using either one of them, it fell short to DFT feature.

By combining all three EEG features, we can achieve accuracies in a range of 88% to 97%. In SVM classification, the increase from using two features to three features is small. However in DNN classification, there is quite a significant improvement in accuracy, resulting in 97% for relax task.

Comparing the two tasks, in almost every classification, relax task gives better accuracies compared to music task. It shows that in different tasks there are different unique patterns found in brainwaves. Although for the two tasks, the difference is not significant, with the largest difference being around 7%.

Generally, DNN has better performance in classifying brainwave of subjects compared to SVM. The difference can be seen easier in classifications with DFT. This feature contains large dimension of features, with 180 DFT features of 45 frequencies from 4 electrodes. With large feature dimension, DNN may be able to extract high level features and find more specific patterns within.

By comparing different EEG features, we found out that the combination of the proposed three types of features resulted in the best classification accuracy. However, pairing DFT with either ZCR or Hjorth parameters give only slightly lower accuracy so using 2 EEG features can be an option if less processing time is required.

Other than EEG features, we also compare different combinations of electrodes. Here are the results:

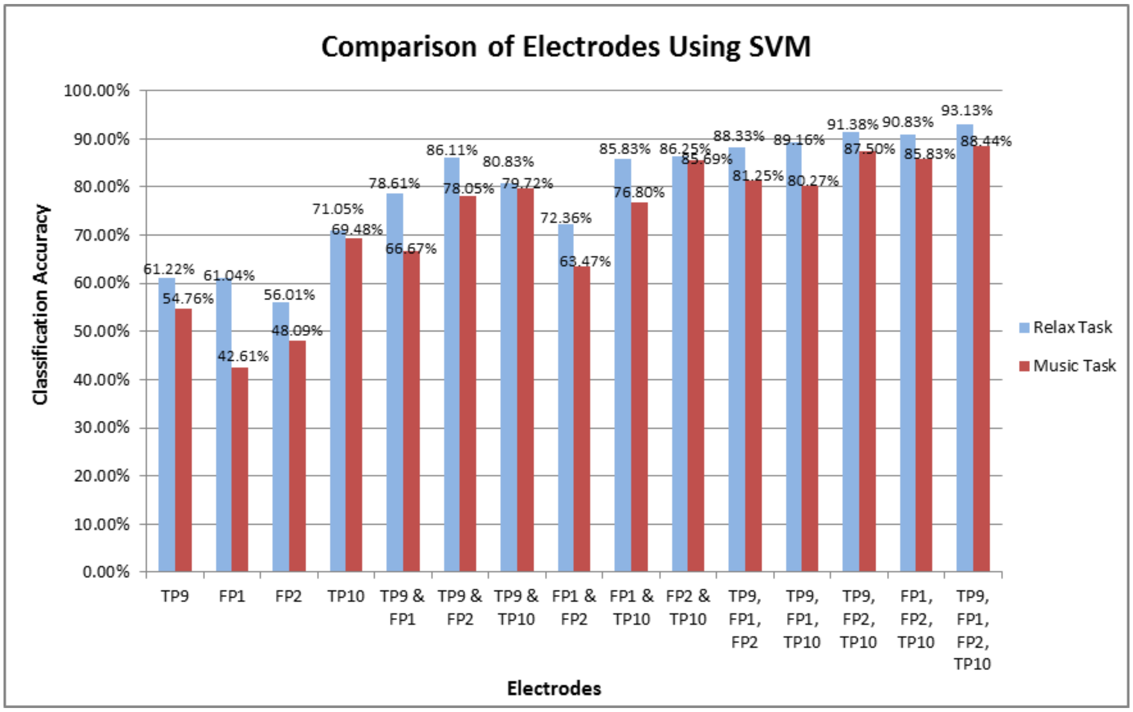

Figure 3.9 Comparison of Electrodes Using SVM

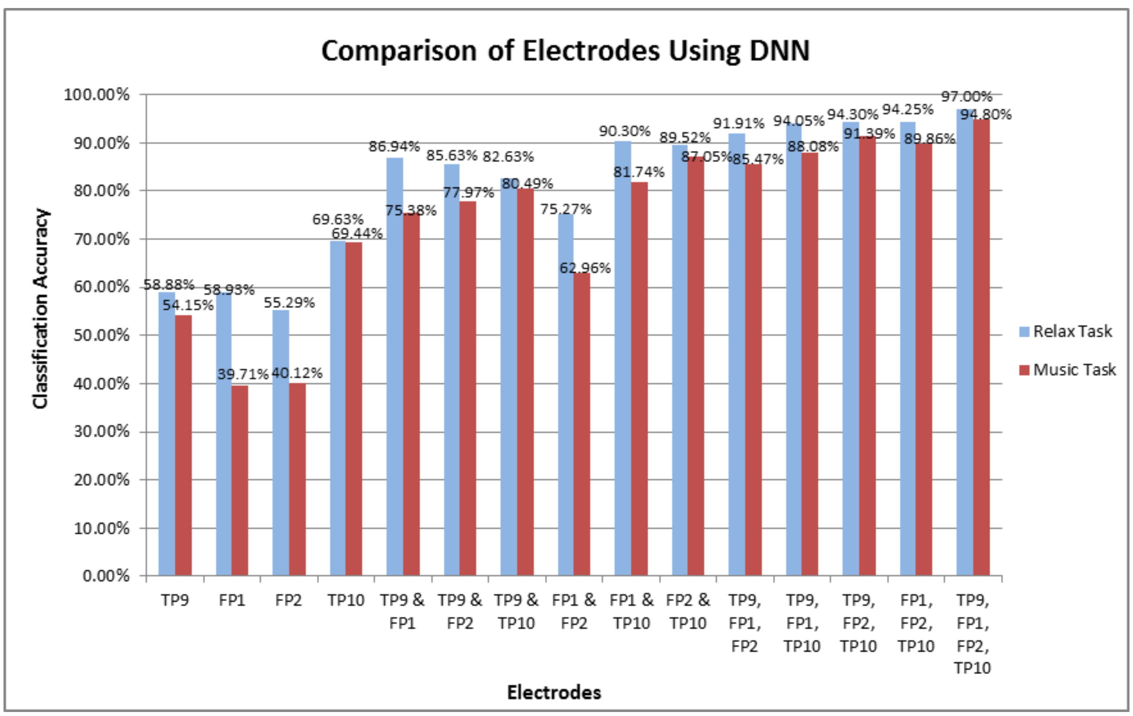

Figure 3.10 Comparison of Electrodes Using DNN

Four electrodes are available in Muse EEG recording device. They are TP9 (left ear), FP1 (left forehead), FP2 (right forehead) and TP10 (right ear). We classify subsets of EEG features which are extracted from brainwave recorded by combinations of electrodes. In all classifications, all three types of EEG features are used.

