Machine Learning Techniques for Brain Signal Analysis

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October 30, 2023

Abstract

Brain signal analysis has revolutionized the research on human-computer interaction. Analyzing brain activity of the human emotions opens greater avenues to advance the research on Brain signal analysis. Human emotions play a significant role in social intercourse, human cognition, and decision making.[1] In this project, Differential Entropy (DE) features of EEG are used to perform emotion classification. The DE features are more suited for emotion recognition than Energy spectrum (ES) features which are used traditionally [2]. We have applied machine learning algorithms to discriminate three categories of human emotion: 1) positive 2) neutral and 3) negative. Feature extraction and dimensionality reduction are performed on the EEG dataset to obtain high-level features which helped to increase the accuracy and efficiency of the classification models. We have performed numerous machine learning models on the EEG data and compared the results of deep learning models and shallow models. .

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Abstract — Brain signal analysis has revolutionized the research on human-computer interaction. Analyzing brain activity of the human emotions opens greater avenues to advance the research on Brain signal analysis. Human emotions play a significant role in social intercourse, human cognition, and decision making.[1] In this project, Differential Entropy (DE) features of EEG are used to perform emotion classification. The DE features are more suited for emotion recognition than Energy spectrum (ES) features which are used traditionally [2]. We have applied machine learning algorithms to discriminate three categories of human emotion: 1) positive 2) neutral and 3) negative. Feature extraction and dimensionality reduction are performed on the EEG dataset to obtain high-level features which helped to increase the accuracy and efficiency of the classification models. We have performed numerous machine learning models on the EEG data and

compared the results of deep learning models and shallow models. The average accuracies of DBN, SVM, KNN, ELM, and Random Forests are 73.9%, 79.8%, 99.8%, 76.6%, and 78.6% respectively.

Keywords— EEG, deep belief networks (DBN), emotion recognition. Machine learning, mental states classification

Introduction

The combination of humans and technology could be powerful than Artificial Intelligence. There are various methods by which brain signals can be acquired. The popular methods to collect signals mainly of two types: Invasive (ECoG) and Non-invasive (EEG & fMRI). Electroencephalography (EEG) is an electrophysiological monitoring method to record electric brain activity via electrodes. It measures voltage fluctuations accompanying neurotransmission activity within the brain. Electrocorticography (ECoG) is an invasive method to acquire brain signals. It provides high temporal and spatial resolution for the data being collected. Although the data collected using ECoG has Increased quality of the signal and has a better signal to noise ratio, they are not widely used because it requires a surgical procedure which may cause medical complications. Functional magnetic resonance imaging (fMRI) is another non-invasive method to capture brain activity. It detects blood flow changes related to the brain's neural activity and processes the data.

During the analysis of brain signals, we detect brain activity and process the signals to convert electric impulses and signals of the human brain to data understood by machine using specialized equipment such as BCI devices. We analyze and understand the collected data and therefore use the processed data to Improve human-computer interaction. It is a new way of communicating with machines and there are enormous advantages to this in the field of medicine like enabling people with disabilities, detecting seizures, etc. Currently, the electroencephalogram (EEG) signal is considered to be one of the widely used non-invasive signals to measure brain activity to acquire the signal in the BCI systems due to its excellent temporal resolution and usability [3]. There is a wide range of research areas for analyzing brain activity however, we will be focusing mainly on the emotion recognition system using EEG signals to detect the brain-activity of Human Emotions. Among various approaches to emotion recognition, electroencephalography (EEG) is the most reliable method because of its high accuracy, unlike other methods that analyze facial expressions and gestures [4].

