A Thesis Report

on

A multi-model Mental Emotion Prediction of EEG-based Brain Signal Data

Submitted To

Dr. Tania Islam

Assistant Professor

Department of Computer Science and Engineering

Submitted By

Gazi Mazharul Islam

Roll: 09-001-06

Course: DSP- 01

Department of Computer Science and Engineering

Department of Computer Science and Engineering

University of Barishal

BARISHAL, BANGLADESH

Abstract

This paper presents an advanced approach to emotional state classification using EEG brainwave data collected through a commercial MUSE EEG headband with four electrodes (TP9, AF7, AF8, TP10). The study evaluated the effectiveness of multiple machine learning models in classifying emotional states elicited by film clips designed to evoke distinct emotional valences. Statistical features were derived from the alpha, beta, theta, delta, and gamma brainwave bands to construct a robust dataset. Additionally, Fast Fourier Transform (FFT) was applied to extract frequency-domain features, which were then integrated with the statistical features to enhance the dataset's comprehensiveness for emotion classification. The data contains total 2548 features. The experimental evaluation of five machine learning models showed varying accuracy in classifying emotional states. The neural network achieved the highest accuracy at 98.83%, followed closely by Random Forest at 98.59%, highlighting the strength of deep learning and ensemble methods for EEG-based emotion classification. Decision Tree reached 95.55% accuracy, with Support Vector Machine 96.25% and k-Nearest Neighbors 94.15% also showing competitive performance. These findings demonstrate the potential of advanced machine learning techniques for accurate emotion classification in EEG analysis, with significant implications for mental health and human-computer interaction applications.

Keywords: *EEG, FFT, KGE, KNN, SVM, DT, RF, NN, MUSE EEG Headband, Mental Health*

Table of Contents

1. INTRODUCTION

Emotion recognition has become an essential area of research in affective computing, with applications spanning mental health assessment, human-computer interaction (HCI), and brain-machine interfaces (BMI). Among the numerous noninvasive methods for tracking emotional states, electroencephalography (EEG) has gained particular interest due to its real-time ability to capture electrical activity from the brain. EEG-based emotion detection offers the promise of real-time, nuanced insights into mental states, potentially facilitating advancements in domains requiring emotional responsiveness, such as assistive technologies and therapeutic tools. An electroencephalogram (EEG) signal is a recording of the electrical activity of the brain, which is captured by sensors attached to the scalp.

Historically, EEG analysis faced significant challenges due to the complex, non-stationary nature of brainwave data, which can be influenced by various external and internal factors. Advances in machine learning have recently enabled more effective processing of EEG data by facilitating feature extraction and classification from noisy, high-dimensional signals. Particularly, statistical analysis of EEG frequency bands—such as alpha, beta, theta, delta, and gamma waves—has become a standard approach for constructing robust datasets for emotion recognition. The extraction of frequency-domain features, often facilitated by the Fast Fourier Transform (FFT), further enhances the ability to analyze these signals by isolating brainwave patterns associated with specific emotions.

Machine learning techniques, especially neural networks and ensemble classifiers like Random Forest, have shown promise in emotion classification by achieving high accuracy with EEG data. For instance, neural networks excel in complex pattern recognition, leveraging multi-layer architectures to capture non-linear relationships in brainwave data. Ensemble methods, on the other hand, combine multiple decision-making models to reduce error and improve generalizability, as evidenced by studies demonstrating their efficacy in EEG classification tasks.

This study employs a commercially available MUSE EEG headband, equipped with four electrodes (TP9, AF7, AF8, TP10), to capture EEG data while participants are exposed to film clips selected to evoke distinct emotional valences. Statistical and frequency-domain features extracted from the alpha, beta, theta, delta, and gamma bands form the basis of a comprehensive dataset, comprising 2,548 features. The effectiveness of multiple machine learning models—neural networks, Random Forest, Decision Trees, Support Vector Machine (SVM), and k-nearest Neighbors (KNN)—is evaluated to classify emotional states based on the collected EEG signals. The neural network and Random Forest models achieved the highest accuracies at 98.83% and 98.59%, respectively, highlighting the robustness of deep learning and ensemble approaches for emotion classification.

The main contributions of this work are as follows:

1. To evaluate multi-model for emotion classification
2. Three emotional classes—positive, neutral, and negative—have been established to account for mental states that are not dominated by prevailing emotions.
3. Fast Fourier Transform has been used for feature extractions in order to improve model accuracy.