Based on the results, we can see an increase in classification accuracy when using more electrodes. This makes sense because brainwaves of humans are unique not only in one but in multiple brain parts. With more electrodes, the uniqueness of brainwaves from more brain parts can be measured. However more electrodes cause more time and difficulty to wear the EEG recording device. That is why finding out the best number of electrodes and recording points are important. In our experiment's case, using 4 electrodes gives at most 97% accuracy in DNN. However using 3 electrodes gives slightly lower accuracies, about 91% to 94%. The increase in accuracy from using 3 electrodes to 4 electrodes is not that significant compared to from using 2 electrodes to 3 electrodes. So using many electrodes to increase accuracy may not be worth the disadvantages in cost of device and preparation time to wear it.

Based on the four individual electrode points, we can see that the accuracy varies from one another. The three electrodes TP9, FP1 and FP2 produce accuracies at most 61% but TP10 produces higher accuracies, around 70%. So the brainwaves from this electrode contain more unique patterns compared to other 3 points. Looking at the brain anatomy, TP10 electrode is located near the right temporal lobe which has the function of handling non-verbal memory and reaction such as sounds and shapes. It also controls basic behavior and social skills. The brain activity of this part might be more unique between individuals, resulting in higher classification accuracy. Using combination of any 2 electrodes, the accuracy still varies between the two points chosen. However, we obtain similar classification accuracies from using any combination of 3 electrodes. So by using more electrodes, the bias caused by selecting a certain electrode point can be reduced.

