Thesis / Report Title

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By

Satyam Saxena
ID No. 2020A3PS1781P

Under the supervision of:

Dr. Abhijit Asati
&
Dr. Dheerendra Singh, Dr.V.K. Chaubey

BIRLA INSTITUTE OF TECHNOLOGY AND SCIENCE PILANI, PILANI CAMPUS
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- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
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Supervisor	*Co-Supervisor*
Dr. Abhijit Asati	Dr. Dheerendra Singh, Dr.V.K. Chaubey
,	Asst. Professor,
BITS-Pilani Pilani Campus	BITS-Pilani Pilani Campus
Date:	Date:

"ML/AI will probably most likely lead to the end of the world, but in the meantime, there'll be great companies."

Sam Altman

BIRLA INSTITUTE OF TECHNOLOGY AND SCIENCE PILANI, PILANI CAMPUS

Abstract

Bachelor of Engineering (Hons.)

EEG Dataset Emotion Classification: Neural Network Training, Deployment, and UI Development

by Satyam Saxena

This thesis explores the development of an emotion classification system using EEG (Electroencephalography) dataset and neural network techniques. Emotion recognition from EEG signals is a challenging task due to the complex nature of brain activity and the variability in emotional responses among individuals. The primary objective of this research is to train a neural network model capable of accurately classifying emotions from EEG data, deploy it for real-world applications, and design a user-friendly interface (UI) for intuitive interaction.

The methodology involves preprocessing the EEG features, followed by the design and training of a neural network model using suitable architectures and optimization techniques. The trained model will then be deployed to create a practical tool for real-time emotion recognition.

Furthermore, this study addresses the crucial aspect of user interaction by developing a graphical user interface (UI) to facilitate the utilization of the deployed model. The UI will provide users with a seamless experience for inputting EEG data, obtaining emotion predictions without needing any Machine Learning knowledge.

Acknowledgements

I would like to express my deepest gratitude to my thesis advisor, Dr Abhijit Asati, for their invaluable guidance, unwavering support, and insightful feedback throughout the entire research process. Their expertise and encouragement have been instrumental in shaping this thesis.

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Lastly, I would like to acknowledge the participants whose EEG data contributed to this research. Their voluntary participation and contribution have been essential in advancing the understanding of emotion classification using EEG signals.

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Chapter 1

EEG Dataset

1.1 Overview

The dataset utilized in this study constitutes EEG recordings gathered from two individuals, encompassing both male and female subjects. Each participant underwent EEG recording sessions for a duration of three minutes per emotional state, namely positive, neutral, and negative. The EEG data acquisition was facilitated through the deployment of a Muse EEG headband, leveraging dry electrodes to capture neural activity from the TP9, AF7, AF8, and TP10 EEG placements.

Additionally, a baseline of six minutes of resting neutral data was recorded to provide a comparative reference point. The stimuli employed to elicit distinct emotional states were carefully curated and administered during the recording sessions. The raw EEG data obtained from the electrodes underwent a transformation process using Muse Lab Streaming Layer (LSL), converting them into structured features amenable for subsequent analysis and classification tasks.

FIGURE 1.1: Generating EEG Dataset

1.2 Muse EEG Headbands and Electrodes

Muse EEG Headbands: The Muse EEG headband serves as a non-invasive wearable device designed to capture electroencephalography (EEG) signals from the brain. This headband, developed by Interaxon Inc., features a sleek and lightweight design, making it suitable for comfortable and extended wear during EEG data collection sessions. Equipped with advanced sensor technology, the Muse headband enables real-time monitoring of brain activity, offering insights into cognitive states, emotional responses, and mental states.

Electrode Placements: The Muse EEG headband incorporates dry electrodes strategically positioned at four key locations on the scalp, namely TP9, AF7, AF8, and TP10. These electrode placements are selected based on established conventions for capturing neural activity from distinct brain regions associated with various cognitive and emotional processes. The specific locations chosen on the scalp correspond to standardized EEG electrode placement systems, facilitating consistency and comparability across studies.