The key sources of inspiration and influences for the study will be discussed in the remaining sections of this paper, along with related research work. The approach, feature extraction, and comparison of the five models will all be covered. After presenting and discussing the findings with related studies, conclusions will be drawn.

2. Related Work

It has been discovered that statistics generated by a time-windowing technique with feature selection are useful for categorizing mental states like concentrated, neutral, and relaxed [1]. Using a dataset that had been pre-processed using the Fast Fourier Transform as a feature extraction an ensemble Random Forest technique demonstrated an observed classification accuracy of 98.59% and a deep neural network accuracy of 98.83%. These encouraging findings implied that a study on the categorization of emotional states with a comparable investigative methodology would also be fruitful.

Fisher's Discriminant Analysis was the most effective state-of-the-art method for classifying emotional EEG data from a low-resolution, inexpensive EEG setup, yielding an accuracy of 95 percent [2]. The goal of the study was to keep participants from getting tight and to avoid blinking, however, the earlier study [1] discovered that EMG data from these activities aided in classification since, for instance, blink rates affect focus. Therefore, when unconscious movements are neither encouraged nor discouraged, the new study detailed in this publication will investigate the classification of emotions in EEG data. Since conscious superfluous movements like sipping water only create outlying or masking points in the data, they will not be permitted. For example, the algorithm will only categorize the electrical data produced by the actions of persons who are feeling good if they are also consuming water. Music [3] and movies [4] are frequently reported to be the most effective emotional stimuli for EEG-based research. Thus, like a recent study that used music videos, this paper focuses on movie snippets that use audio tracks (music and/or speech) to elicit emotions [5].

For the classification of emotions, common spatial patterns have shown remarkable efficacy, achieving an overall best solution of 93.5% [6]. Different levels of enjoyment throughout a task were effectively used to classify high resolutions of valence using a MUSE EEG headband [7]. When examining binary classes of positive and negative, Deep Belief Network (DBN), Artificial

Neural Network (ANN), and Support Vector Machine (SVM) techniques were found to be highly effective in classifying emotions from EEG data [8]. In order to take use of their various advantages and disadvantages, this study will build on all of these findings using comparable techniques as well as an ensemble. In order to facilitate emotional classification in a setting where emotions are not prominent, the study also recommends for the use of a neutral class as a bridge to real-world applications. Since this has been shown to be beneficial in the learning processes for web-based chatbots, it adds valence or perceived sentiment [9]. This paper utilized Mental emotional sentiment classification EEG-based brain data [10].

3. Objectives

- To develop effective machine learning models for classifying emotional states using EEG data.
- To evaluate the effectiveness of feature extraction methods in enhancing classification performance.
- To validate the feasibility of using a low-cost, commercially available EEG device for emotion classification.

4. Research Questions

- How can EEG signals be effectively processed and simplified to classify emotional states accurately?
- Which machine learning models (single and ensemble) provide the highest accuracy for classifying emotional states from EEG data?
- Can low-cost, commercially available EEG devices provide sufficient accuracy for practical emotion classification applications?
- What impact do feature selection techniques have on the performance of different classification models?

5. BACKGROUND

5.1. Electroencephalography

Electroencephalography (EEG) is a method for recording data and signals generated by the brain using electrodes [11, 12]. Electrodes can be placed subdurally that is under the skull and on top of or even into the brain tissue [13]. They can be external (wet or dry electrodes on the skin around the skull for noninvasive EEG methods) [14]. The electrical signals recording in microvolts (µV) capture brain-dominant waves response during a period of time, starting from the first instant t to another instant at t+n.

5.2. Human Emotion

Although human emotions are diverse and complicated, they can be broadly classified into two categories: positive and negative [15]. Certain feelings can coexist, such as when a character's survival in a movie evokes a mix of hope and doomed sadness. The non-overlapping emotions that actually distinguish high from low experiences will be investigated in this study.