Comparing the two machine learning algorithms, in using 1 or 2 electrodes, the accuracy varies and neither SVM nor DNN gives better overall performance compared to the other. However in using 3 and 4 electrodes, DNN produces higher accuracy in all of the classifications. This might be because DNN can extract higher level features from more data dimension.

Result from two mental tasks shows that relax task is better than music task in almost every classification. The difference is not that significant in using combination of 3 or 4 electrodes. However quite a difference can be observed in classifications using 1 or 2 electrodes. The source of this difference is the significant differences of accuracies between relax task and music task from electrodes FP1 and FP2. In classifications containing either electrode FP1 and FP2, performance of relax and mental task is different. In individual electrode classifications of FP1 and FP2, relax task has higher accuracies than music task. The difference is quite considerable, from 15% to 20% difference. Since FP1 and FP2 are located on the forehead, it shows that the brainwave near that part is more unique when subjects are doing relax task. The frontal lobe part of the brain is involved in motor activities and problem solving. When subjects are focusing in listening to music, they don't think about other things so the brain activity of the frontal lobe might be decreased. In relax task, subjects might think about other thoughts, so frontal lobe might be more active. The activity causes clearer EEG features that can be extracted, such as the amplitude range of brainwaves.

In this set of experiment, we compare different factors in brainwave classification. The best accuracy is obtained in DNN classification of 3 types of EEG features (DFT, ZCR, Hjorth) from 4 electrodes (TP9, FP1, FP2, TP10) while subject is performing relax task. In classifying brainwave of 20 subjects, we achieve 97% classification accuracy.

3.4. Time-invariance

After finding out suitable factors for subject classification, we evaluate the property of time-invariance. Users use authentication systems in a long period of time since every time users want to access a computer system, authentication is needed. So it is vital to have a stable and reliable performance over time.

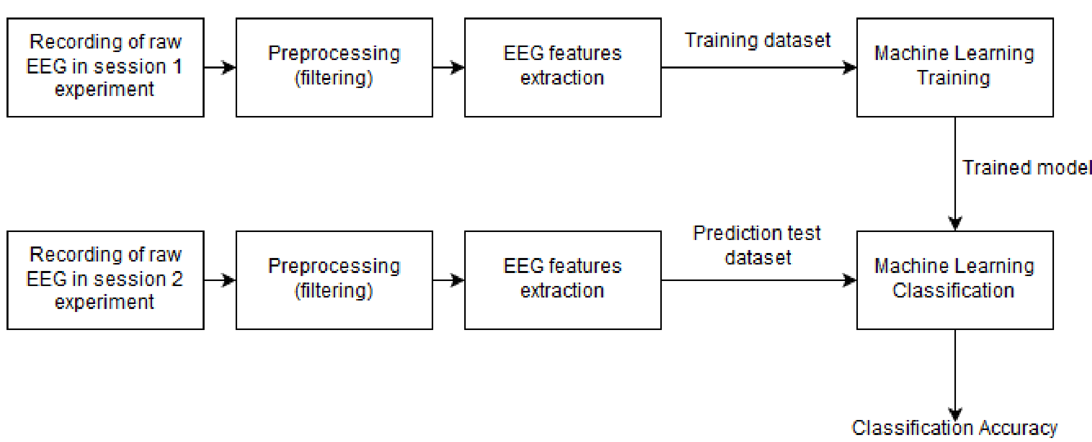

Figure 3.11 Data Processing of Second Experiment Set

To test time-invariance property, we perform machine learning training and classification using two datasets recorded in two different times. There are two experiment sessions with time interval between them. Data recorded in session 1 is used for training process and data recorded in session 2 is used for classification process.

3.4.1. Raw EEG Data Collection

For this set of experiment, other than the two mental tasks used before, we add another variation of task. In total there are 3 kinds of mental task performed by subjects. The tasks are done in both sessions of experiments. For each task, 3 minutes worth of EEG recording data are collected. The three tasks are:

1. Relax Task

   Subjects are asked to relax with their eyes closed and making as minimal movement as possible. Outer interferences such as sounds and noises are minimized so subjects can relax.