Output Generation: The Muse headband generates output in the form of raw EEG data, capturing electrical signals originating from the brain's neural networks. These signals are detected by the dry electrodes and transmitted to the device's processing unit for amplification, filtering, and digitization. The resulting EEG data comprises voltage fluctuations over time, representing the collective electrical activity of neuronal populations in the vicinity of the electrode placements. This raw EEG output serves as the primary input for subsequent processing

1.3 Muse LSL

Muse LSL is an Open Source Python package for streaming, visualizing, and recording EEG data from the Muse devices developed by InteraXon. Under the hood it employs statistical extraction for each sliding window.

The program depends on various Bluetooth backends to establish connections with the Muse device. While we suggest utilizing the bleak backend, which is enabled by default, alternative options include BlueMuse for Windows users seeking a graphical interface to identify and link to Muse devices, or [bgapi] for Mac users equipped with a BLED112 dongle.

The code is compatible with both Python 2.7 and Python 3.x versions.

It is compatible with the Muse 2, Muse S, as well as the classic Muse (2016) models.

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)

Figure 1.2: Emotion Categories

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

Figure 1.3: Clips used as stimuli

1.4 Dataset Generated

Because of the intricate, erratic, and non-stationary nature of brainwave data, classifying it directly from raw EEG streams poses significant challenges. To address this, stationary techniques like time windowing are essential. This involves segmenting the data into discrete windows and extracting features from each window. Numerous statistics can be computed from these EEG windows, each with varying effectiveness in classification depending on the specific objective. Therefore, feature selection becomes imperative to pinpoint the most relevant statistics and streamline the model generation process. By doing so, both time and computational resources are conserved during training and classification tasks.

The outcome of this process is a CSV file containing various features extracted from each window, such as mean value, standard deviation, kurtosis, FFT (Fast Fourier Transform) transform, skewness, maxima, minima, and Shannon entropy. These features contribute to a total of 2549 features per window, providing rich information for subsequent analysis and classification purposes. The final column in each sample indicates the emotion for that time window as positive, negative and neutral. These emotional responses are generated in response to the list of movies which were shown.

Chapter 2

Data Preprocessing and Model Training

2.1 Label Distribution Analysis

Upon examining the pie chart, it is evident that the distribution of labels, representing different emotional states, is relatively balanced. This equitable distribution across emotional categories is crucial for ensuring that the model is trained on a representative sample of each class. A balanced label distribution minimizes the risk of bias towards dominant classes and enhances the model's ability to generalize effectively across diverse emotional states. This section delves into the strategies employed for data preprocessing to maintain label balance and ensure robust model training.

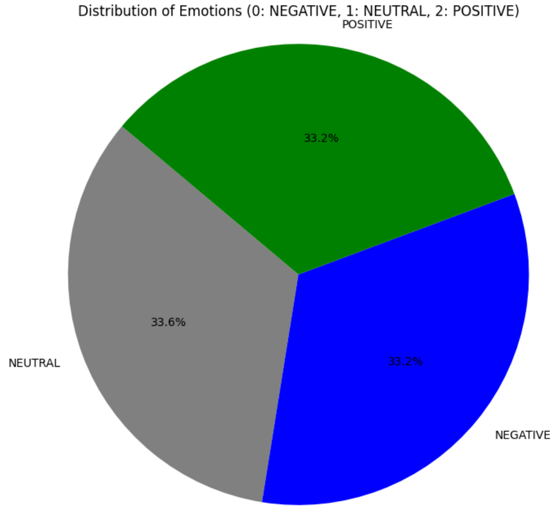

FIGURE 2.1: Balanced Label Distribution

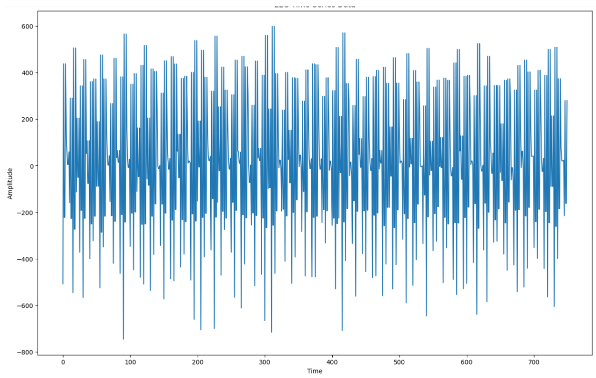

FIGURE 2.2: FFT Values Plot

2.2 FFT Values Plot Analysis

Upon reviewing the FFT values plot, it is evident that the data exhibits characteristics typical of time series data. The FFT (Fast Fourier Transform) plot provides insights into the frequency-domain representation of the EEG signals, highlighting the presence of distinct frequency components and patterns over time. The prominence of temporal patterns in the data underscores its suitability for time series analysis techniques.