The research on emotion recognition involves interdisciplinary fields such as computer science, psychology, neuroscience, and cognitive science. The contribution from each of those fields is essential for the progress of emotion research. The acquisition of emotion signals can be divided mainly into two categories namely physiological and non- physiological. The non-physiological signals such as facial expressions [2] and voice [3] have been used in many studies however, they can be easily manipulated or deliberately concealed making them unreliable for research purposes. On the contrary, the physiological signals referring to electroencephalography (EEG), electromyogram (EMG), electrocardiogram (ECG), skin resistance (SC) seem to have been proven to be more reliable because they are inherent and cannot be controlled or manipulated by humans. Among all the physiological signals, EEG-based emotion recognition has become the most recognized method. EEG uses extracranial devices which include wearable and non-wearable technologies. The extracranial devices which acquire EEG signals are non-invasive, easy to wear and their range of applications has been widening ever since.

In this project, various videos of different emotions are shown to individuals to acquire the data. The 15 Chinese film clips were chosen from the pool of material. On each individual, 15 trials were conducted as an experiment and the participants were asked for the feedback after each clip. The objective considered here is to distinguish among different categories of emotion detection. Furthermore,analyzed brain wave patterns are classified into 3 categories – Positive, Neutral and Negative. We have concentrated on the EEG signal performances of the subjects when they were watching movies that were deliberately designed for eliciting positive, neutral or negative responses. After collecting EEG data, differential entropy (DE) features are extracted and their classification accuracies are compared. We also chose the autoencoder to reduce the feature dimensions to save the storage space and speed up the classification procedure. Following the feature extraction, some of the commonly used classifiers such as Support Vector Machines (SVM), Logistic Regression, etc., are used for the classification of the emotions. Finally, we have also used Deep Belief Network (DBN) which also performs feature extraction and dimensionality reduction and drew the comparisons between the network models and their accuracies.

The remainder of the paper proceeds as follows. Related works are summarised in section II. The experimental setup, including the subject's participation, and details about the dataset are described in section III. The methods tested to perform feature selection and the criteria used to compare the different classifiers are presented in section IV. The experiment results are presented in section V. The possible extension of this research is discussed in section VI. A discussion on the conclusions drawn from the experimental results is provided in section VII.

Related work

Analyzing and interpreting brain signals takes human-computer interaction to the next level. Brain signal analysis has varied applications in many fields such as robotics, neurotechnology, Medicine, etc. Brain signals are captured using BCI devices. These are Initially developed with biomedical applications in mind. The BCI system comprises four basic components: Signal acquisition, Signal preprocessing, Feature extraction and Classification. Statistical features derived from EEG data are commonly used alongside machine learning techniques to classify mental states [18], [19]. A headband has been recognized by neuroscientists to collect the data based on its effectiveness and accuracy. Besides, its relatively low cost helps to increase the range of its application.

In some of the recent researches, the EEG signal is collected when individual participants were watching movies that were designed for eliciting positive, neutral or negative emotional states. After collecting EEG data, the energy spectrum (ES), differential entropy (DE), rational asymmetry (RASM), and differential asymmetry (DASM) are extracted as features and compared their classification accuracy in five frequency bands. The average classification accuracies using features DE, DASM, RASM, and ES on EEG data are collected [2]. A new EEG feature named differential entropy (DE) was proposed and compared with the traditional frequency-domain feature named energy spectrum (ES). Consequently, DE and its combination of symmetrical electrodes were proved to be performing better than ES feature. In neuroscience research, one of the main goals is to observe the patterns of brain activities for specific emotions and examine these patterns that exhibit commonality to any extent across individuals. Various studies have examined the neural correlations of emotions. Davidson et al. [7], [8] showed that frontal EEG asymmetry is related to approach and withdrawal emotions, with approach tendencies reflected in left frontal activity and withdrawal tendencies reflected in a relative right-frontal activity.