2. Music Task

   Subjects are asked to listen to instrumental classical music through earphones. They also need to close their eyes and try to make minimal body movement.

3. Count Task

   Subjects are asked to count the multiplication of a given number in their mind. The number is randomly selected between 1 and 9. For example if the selected number is 4, then subjects need to count 4, 8, 12, 16, and so on until time is up. Same with other tasks, subjects need to close their eyes and not make a lot of body movements.

In experiment to improve classification accuracy, the two original mental tasks are passive tasks which don't require subjects to actively use their brain in calculation or problem solving. We add another task which is an active task to see whether there is a difference between the two types of tasks regarding time-invariance property.

Each subject participated in two sessions of experiment with 1 to 2 weeks of time interval. There are 10 subjects consist of 6 males and 4 females. The average age of all subjects is 23.1 years old with standard deviation of 0.99. Data are collected using Muse EEG recording device with 4 electrodes.

3.4.2. Data Processing

Data preprocessing and feature extraction is the same procedure as the previous set of experiments. For each raw EEG recording, passband filter using FFT with passband frequencies of 1 Hz to 45 Hz is applied. Then the filtered data go through EEG features extraction process.

Each 3 minutes EEG recording is divided into 1 second window size segments and EEG features are calculated. Each segment results in 180 data rows with three types of EEG features from 4 electrodes as the data dimension. The features are DFT, ZCR and Hjorth parameters. A summary of the three features:

1. Discrete Fourier Transform (DFT)

   DFT of frequencies between 1 Hz to 45 Hz are calculated from each segment. Calculation is done using fft() function in R environment. 45 DFT features are collected for each electrode. Since there are 4 electrodes, 180 DFT features are available for one second EEG segment.

2. Zero Crossing Rate (ZCR)

   One ZCR feature is computed for each segment. The mean of EEG signal is used as the zero axis. The function zcr() from R package seewave [24] is utilized. From all 4 electrodes there are 4 ZCR features.

3. Hjorth Parameters (Hjorth)

   There are 3 Hjorth parameters: Activity, Mobility and Complexity. They are calculated using each of the respective formulas. Three Hjorth parameters features are extracted from each segment for a total of 12 Hjorth parameters features from 4 electrodes.

Six datasets of EEG features are collected from 2 sessions of experiment. Each dataset consist of 1800 rows of data from 10 subjects with 196 columns of EEG features dimension. The six datasets are:

- Session 1 Relax Task dataset
- Session 1 Music Task dataset
- Session 1 Count Task dataset
- Session 2 Relax Task dataset
- Session 2 Music Task dataset
- Session 2 Count Task dataset

3.4.3. Machine Learning Training and Classification

Machine learning training is done to learn patterns of EEG from different subjects. Then classification is performed to evaluate the model's performance. In this set of experiment, we want to measure the accuracy of classification using data from different time. Real authentication systems also apply this process to authenticate users after some time has passed.

From the experiment, we obtained 6 dataset of EEG features from 10 subjects. Three of them are from session 1 and the other three from session 2. Each session contain 3 datasets of 3 mental tasks. For machine learning training, session 1 datasets are used for training data. Machine learning classification use session 2 datasets as prediction test data. Different models are trained to compare the three different tasks. Gaussian normalization is applied to each dataset before feeding them into the models.

Two kinds of machine learning are used, support vector machine and deep neural network. The following are the configurations for both machine learning:

1. Support Vector Machine (SVM)

   We use SVM algorithm implementation of ksvm() function from kernlab package [25] in R environment. The parameters for the model are:

   - Type = C classification
   - Kernel = Gaussian radial basis function kernel
   - Cost = 1
   - Cross validation = 10

2. Deep Neural Network (DNN)

   We use Keras neural networks library [26] of Tensorflow architecture in Ubuntu OS. The configuration:

   - Layers = input layer, 3 hidden layers and output layer
   - Nodes in hidden layers: Hidden layer 1 = 250 nodes
Hidden layer 2 = 300 nodes
Hidden layer 3 = 100 nodes
   - Activation functions = ReLU function in hidden layers and softmax function in output layer
   - Optimization = stochastic gradient descent (SGD) optimizer with 0.01 learning rate
   - Fitting process = 100 epochs with batch size of 50, data chosen randomly

Machine Learning Training and Classification Result

The accuracies of both training process and classification process are displayed. This is so we can observe the change in performance between 2 different experiment sessions. Training accuracy displayed are the cross validation error values from SVM training and the learning accuracy values from DNN. The classification accuracies are calculated the same as previous set of experiment. They are the percentage of data units that are classified to the correct subject classes.