Given the nature of the dataset as time series data, utilizing a deep neural network (DNN) is deemed appropriate for effective modeling and classification tasks. DNNs are well-suited for capturing temporal dependencies and patterns present in sequential data, making them a compelling choice for processing EEG signals.

2.3 Z-Scale Normalization

Prior to feeding the dataset into the Deep Neural Network (DNN), a preprocessing step involving Z-scale normalization has been performed. Z-scale normalization, also known as standardization, is a common technique used to standardize the distribution of features by subtracting the mean and dividing by the standard deviation. This process ensures that all features have a mean of zero and a standard deviation of one, thereby preventing features with larger scales from dominating the model's training process.

2.4 Feedforward Deep Neural Network Architecture

In crafting our neural network model for this study, we opted for a feedforward architecture, meticulously designed to analyze preprocessed EEG data and perform emotion classification.

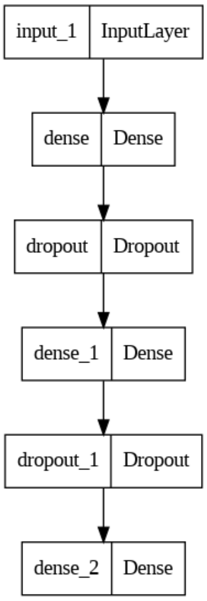

FIGURE 2.3: Model's Structure

Our approach leverages the TensorFlow.keras Sequential API, allowing for a structured sequence of layers to be built.

Model Structure Input Layer: Serving as the entry point for our EEG data, the input layer is defined with dimensions corresponding to the number of features in our dataset. This pivotal layer acts as the gateway for information to flow into our neural network.

Dense Layers: Our network incorporates two dense layers, densely interconnected to facilitate the learning of intricate patterns within our data. With 256 and 128 neurons respectively, these layers apply the rectified linear unit (ReLU) activation function to introduce non-linearity, aiding in feature extraction.

Dropout Layers: To counteract overfitting, dropout regularization is implemented. After each dense layer, dropout layers are introduced, randomly deactivating a portion of neurons during training. This technique promotes generalization and prevents the over-reliance on specific features.

Output Layer: At the heart of our network lies the output layer, comprising three neurons representing the three emotion classes: positive, neutral, and negative. The softmax activation function is applied to yield probabilistic outputs, offering insights into the likelihood of each class. Model Compilation: Our model is compiled using the Adam optimizer, renowned for its adaptive learning rate capabilities, which accelerates convergence during training. For the loss function, we've chosen sparse categorical cross-entropy, a suitable choice for multiclass classification tasks where target labels are integers. Moreover, accuracy serves as our evaluation metric, providing a comprehensive assessment of our model's performance across training and testing phases.

Model Evaluation:

The code evaluates the model's performance using metrics like accuracy, and it generates a confusion matrix to visualize the model's predictions.

```
[ ] # Evaluate the model
    model_acc = model.evaluate(X_test, y_test, verbose=0)[1]
    print("Test Accuracy: {:.3f}%".format(model_acc * 100))

    model.save('nueral_network.h5')

    Test Accuracy: 96.094%
```