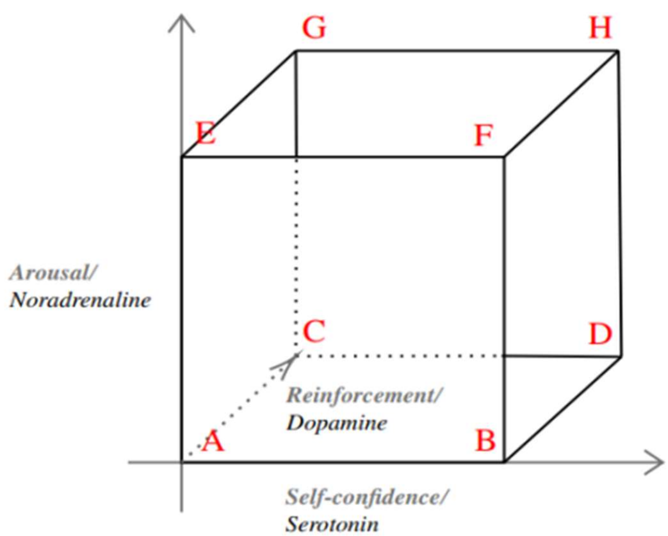

Figure 1: Lövheim's Cube of Emotional Categorization is a 3D model

Lövheim's three-dimensional model of emotions [16] described the brain's chemical composition and linked it to a number of categories of largely positive and negative valence. A chemical mixture corresponds to feelings within both positive and negative classes, as seen in Figure 1, where emotion categories A–H are situated at the model vertices listed in Table I. Furthermore, there is some literature-based evidence that brainwave activity can be directed by neural oscillations in conjunction with chemical composition [17]. This study suggests that emotional states can be categorized using statistical features of filtered brain waves, based on the interplay between chemical signaling that produces electrical activity in the brain and the literature on muscles and emotional expressions from electromyogram signals embedded within mixed neurophysiological data.

Tabel I: A table presenting Lövheim's emotional categories

Emotion Category	Emotion/Valence
A	Shame (Negative) Humiliation (Negative)
B	Contempt (Negative) Disgust (Negative)
C	Fear (Negative) Terror (Negative)
D	Enjoyment (Positive) Joy (Positive)
E	Distress (Negative) Anguish (Negative)
F	Surprise (Negative) (Lack of Dopamine)
G	Anger (Negative) Rage (Negative)
H	Interest (Positive) Excitement (Positive)

5.3. Machine Learning Algorithms

The application of machine learning algorithms to the classification of emotions has drawn a lot of interest, and different models provide unique benefits for analyzing complex, multi-dimensional datasets, like those generated by brainwave signals. Several algorithms were used in this work; they were chosen based on how well they handled the particular characteristics of electrophysiological data.

K-Nearest Neighbors (KNN) is a straightforward yet effective classification technique that is frequently applied to pattern recognition. If you know the data points, or "neighbors," of a new piece of data, as well as what the most beautiful class is, KNN will work. KNN tends to work well on short, highly separable datasets, but it is a fairly straightforward and interpretable technique for classifying emotions.

Support Vector Machines (SVM), which is mostly used in classification, are a great model for supervised learning. SVM is a great option for binary classification since it looks for the optimal hypersurface that also indicates the greatest separation between the classes in the data space. Support vector machines (SVMs) are especially helpful for applications involving complicated neural signals where feature separation is crucial because of their specialized tolerance to high-dimensional input and reduced risk of overfitting