Table 3.15 Training and Classification Accuracies Between 2 Sessions

Machine Learning	Task	Training Accuracy	Classification Accuracy
SVM	Relax Task	94.67%	51.72%
	Music Task	92.94%	45.89%
	Count Task	92.73%	22.88%
DNN	Relax Task	89.72%	47.64%
	Music Task	83.44%	38.97%
	Count Task	87.16%	19.62%

3.4.4. Discussion

The results of machine learning training and classification are compiled in the graphs below. SVM and DNN results are separated in different graphs.

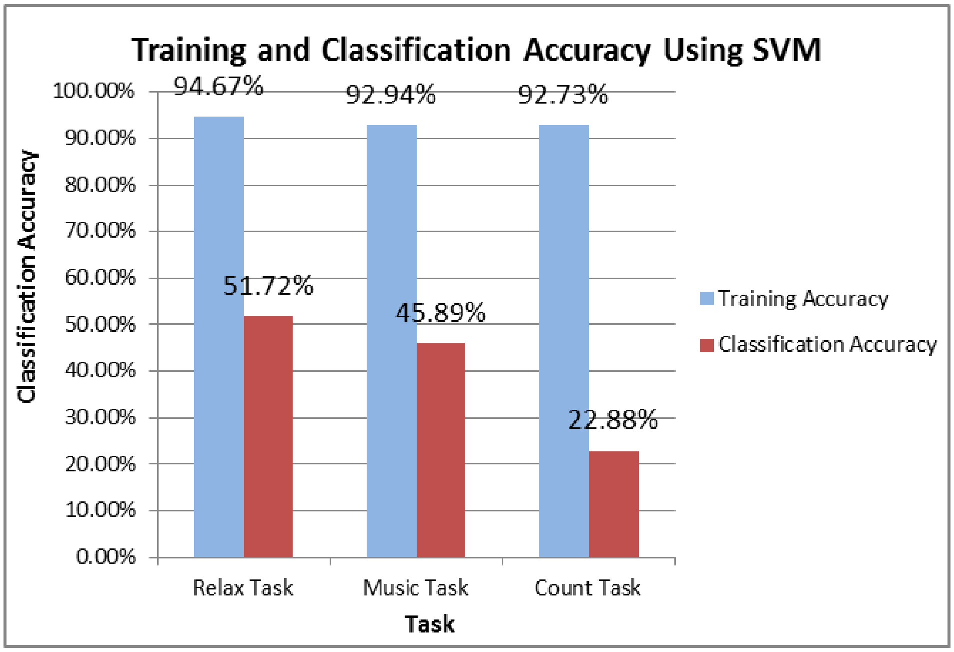

Figure 3.12 Training and Classification Accuracy Using SVM

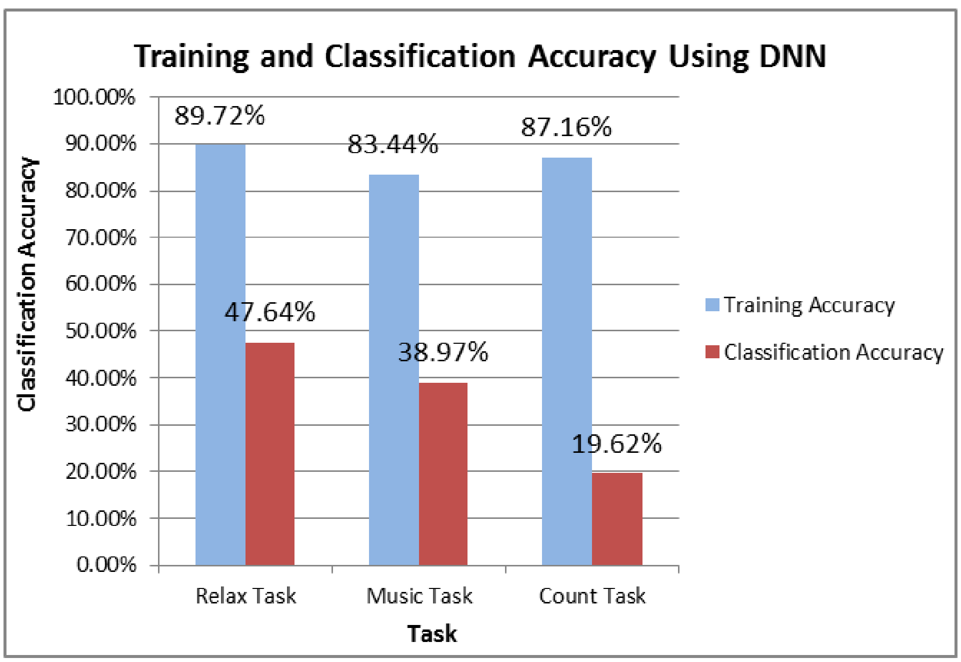

Figure 3.13 Training and Classification Accuracy Using DNN

The first thing that can be observed in both two graphs is that there is huge difference between training accuracy and classification accuracy in every task. Even though during training process the accuracies are around 80% to 90%, the classification of session 2 data only has the maximum of 50% accuracy. This shows that brainwave of subjects changes over time and in the two sessions, some brainwave patterns are not the same. However, some brainwave characteristics are retained since the classification accuracies are higher than the random identification chance of picking the correct subject (10%).

We can see difference of classification accuracies based on tasks. From the 3 tasks, relax task gives the best performance, and count task only produces half of the other 2 tasks. A possible reason is because count task is an active task, and it might be difficult for subjects to reproduce the same brainwave voluntarily. On the other hand, in both passive tasks of relax and listening to music, subjects seem to respond to stimuli involuntarily, and classification is better than voluntary task. With 3 minutes of recording time, subjects may think of things unrelated to the given task, causing different brainwave patterns to appear in different sessions. Giving subjects passive tasks in less recording time to reduce the chance of subjects losing focus, and adding more training sessions may produce better results. This supports the research of [22] where high identification accuracy is achieved over 6 months using non-volitional EEG.