Recently, deep learning methods have been gaining the attraction to processing physiological signals such as EEG, EMG, ECG, and SC. Martinez et al. [9] trained an efficient deep convolution neural network to classify four cognitive states (relaxation, anxiety, excitement, and fun) using skin conductance and blood volume pulse signals. They have demonstrated that the traditional feature extraction and selection methods could be outperformed by the proposed deep learning approach providing a more accurate effective model. Martin et al. [10] applied deep belief nets and a hidden Markov model to detect the sleep stage using multimodal clinical sleep datasets. To classify the emotions for the data collected using EEG a Hierarchical Network with Subnetwork Nodes for Emotion Recognition has been proposed to get achieve high accuracy. It is composed of two parts: 1) local features extracted from mid-level layers and 2) feature level fusion and classification [1].

EEG signals are known to having a low signal-to-noise ratio and therefore, the signals often mixed with much noise when collected. EEG signals have temporal asymmetry and are nonstationary. These attributes of EEG pose a challenging problem of having a more complex learning system to study and analyze EEG signals, unlike image or speech signals.

Experimental Setup

Experiment

Individual participants have been shown various videos of different categories. A total of 15 Chinese film clips (positive, neutral and negative emotions) were chosen from the pool of materials as stimuli. The video clips have been selected following the below guidelines:

- The duration of the whole experiment should not be too long otherwise it might cause fatigue in subjects
- The videos clips should be easy to understand without explanation
- The videos clips should elicit a single desired target emotion

The length of each film clip is about 4 minutes. Each film clip is well-edited to create coherent emotion eliciting and maximize emotional meanings [14]. The details of the film clips used in the experiments are shown in Table 1.

For each experiment, 15 trails have been conducted. Before each video clip is shown, 5s hint has been given and 45s self-assessment forms are provided after the clip. Between the video clips, 15s rest is given in every session. The order of presentation is arranged so that two film clips targeting the same emotion are not shown consecutively. For the feedback, participants are told to report their emotional reactions to each film clip by completing the questionnaire immediately after watching each clip. The flow of the experiment is represented in Figure a.

Subjects

Fifteen Chinese individuals (7 males and 8 females; MEAN: 23.27, STD: 2.37) participated in the experiments. To protect personal privacy, the names of the participants were hidden and indicated each subject with a number from 1 to 15. They were equipped with an EEG headset while watching these videos to capture participant's brain signals at that time. Each clip was designed to trigger certain emotions in the participant.

Data

The SJTU Emotion EEG Dataset (SEED) is provided by the BCMI laboratory led by Prof. Bao-Liang Lu The SEED dataset contains the subject's EEG signals when they were watching films clips. The film clips are carefully selected to induce different types of emotion, which are positive, negative, and neutral ones. After loading these EEG signals into the system, a simple analysis could be done initially. We could see that the data we received has 310 dimensions which means it has 310 features. We can see that categories are almost equally distributed in our data which means there is no class imbalance in this data. Class imbalance means a category has significantly more records than others. This will negatively affect the accuracy of machine learning predictions as machine learning methods tend to classify data into the majority class.

Preprocessing and Data Transformation

Data preprocessing is done to clean the data by removing noise and insignificant features. All the features were further smoothened with conventional moving average and linear dynamic systems (LDS) approaches. We can use correlation as a matrix for feature selection. Correlation checks if variables are dependent which means checking if there is a proportional increase or decrease in future values. Correlation can be in range

-1 and 1. -1 means there is a high negative correlation and 1 means there is a high positive correlation. 0 means there is no correlation at all. Heat maps can be used to visualize these correlations between the features. We can remove one from a pair of features having a high positive or negative correlation.

To better understand the data, we need to visualize it first. Since our data has 310 dimensions, we can't plot it in a 2D graph. We can use principal component analysis to reduce the dimension of the data without losing any meaning. The principal component analysis will club collinear variables together. After reducing dimension and plotting into a 2D graph we could see if classes are linearly separable or not. This will help us make decisions on selecting the machine learning techniques needed to classify the data accurately.