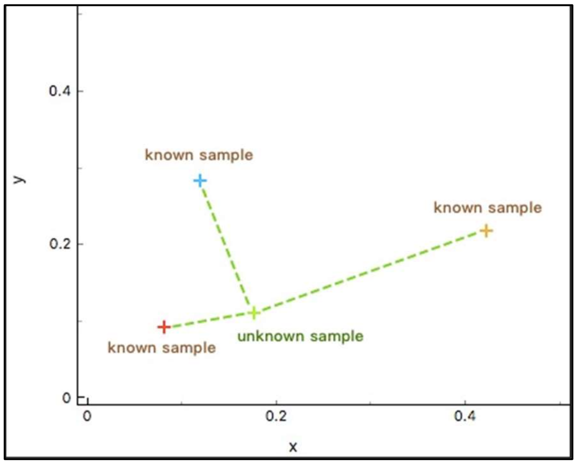

Figure 2: K-Nearest Neighbor

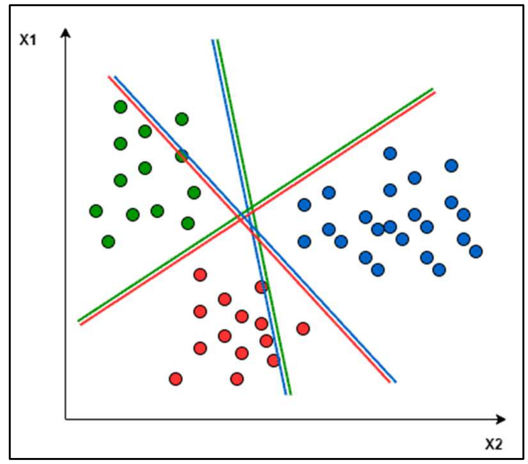

Figure 3: Support Vector Machine

Decision Trees is another solid and easy to interpret class of models, which splits the dataset by analyzing via feature values and utilizing decision rules in a tree format to classify every instance. Decision trees often have nice properties that allow them to be transparent and readable, which give clear information on the decisions being made. Nevertheless, the tendency to overfit noisy data can constrain their performance on high dimensional spaces.

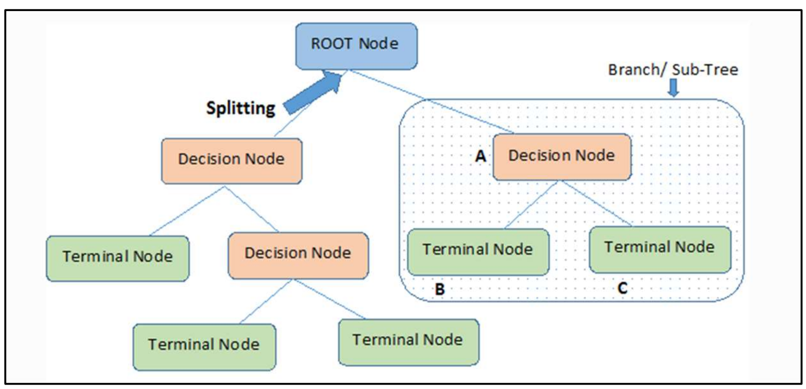

Figure 4: Decision Tree

Random Forests take the basic idea of a decision tree and run with it, creating many trees through randomness, to create an ensemble model based on combining their results. Random Forests prevent overfitting and improve predictive accuracy by averaging the outputs of many decision trees. This is especially for scenarios in emotion classification task which need to combine the information from different brainwave features, since there may be hidden phenomena that represent two totally different emotions with subtle differences.

Neural Network, a more advanced type of machine learning that is modeled after the human brain. Neural networks are made up of layers that are connected by nodes, which are also referred to as "neurons" because they influence a particular aspect of the network. Together, these layers are able to recognize increasingly complex patterns in data. In high-dimensional, non-linear data, where relationships are complicated, as brainwave signals frequently exhibit, neural networks are renowned for their exceptional performance. They are particularly useful for simulating the intricate connections between emotions and brain impulses because of their adaptability.