Comparing the two machine learning algorithms, in this experiment SVM performs better in both training and classification processes. The difference is not that significant in most cases, around 3% to 10%. Another observation that can be made is that in this experiment with 10 subjects, SVM has better results than DNN. However in first set of experiment with 20 subjects, DNN is the one that gives better results. The highest classification accuracy of 97% is achieved with all EEG features of relax task using DNN. However in this experiment the accuracy is only 89%. These results show that DNN can learn better when there are more number of subject classes. Since the learning process of DNN is done in epochs, and in each epoch all of data are fed into the model, it can adjust the parameters to distinguish different subject classes better. For implementations of EEG-based Authentication using machine learning in real life practice where there are a lot of users, DNN might be a better choice than SVM.

Chapter 4

Conclusion and Future Works

4.1. Conclusion

EEG-based biometrics is an alternative authentication mechanism that offers advantages compared to other commonly used authentication methods such as passwords and fingerprint scan. To realize it in the future, several aspects of biometric system need to be investigated. In this thesis we explore two of the vital aspects, performance and permanence of EEG-based authentication system.

From the experiments, we made several observations about the factors that affect classification accuracy. High accuracy of 97% is achieved by utilizing the proposed 3 EEG features from 4 electrode points. Individual electrode points produce varying accuracies but by combining EEG captured from multiple electrodes, stable accuracies can be achieved. In classifying subjects, we use two types of machine learning which are support vector machine and deep neural network. We found out that deep neural network performs better in classifications with larger number of subjects. In applying for real life practice, deep learning might be the more suitable machine learning.

Time-invariance aspect was also tested. EEG of subjects was recorded in two different sessions. From the results, we found out that performance degrades over time. We compare three different mental tasks. When subjects perform passive tasks, more EEG characteristics of individuals can be identified in later session, resulting in better classification. In implementing EEG-based authentication, involuntary tasks might be better since subjects can just respond naturally to the presented stimuli.