Data transformation is done so that the system can better process the data. We do normalization to rescale all the feature values between 0 and 1. Normalization helps prevent the features with bigger values overshadowing other features and influencing the classification accuracy. The machine learning models, usually, are resource-intensive tasks. Making the feature values smaller by normalizing will make the whole process a lot faster and help run machine learning models to take up fewer resources.

The autoencoder has been used to reduce the dimensions of the data and extract more meaning high-level features from the dataset. The autoencoder deconstructs the data to the simple representation of input and deconstructs it back to the original input. During this process, the dimensions obtained from the latent layer of the trained model give us the high-level features that best represent the data.

Environment

We have used Python 3 to apply different machine learning models on EEG data. We have imported Multiple libraries like Scikit-learn so that we don't have to code machine learning models from scratch, matplotlib to create graphs, etc. Below are the tools that are currently being used for the development of this project.

- Programming language : Python
- Version : 3.7
- Environment : Anaconda 3
- IDE : Jupyter notebook, PyCharm
- Python libraries :NumPy, TensorFlow, Keras, pandas, matplotlib

Methods

Generally, the dataset is divided into train and test datasets in any machine learning problem. Furthermore, the network model is created to analyze the data. Some of the machine learning networks models which could be employed in this case are machine learning classifiers, Auto-encoders, DBN. The machine learning process involves three steps as listed below

- Data pre-processing
- Train the network model
- Test the network model

Machine learning techniques help to find patterns and predict the outcomes. The research objective is to find optimal accuracy on the EEG dataset as we analyze brain signals and compare the results among the various deep learning algorithms. The performance of the model is improved by applying methods such as

- Feature extraction
- Dimensionality Reduction
- Classification algorithms

Autoencoder

Autoencoders are a special case of neural networks used to represent data as a simpler and in lower dimensions. An autoencoder consists of two components: Encoder and Decoder.

The encoder function deconstructs the input data and as the number of features is reduced in each hidden layer the data is represented in lower dimensions. The last layer of the encoder is called the latent layer. The decoder function reconstructs from the reduced dimensions to recreate the given input at the output layer. If the output is the same as the input layer, the network model is accurate, and the dimensions obtained from the latent layer are considered the best representation of the underlying features of the data. Refer to figure c for your understanding. Autoencoder is mainly used for dimensionality reduction.

We use autoencoder as a classifier and the network model is created in two stages. In the first stage, we initialize a simple autoencoder and train the model for the best accuracy. After the autoencoder is trained, we store the weights of the autoencoder to be used later. In the second stage, we remove the decoder and plugin the SoftMax layer to convert the autoencoder to a classifier. Using the previously stored weights of an autoencoder, we now train only the classifier layer with lower parameters to give the high performance.

Support Vector Machine (SVM)

The support-vector machines are supervised learning models that can be used for classification or regression problems. We have used just plain SVM without any feature extraction methods or dimensionality reduction methods. It is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. The python implementation of this model is shown in Figure d.

Autoencoder with SVM

An autoencoder is one of the most commonly used methods for Feature extraction. Four dense layers are used here to reduce the dimensionality of the input for better performance. Initially, using an autoencoder, the model is pre-trained with the training dataset. To use autoencoder as a classifier, after training the model the decoder part is removed and replaced with the SVM classifier. The autoencoder and classifier are built using Keras library in python. The autoencoder is a neural network with 4 dense layers.

Extreme Learning Machine (ELM)

The extreme learning machine (ELM) is a rapid learning algorithm of the single-hidden-layer feedforward neural network. The weights have randomly initialized the weights between the input layer and the hidden layer and the bias of hidden layer neurons and finally uses the least-squares method to calculate the weights between the hidden layer and the output layer.