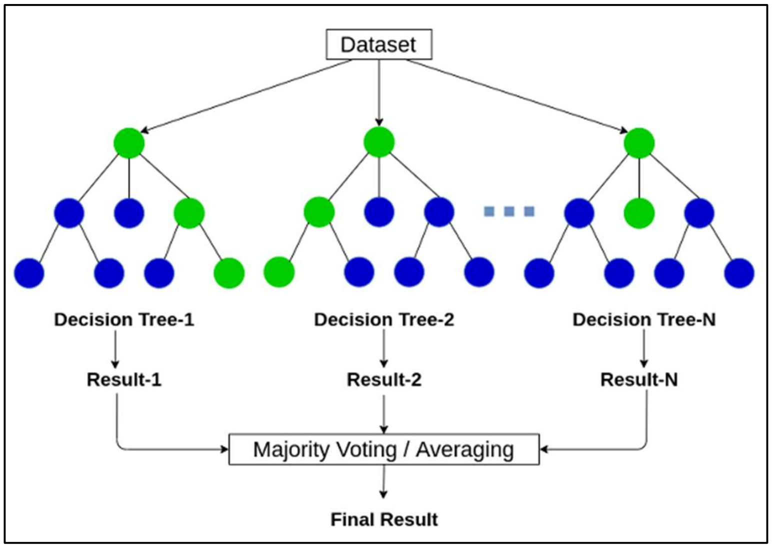

Figure 5: Random Forest

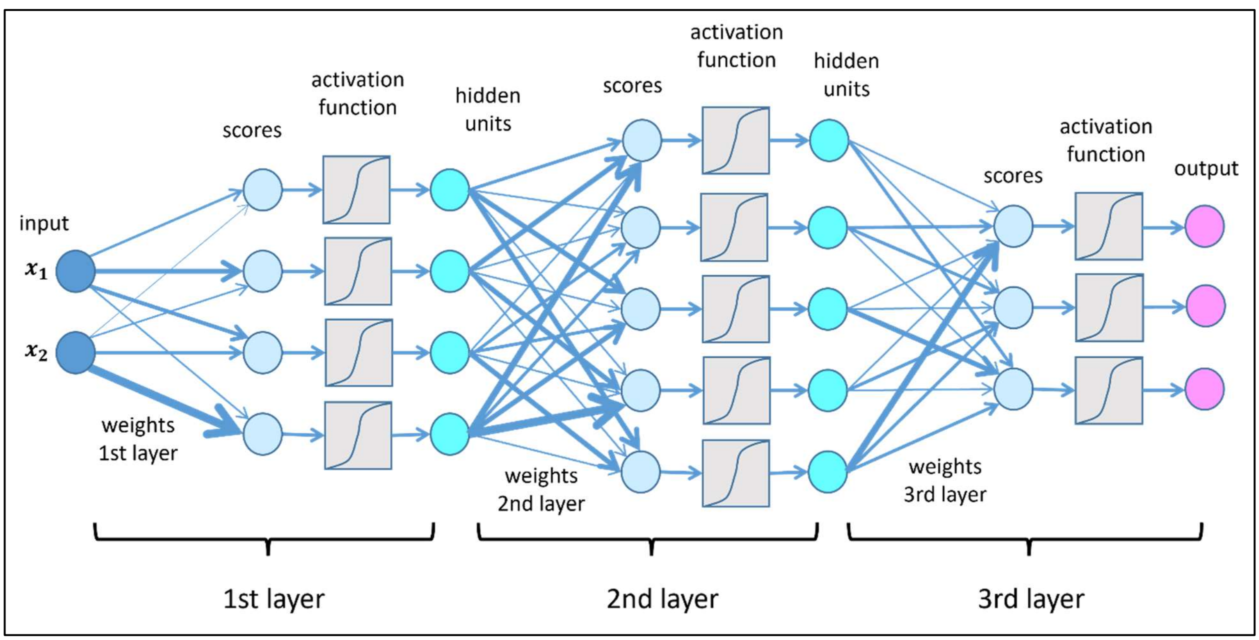

Figure 6: Neural Network

6. METHOD

This involves a MUSE EEG headband that is commercially available with four electrodes attached externally and using dry contact. As shown in Fig. 7, the microvoltage data are measured from four electrode sites: TP9, AF7, AF8 and TP10. The EEG data from two participants (1 male and 1 female, aged 20 to 22) were collected for 60s in every trial while viewing each of the six film clips shown in Table II, summing up a total of 12 min (720 s) for brain activity data (6 min per emotion type). Moreover, one of six minutes of neutral brainwave data was collected which yielded 36-minutes spent in their EEG across subjects. The dataset consisted of 324,000 data points from

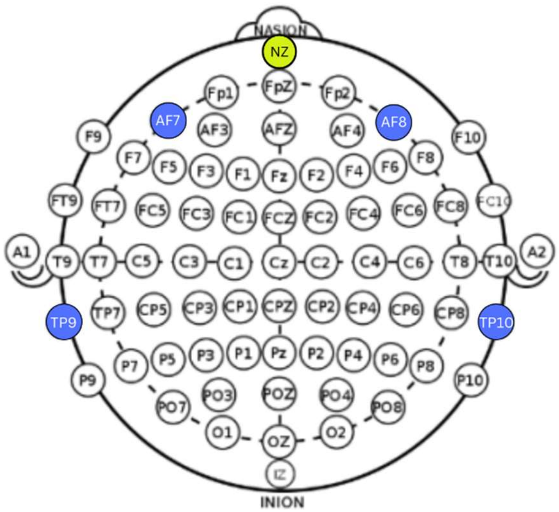

Figure 7: The Muse headband's EEG sensors—TP9, AF7, AF8, and TP10—are positioned according to the international standard EEG placement system [18].

activities designed to elicit an emotional response from a set of emotions listed in Table I. These activities are recorded from brain waves at a resampled frequency of 150Hz. A selection of emotions was classified into positive and negative based on their valence, and not based on the exact type of emotions being felt. A third category of data consisted of neutral data, which was collected prior to the presentation of any emotional stimuli, representative of the subject's resting emotional state uncontaminated by emotional data. To reduce the resting emotional state, three minutes of data were collected each day.