4.2. Future Works

Even though high classification accuracy in single session of experiment was achieved, the performance decreased after one to two weeks had passed. In order to make the implementation of EEG-base authentication come true, time-invariance is an issue that needs to be investigated further. In future research, different experiment methods with more varieties of mental tasks and different time will be explored. Other EEG features, particularly features that can be observed in involuntary mental tasks are investigated deeper. Number of subjects also needs to be increased to produce more reliable results.

In a system where there are a huge number of users, the accuracy of authentication and processing time need to be considered. More detailed optimization of deep learning shall be investigated to increase performance. Other than deep neural network, we can also try other deep learning algorithms such as convolutional neural network and recurrent neural network. Configurations of the network including number of hidden layers and number of nodes affect performance so they also need to be considered.

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[2] F. P. Sjamsudin, M. Suganuma, W. Kameyama, "On Time-invariance of EEG-based Person Identification", IEICE General Conference 2017, March 2017 (forthcoming)

Experimental Results on EEG-based Person Identification with Machine Learning

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1. Introduction

Electroencephalogram (EEG) based authentication uses human brainwave patterns to identify users. Compared with other biometrics, EEG authentication has the combined benefits of different authentication methods[1]. Previous research by Ashby et al. uses machine learning in person classification by using a set of EEG features including autoregression coefficients and power spectral density[2]. In our research, we propose a different set of EEG features to classify individuals using SVM machine learning.

2. Experiment

In our experiment, we use the 4 electrode EEG device, Muse: the brain sensing headband[3], to measure EEG of 15 healthy subjects (13 males, 2 females, 23.67 average age with 2.19 SD). EEG data from 4 electrodes (TP9, FP1, FP2, and TP10) are recorded from each subject while performing two different tasks. The first task is to relax, and the second task is to listen to classical music. In both tasks, subjects are asked to stay still and close their eyes. Three minutes of data are collected for each task.

3. Analysis and Results

The procedure of data processing and analysis is as follows:

1) Preprocessing: The raw EEG data is filtered using FFT with the passband frequencies from 1 [Hz] to 45 [Hz] to remove noises and artifacts.
2) Feature Extraction: The filtered EEG data are segmented into one-second long segments each. Three types of features are extracted from each EEG segment:
   a) Discrete Fourier Transform (DFT): Fast Fourier Transformation is applied and 45 DFT features of frequencies from 1 [Hz] to 45 [Hz] are collected.
   b) Zero Crossing Rate (ZCR): ZCR is computed using the mean amplitude as the zero base.
   c) Hjorth parameters (Hjorth): 3 Hjorth parameters consist of activity, mobility, and complexity.
3) SVM training and classification: For each classification, data are randomly divided into 70% training data and 30% prediction test data. SVM with radial basis function kernel is trained using the training data, and 10 fold cross validation is performed. Then the prediction test data is classified into the classes of the 15 subjects.

Table 1 compares the SVM classification accuracy for each individual EEG feature and for the combination of all 3 features where the data from 4 electrodes are used. Classification accuracy shown is the percentage of the prediction test data which are classified into the correct subject classes.

Table 2 compares the SVM classification accuracy for each individual electrode where all EEG features are used.

Table 1 SVM Result for Combination of EEG Features

Task	EEG Features Accuracy			
	DFT	ZCR	Hjorth	All Features
Relax	92.48%	49.08%	68.51%	95.06%
Listening to Music	89.31%	48.10%	69.35%	92.47%

Table 2 SVM Result for Individual Electrode

Task	Individual Electrode Accuracy			
	TP9	FP1	FP2	TP10
Relax	71.23%	64.07%	62.22%	80.74%
Listening to Music	62.09%	50.12%	50.49%	71.48%

From the 3 different features, DFT results in the highest accuracy. Compared to ZCR and Hjorth, the classification accuracy is much higher. Just using the single feature DFT, we achieve around 90% accuracy in both tasks. But when we combine all three features, the accuracy can be further increased by around 3%.