Random Forest

Random Forest method is a tree & bagging approach-based ensemble classifier. It reduces the number of features automatically by its probabilistic entropy calculation approach. This method builds multiple decision trees and merges them to get a more accurate and stable prediction. Random Forest is a flexible, easy to use machine learning algorithm that produces, even without hyper-parameter tuning, a great result most of the time. It is also one of the most used algorithms, because of its

Models	Feature Extraction	Shuffled Training and Testing data	Batch Normalized	Avg Testing Accuracy

Models	Feature Extraction	Shuffled Training and Testing data	Batch Normalized	Avg Testing Accuracy
DBN	Yes	No	Yes	73.9%
ELM	NA	No	Yes	76.6%
SVM	AutoEncoder	No	Yes	78.9%
SVM	NA	No	Yes	79.1%
K-NN	NA	Training - 10%, testing – 90%	Yes	99.8%
Random Forests	Na	No	Yes	78.6%

simplicity. Besides, it also can be used for both classification and regression tasks. The python implementation of this method is shown in Figure e.

Nearest Neighbors (K-NN)

Table 2

The k-nearest neighbors (KNN) algorithm is a simple, easy-to-implement supervised machine learning algorithm that can be used to solve both classification and regression problems. K-NN is one of the most famous classification algorithms as of now in the industry simply because of its simplicity and accuracy. K-NN is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions). In K-NN, K is the number of nearest neighbors. The number of neighbors is the core deciding factor. We have experimented with the data by shuffling the testing and training data and used 10% of the dataset for training and remaining for testing. The python implementation of this method is shown in Figure f.

Deep Belief Network (DBN)

A deep belief network (DBN) is a network consisting of several layers of Restricted Boltzmann Machines (RBM) which is then connected to a classifier. Restricted Boltzmann machines are some of the most common building blocks of deep probabilistic models. RBMs Consists of 2 layers of visible layer and hidden layer. These RBMs acts as encoder during feed-forward connection and as decoder during backward propagation. These simple networks can be used for feature extraction effectively. A recurrent RBM network is created and on top of that, a DBN network with a classifier is built with dense layers to classify the emotion

Experiment results

The performances of the above-mentioned classifiers in terms of accuracies are shown in the above table 2. The experiment results have been summarized in table 2 with their average testing accuracies. Each model has been executed for three runs and the average accuracy is calculated for consistency. From table 2, we can observe that SVM has produced the highest accuracy among others without changing the training and testing data. The accuracy of SVM is around 79.1% however, the accuracy of SVM with autoencoder has dropped by a few points. Although the SVM method gave us the best result for classifying EEG data, we tried to increase the performance further by combining autoencoder with SVM. We also tried combining

PCA and SVM, but they did not give any better classification accuracy. The autoencoder was used on the dataset to obtain reduced dimensions extracting the best features. When SVM applied on top of the autoencoder, it yielded only 78.9% accuracy. The ELM has produced 76.6% with 7000 neurons, while the DBN algorithm has only produced approximately74%. After SVM, and SVM with autoencoder methods, the Random Forest network has given the highest accuracy of 78.6%. However, The SVM method took less time to train compared to random forest giving better predictions at the same time.

We tried to experiment with the dataset, where training and testing datasets were given to us separately. We have selected only 10% of the training data from the complete dataset at random and trained the model using the K-NN method and tested the new model against the remaining data for testing. The results were surprisingly interesting. The testing accuracy peaked at 99.8%. So from all of the methods presented in this paper, the highest accuracy is obtained by the K-NN model, followed by SVM, SVM with autoencoder, Random Forests, ELM, and DBN. The comparison of the accuracies of these models can be observed in figure h.

Future work

We have applied various machine learning models on the EEG dataset and the results have been compared. We propose to use the data augmentation by introducing noise in the data by the Gaussian distribution method to achieve better accuracy.

Furthermore, deep network models like LSTM and capsule networks could be applied to see if they give better performance than what we have achieved. We could also explore the ideas of feature fusion and more robust feature extraction methods. Additionally, other methods such as using the CNN network as a classifier can also be tried to increase the accuracy of the model.