Participants were instructed to watch the film without making any deliberate movements (e.g., drinking coffee) to avoid contaminating the data with Electromyographic (EMG) signals, which are typically more prominent than brainwave signals in terms of strength. This approach was inspired by a previous study that demonstrated the potential of blinking patterns for classifying mental states [1]. While the study did not actively encourage or discourage unconscious movements, observations during the experiment noted that one participant briefly smiled during the 'funny dogs' compilation clip and appeared visibly upset during the death scene in the film *Marley and Me*. Facial expressions, while influencing the recorded data, are integrated into the

Table II: Source of Film Clips used as Stimuli for EEG Brainwave Data Collection

Stimulus	Valence	Studio	Year
Marley and Me	Neg	Twentieth Century Fox, etc.	2008
Up	Neg	Walt Disney Pictures, etc.	2009
My Girl	Neg	Imagine Entertainment, etc.	1991
La La Land	Pos	Summit Entertainment, etc.	2016
Slow Life	Pos	BioQuest Studios	2014
Funny Dogs	Pos	MashupZone	2015

classification model as they authentically represent real-world behavior, where such emotional responses naturally occur. Consequently, to accurately simulate realistic scenarios, both EEG and facial EMG signals are regarded as informative. To create a dataset of statistical features, a robust methodology from a previous study [2] was applied, enabling the extraction of 2400 features using a 1-second sliding window starting at t=0 and t=0.5. The data were down-sampled to the lowest observed frequency of 150Hz.

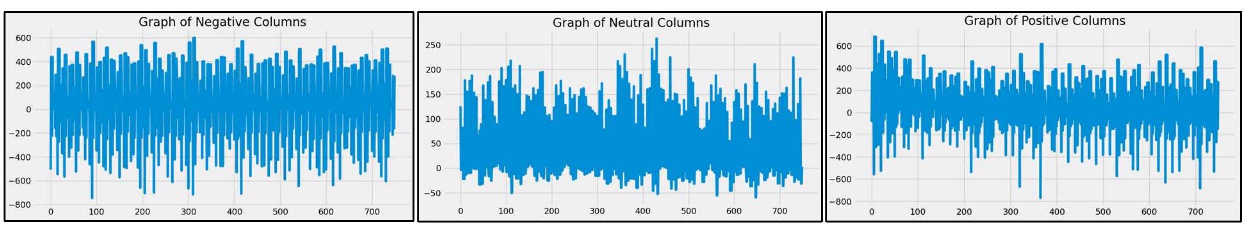

Figure 8: Features extraction using Fast Fourier Transform

The Fast Fourier Transform (FFT) is applied for feature extraction to derive time-frequency domain features, which are subsequently integrated with the statistical features. This combination yields a total of 2549 source attributes. Fig. 8 shows the feature extraction of negative, neutral and positive columns. Classification models, including K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Neural Network (NN), are then employed using the EEG brain signal data. Table III shows the performance of each classification model. The experimental evaluation employed five distinct machine learning algorithms: K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Neural Network (NN). The models' performance was assessed using three standard evaluation metrics: Precision, Recall, and F1-Score, across three classes (0, 1, and 2).

Table III: Performance metrics of Five models

Class Label	K- Nearest Neighbor			Support Vector Machine			Decision Tree			Random Forest			Neural Network		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score
0	0.90	**0.99**	0.94	0.96	0.98	0.97	0.93	0.96	0.94	0.97	**0.99**	0.98	**0.99**	**0.99**	**0.99**
1	0.97	0.98	0.97	0.99	0.97	0.98	**1.00**	**0.99**	0.99	**1.00**	**0.99**	**1.00**	**1.00**	**0.99**	0.99
2	0.97	0.85	0.90	0.94	0.94	0.94	0.94	0.92	0.93	**0.99**	0.97	**0.98**	0.98	**0.99**	**0.98**

7. RESULTS

There are three class labels in all for the EEG brain data: 0 for negative emotion, 1 for neutral emotion, and 2 for positive emotion. The overall class labels are 708, 716, and 708, respectively, for negative, neutral, and positive categories. Fig. 9 shows the EEG emotion label data distribution.