The accuracy of using single electrode is considerably lower than using all four electrodes, only between 50% to 80%. Each electrode results in different accuracy. Among them, TP10 electrode results in the highest.

Between the two tasks, generally, the relax task has higher accuracy. The exceptions are in ZCR and Hjorth feature classifications where the two tasks are similar.

4. Conclusion and Future Work

In this research, we classify subjects by extracting EEG features and apply machine learning. We have achieved above 90% classification accuracy by using 3 different features of EEG from 4 electrodes. In future studies, we improve the experiment by adding more subjects and trying other machine learning algorithms.

Acknowledgement

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On Time-invariance of EEG-based Person Identification

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1. Introduction

In our previous report, we have explored the possibility of using electroencephalogram (EEG) in person identification using 3 EEG features and multiple electrodes[1]. However, we have not tested whether the identification is stable after some time has passed. In this report, we tackle the issue of time-invariance, and also compare performed tasks and machine learning algorithms for classification.

2. Proposed Method and Experiment

We have recorded the brainwave of different subjects in 2 separate sessions with 1-2 weeks interval. We extract EEG features from the initial session and use them to train machine learning models. Then we classify the features obtained from the second session. In the experiment, we have used Muse, the brain sensing headband[2]. The device has 4 electrodes and sampling rate of 500 [Hz]. We have recorded EEG of subjects performing 3 separate tasks. The first task is to relax, the second is to listen to classical music, and the third is to count the multiplication of a given number. In all tasks, subjects are asked to stay still and close their eyes. Three minutes of EEG are recorded for each task. There are 10 subjects of 6 males and 4 females with 23.1 average age and 0.99 SD.

3. Results and Analysis

Each EEG recording is processed with the procedure:

1) Preprocessing: the raw EEG is filtered using FFT with 1[Hz]-45[Hz] passband frequencies to remove noises.
2) Feature Extraction: EEG features of discrete fourier transform, zero crossing rate, and Hjorth parameters are computed in the same way as in [1].
3) Normalization: each set of feature data are normalized using Gaussian normalization.

There are 1800 data entries from all 10 subjects and 4 electrodes with total dimension of 196 features. The data are fed to 2 types of machine learning training and classification. The first is support vector machine (SVM) with radial basis function kernel where 10 fold cross validation is performed during the training process. The second is deep neural network consisted of 3 hidden layers (ReLu function) with 250, 300 and 100 hidden nodes and 1 output layer (softmax function) where stochastic gradient descent optimizer is applied. In both, training process uses data from the initial session of experiment, and classification process uses the second session data. The classification results are shown in Table 1.

Table 1 Training and Classification Accuracy Results

Machine Learning	Task	Training Accuracy	Classification Accuracy
SVM	Relax	94.67%	51.72%
	Music	92.94%	45.89%
	Count	92.73%	22.88%
DNN	Relax	89.72%	47.64%
	Music	83.44%	38.97%
	Count	87.16%	19.62%

About 80-90% training accuracy is achieved but the highest classification accuracy is only about 50%. It shows that accuracy decreases over time. However, some EEG characteristics are retained since the accuracy is higher than the random identification chance of 10%. From the 3 tasks, the relax task gives the best performance, and the count task is only half of the other 2 tasks. A possible reason is because the count task is an active task, and it might be difficult for subjects to reproduce the same brainwave voluntarily. On the other hand, in the passive tasks of relax and listening to music, subjects seem to respond to stimuli involuntarily.

With 3 minutes of recording time, subjects may think of things unrelated to the given task, causing different patterns in each session and producing the low accuracy. Giving subjects passive tasks in less recording time to reduce the chance of subjects losing focus, and adding more training sessions may produce better results. This supports the research of [3] where high identification accuracy is achieved over 6 months using non-volitional EEG. Overall, SVM gives higher accuracy than DNN but further optimization may produce better results.

4. Conclusion and Future Work

In this report, we have tested the time-invariance of EEG-based person identification. The results show that performance degrades over time, and it varies based on the performed tasks. We observe that the passive tasks give better performance than the active task. For the future work, other passive tasks and machine learning training conditions are to be explored to increase reliability.

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