Conclusion

In this paper, a series of experiments were conducted on the EEG dataset where DE features were collected. A new EEG feature named differential entropy (DE) is considered better when compared to the traditional domain feature named energy spectrum (ES) based on the results it produced in previous researches. we have performed six classification methods on the data and compared the results to get the best accuracy. The performances of the classifiers are assessed with the same dataset, data preprocessing and feature extraction methods. The experimental results also show that the KNN model has obtained higher accuracy when testing and training datasets were shuffled and selected 10% of the data for training at random.

We have used autoencoder for feature extraction and dimensionality reduction. However, using autoencoder has only decreased the accuracy when used with other classification models. In addition to the KNN model, we have applied SVM, SVM with autoencoder, ELM, Random Forests and Deep belief network (DBN) and their accuracies are 79.1%, 78.9%, 76.6%, 78.6%, and 74% respectively.

Acknowledgment

The authors are grateful to Dr. Fiaidhi Jinan for her support and guidance during this project. This project has been carried out under her supervision and guidance. We also like to thank all the graduate students at Lakehead University for the inputs and the queries raised during the demonstration of this project. We also like to extend our gratitude to the creators of the SEED dataset and the other researchers mentioned in the reference section

References

1. Y. Yang, Q. Wu, W. L. Zheng and B. L. Lu, ”EEG-based emotion recognition using hierarchical network with subnetwork nodes,” EEE Transactions on cognitive and developmental systems, vol. 10, no. 2, pp. 408-419, 2018.
2. R. N. Duan, J. Y. Zhu and B. L. Lu, ”Differential Entropy Feature for EEG-based Emotion Classification,” in 6th Annual International IEEE EMBS Conference on Neural Engineering, San Diego, California, 2013.
3. B. Wang, C. M. Wong, F. Wan, P. U. Mak, P. I. Mak and M. I. Vai, ”Comparison of Different Classification Methods for EEG-Based,” in Proceedings of the 2009 IEEE International Conference on Information and Automation, Zhuhai/Macau, China, 2009.
4. G. L. Ahern and G. E. Schwartz, ”Differential lateralization for positive and negative emotion in the human brain: EEG spectral analysis,” Neuropsychologia,, vol. 23, no. 6, pp. 745-755, 1985.
5. T. Chai, S. Woo, M. Rizon and C. Tan, ”Classification of human emotions from EEG signals using statistical features and neural network,” In International Penerbit UTHM, vol. 1, no. 3, pp. 1-6, 2010.
6. H. Tanaka, M. Hayashi and T. Hori, ”Statistical features of hypnagogic EEG measured by a new scoring system.,” leep, vol. 19, no. 9, pp. 731-738, 1996.
7. R. J. Davidson and N. A. Fox, ”Asymmetrical brain activity discriminates between positive and negative affective stimuli in human infants,” Science, vol. 218, no. 4578, pp. 1235-1237, 1982.
8. R. J. Davidson, ”Anterior cerebral asymmetry and the nature of emotion,” Brain Cogn., vol. 20, no. 1, pp. 125-151, 1992.
9. H. P. Martinez, Y. Bengio and G. N. Yannakakis, ”Learning deep physiological models of affect,” IEEE Computat. Intell. Mag, vol. 8, no. 2, pp. 20-33, 2013.
10. D. Mathersul, L. M. Williams, P. J. Hopkinson and A. H. Kemp, ”Investigating models of affect: Relationships among EEG alpha asymmetry depression, and anxiety,” Emotion, vol. 8, no. 4, p. 560, 2008.
11. W. L. Zheng and B. L. Lu, ”Investigating Critical Frequency Bands and Channels for EEG-Based Emotion Recognition with Deep Neural Networks,” Investigating Critical Frequency Bands and Channels, vol. 7, no. 3, pp. 162-175, 2015.
12. ”SEED Dataset,” Brain-like computing and Machine Learning (BCMI), [Online]. Available: http://bcmi.sjtu.edu.cn/~seed/index.html. [Accessed 4 April 2020].
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