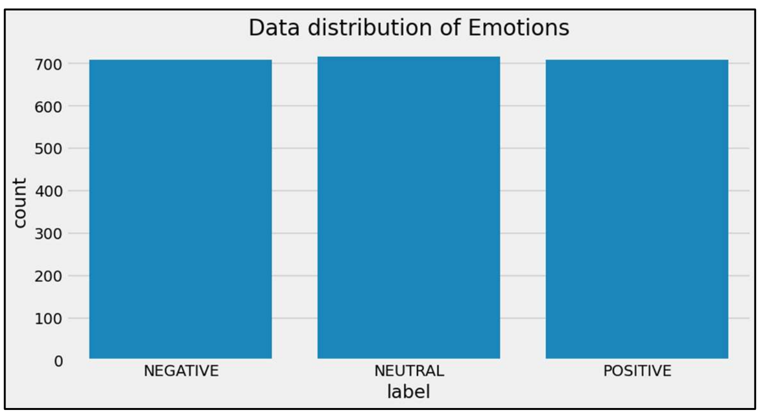

Figure 9: EEG emotion label data distribution

The experimental evaluation of five different machine learning models revealed varying levels of classification accuracy. The neural network emerged as the top-performing model with an accuracy of 98.83%, closely followed by the Random Forest classifier at 98.59%. These results demonstrate the superior capability of both deep learning and ensemble methods for the classification task at hand. The Decision Tree classifier achieved an accuracy of 95.55%, while Support Vector Machine (SVM) and k-Nearest Neighbors (KNN) models showed relatively lower but still competitive performance, with accuracies of 96.25% and 94.15% respectively. Fig. 10

shows a comprehensive comparison of the model accuracies. The performance difference between the best-performing model (Neural Network) and the lowest-performing model (KNN) was 4.68 percentage points, indicating a notable variation in classification capabilities across different algorithmic approaches. Both the Neural Network and Random Forest models achieved exceptional accuracy rates of nearly 99%, suggesting their particular suitability for this classification task. The high accuracy rates achieved by both the Neural Network and Random

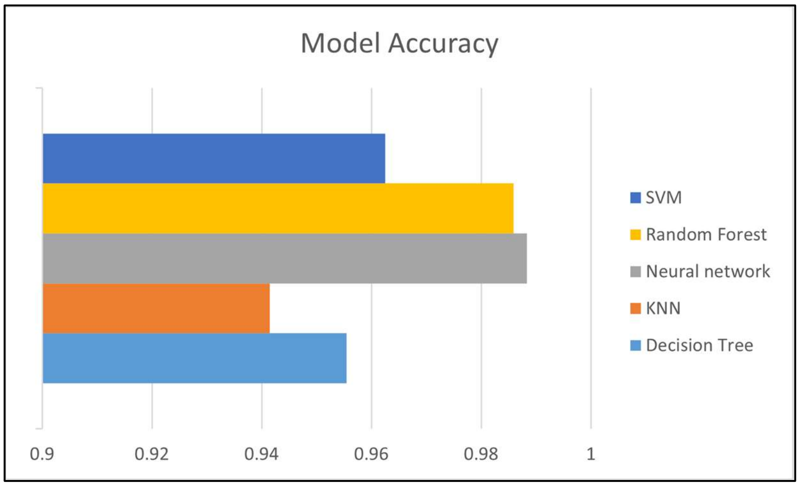

Figure 10: Comparison of the model accuracy

Forest models can be attributed to their architectural advantages. Neural Networks excel at capturing complex non-linear relationships in the data, while Random Forests benefit from ensemble learning, combining multiple decision trees to reduce overfitting and improve generalization. The similar performance of these two distinct approaches suggests that the classification patterns in the dataset are both well-defined and learnable through different algorithmic paradigms.