FIGURE 2.4: Model's Accuracy

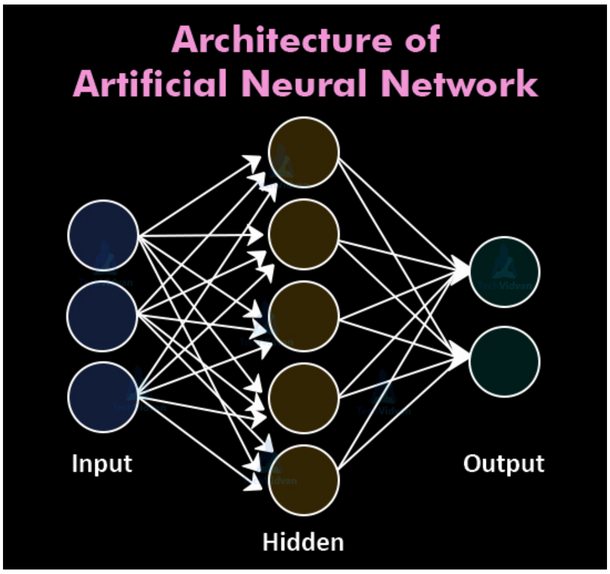

FIGURE 2.5: Diagram of Feed Forward Neural Network

With this meticulously crafted feedforward DNN architecture, reinforced by dropout regularization and thoughtful activation choices, we're poised to effectively process our preprocessed EEG data and deliver accurate predictions across diverse emotion classes.

After training the model using the provided dataset, we achieved an impressive accuracy of 96 percent. The training process involved fitting the model to the training data, with 20 percent of the data reserved for validation. We trained the model for 70 epochs, with a batch size of 32 samples per batch. The training progress was monitored closely, with verbosity set to level 2 to provide detailed updates throughout the training process. This remarkable level of accuracy underscores the effectiveness of our neural network architecture in accurately classifying emotions based on EEG data.

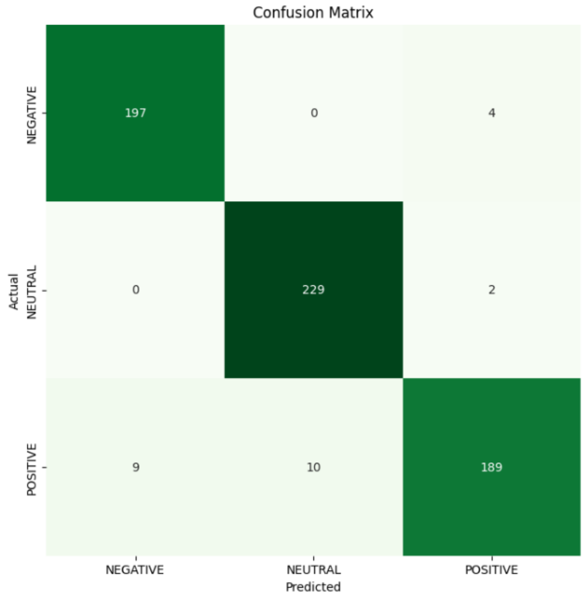

FIGURE 2.6: Confusion Matrix

2.5 Model Evaluation

We first evaluated the trained model's performance using metrics such as accuracy, providing insights into its overall classification performance. Additionally, we utilized a confusion matrix to visualize the model's ability to correctly classify each emotion category and identify any potential misclassifications. This visualization aids in understanding the model's strengths and weaknesses across different emotion classes, providing valuable insights for further refinement and optimization. By leveraging both quantitative metrics and visualizations, we gain a comprehensive understanding of the model's effectiveness in emotion classification tasks.

2.6 Saving Model

As part of the project's scope, the next step involves deploying the trained model. To facilitate this deployment, we will save the trained model as a .h5 file. This file format is compatible with various deployment platforms, including cloud-based services. Saving the model in this format preserves its architecture, weights, and configuration, allowing for seamless deployment and utilization.

To save the trained model, we will use TensorFlow's built-in functionality for model serialization. By exporting the model as a .h5 file, we ensure its portability and compatibility with cloud deployment environments.

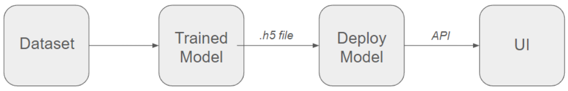

FIGURE 2.7: Project Workflow

Once saved, the .h5 file containing the trained model can be easily uploaded and deployed to cloud-based platforms, enabling real-time inference and utilization for emotion classification tasks. This approach ensures the scalability and accessibility of the trained model, facilitating its integration into various applications and services deployed on the cloud.

Appendix A

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