8. CONLUSION

This study highlights the considerable potential of machine learning techniques for emotion classification using EEG data gathered from a commercial-grade, low-resolution headband. Advanced machine learning methods, particularly ensemble techniques like Random Forest and individual models such as Neural Networks, have achieved impressive accuracy levels. There is a strong opportunity to develop classification algorithms that can provide practical value in real-world decision support systems. By responding to emotional states, these algorithms can improve interactions and, in mental health contexts, assist in evaluating issues and identifying appropriate solutions. Future research should concentrate on feature selection for the vast EEG data, which would help reduce data dimensions and computational costs. Additionally, exploring various ensemble models could further enhance the accuracy of emotion detection from brain signal EEG data.

9. References

1. Ding, W. and Marchionini, G. 1997. A Study on Video Browsing Strategies. Technical Report. University of Maryland at College Park. J. J. Bird, L. J. Manso, E. P. Ribiero, A. Ekart, and D. R.
2. Faria, "A study on mental state classification using eeg-based brain-machine interface," in 9th International Conference on Intelligent Systems, IEEE, 2018.
3. D. O. Bos et al., "EEG-based emotion recognition," The Influence of Visual and Auditory Stimuli, pp. 1–17, 2006.
4. Y.-P. Lin, C.-H. Wang, T.-P. Jung, T.-L. Wu, S.-K. Jeng, J.-R. Duann, and J.-H. Chen, "EEG-based emotion recognition in music listening," IEEE Transactions on Biomedical Engineering, vol. 57, no. 7, pp. 1798–1806, 2010.
5. X.-W. Wang, D. Nie, and B.-L. Lu, "Emotional state classification from eeg data using machine learning approach," Neurocomputing, vol. 129, pp. 94–106, 2014.
6. S. Koelstra, A. Yazdani, M. Soleymani, C. Mühl, J.-S. Lee, A. Nijholt, T. Pun, T. Ebrahimi, and I. Patras, "Single trial classification of eeg and peripheral physiological signals for recognition of emotions induced by music videos," in Int.
7. Conf. on Brain Informatics, pp. 89– 100, Springer, 2010.M. Li and B.-L. Lu, "Emotion classification based on gamma-band eeg," in Engineering in medicine and biology society, 2009. EMBC 2009. Annual international conference of the IEEE, pp. 1223–1226, IEEE, 2009.
8. M. Abujelala, C. Abellanoza, A. Sharma, and F. Makedon, "Brainee: Brain enjoyment evaluation using commercial eeg headband," in Proceedings of the 9th acm international conference on pervasive technologies related to assistive environments, p. 33, ACM, 2016.
9. W.-L. Zheng, J.-Y. Zhu, Y. Peng, and B.-L. Lu, "Eeg-based emotion classification using deep belief networks," in Multimedia and Expo (ICME), 2014 IEEE International Conference on, pp. 1–6, IEEE, 2014.
10. Bird, Jordan J., Aniko Ekart, Christopher D. Buckingham, and Diego R. Faria. "Mental emotional sentiment classification with an eeg-based brain-machine interface." In Proceedings of theInternational Conference on Digital Image and Signal Processing (DISP'19). 2019.

11. J. J. Bird, A. Ekárt, and D. R. Faria, "Learning from interaction: An intelligent networked-based human-bot and bot-bot chatbot system," in UK Workshop on Computational Intelligence, pp. 179–190, Springer, 2018.
12. B. E. Swartz, "The advantages of digital over analog recording techniques," Electroencephalography and clinical neurophysiology, vol. 106, no. 2, pp. 113–117, 1998.
13. A. Coenen, E. Fine, and O. Zayachkivska, "Adolf beck: A forgotten pioneer in electroencephalography," Journal of the History of the Neurosciences, vol. 23, pp. 276–286, 2014.
14. A. K. Shah and S. Mittal, "Invasive electroencephalography monitoring: Indications and presurgical planning," Annals of Indian Academy of Neurology, vol. 17, pp. S89, 2014.
15. B. A. Taheri, R. T. Knight, and R. L. Smith, "A dry electrode for eeg recording," Electroencephalography and clinical neurophysiology, vol. 90, no. 5, pp. 376–383, 1994.
16. K. Oatley and J. M. Jenkins, Understanding emotions. Blackwell publishing, 1996.
17. H. Lövheim, "A new three-dimensional model for emotions and monoamine neurotransmitters," Medical hypotheses, vol. 78, no. 2, pp. 341–348, 2012.
18. R. Rojas, "Adaboost and the super bowl of classifiers a tutorial introduction to adaptive boosting," Freie University, Berlin, Tech. Rep, 2009.