**CS767 ADVANCE MACHINE LEARNING AND NEURAL NETWORKS**

**Unveiling Emotions through Sound: A Case Study on Speech-based Emotion Recognition**

***Abstract***

Speech Emotion Recognition (SER) is a pivotal area of study due to its applications in various fields like human-computer interaction, mental health assessment, and customer feedback analysis. This project aimed to develop an effective SER model using Convolutional Neural Networks (CNNs) to accurately classify emotions from speech audio data.

The dataset comprised audio recordings across seven emotion classes, encompassing neutral, happy, sad, angry, surprise, fear, and disgust. Preprocessing involved feature extraction methods such as Zero Crossing Rate, Mel-frequency Cepstral Coefficients (MFCC), and spectral analyses like Spectral Centroid and Spectral Flux.

The CNN architecture consisted of multiple Conv1D layers, batch normalization, max-pooling, and dropout layers to capture complex audio features and prevent overfitting. Model training utilized the Adam optimizer and categorical cross-entropy loss function.

During testing, the model achieved a commendable 94% accuracy on the evaluation dataset, showcasing robustness in identifying surprise and angry emotions. While the accuracy was notable, ongoing enhancements were identified, including exploring diverse augmentation techniques and alternative feature extraction methods to potentially improve generalization across varied audio samples.

The project's working example showcased the model's proficiency in recognizing emotions from speech, offering promising prospects for real-world applications in sentiment analysis, customer sentiment monitoring, and mental health diagnostics. However, continuous refinement remains essential to address challenges like data diversity, real-world noise, and model generalization to elevate the model's effectiveness and practical applicability.

***About the Datasets***

1. **The Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS):** The RAVDESS is a validated multimodal database of emotional speech and song. The database is gender balanced consisting of 24 professional actors, vocalizing lexically-matched statements in a neutral North American accent. Speech includes calm, happy, sad, angry, fearful, surprise, and disgust expressions, and song contains calm, happy, sad, angry, and fearful emotions.
2. **Crowd-sourced Emotional Multimodal Actors Dataset (CREMA-D):** CREMA-D is a data set of 7,442 original clips from 91 actors. These clips were from 48 male and 43 female actors between the ages of 20 and 74 coming from a variety of races and ethnicities (African America, Asian, Caucasian, Hispanic, and Unspecified). Actors spoke from a selection of 12 sentences. The sentences were presented using one of six different emotions (Anger, Disgust, Fear, Happy, Neutral and Sad) and four different emotion levels (Low, Medium, High and Unspecified).
3. **Toronto emotional speech set (TESS):** This is a set of 200 target words spoken in the carrier phrase "Say the word \_' by two actresses (aged 26 and 64 years) and recordings were made of the set portraying each of seven emotions (anger, disgust, fear, happiness, pleasant surprise, sadness, and neutral). There are 2800 data points (audio files) in total.

***Libraries***

1. **Pandas:** For data manipulation and analysis.
2. **NumPy:** For numerical operations and handling arrays/matrices.
3. **os** and **sys:** Python libraries for interacting with the operating system and system-specific parameters.
4. **Librosa:** Used for audio and music analysis, including extracting data from audio files and visualizing audio features.
5. **Seaborn** and **Matplotlib:** For data visualization purposes.
6. **StandardScaler**, **OneHotEncoder**, **ConfusionMatrix**, **ClassificationReport**, **TrainTestSplit:** Various tools from scikit-learn (sklearn) for data preprocessing, evaluation, and machine learning model building.
7. **IPython.display** and **Audio**: For displaying and playing audio files in Jupyter notebooks or IPython environments.
8. **Keras**: A high-level neural networks API for building and training deep learning models.
9. **TensorFlow**: Deep learning library used as a backend for Keras.

***Overview of the Project***

1. **Data Import**

Datasets were imported from Kaggle and combined into a single data frame.

1. **Data Preprocessing and Augmentation**

Several preprocessing stages were necessary before the data could be utilized for training purposes. Various plots were created to examine and understand the data.  
Normal audio files were randomly stretched, shifted, noise was introduced and pitch was changed to augment the dataset to make the model robust.

1. **Feature Extraction**

Considerable focus was placed on extracting essential features from the dataset, a pivotal step in readying the data for subsequent modelling stages.

1. **Data Preparation**

Fundamental changes were made to the data, encompassing encoding categorical labels, division into training and testing sets, and scaling features to align with the model's requirements.

1. **Data Modeling**

A Convolutional Neural Network (CNN) was designed to tackle speech emotion recognition. This model design encompassed multiple layers—convolutional, pooling, dense, and dropout layers — to proficiently capture emotional features from audio data.

1. **Model Evaluation**

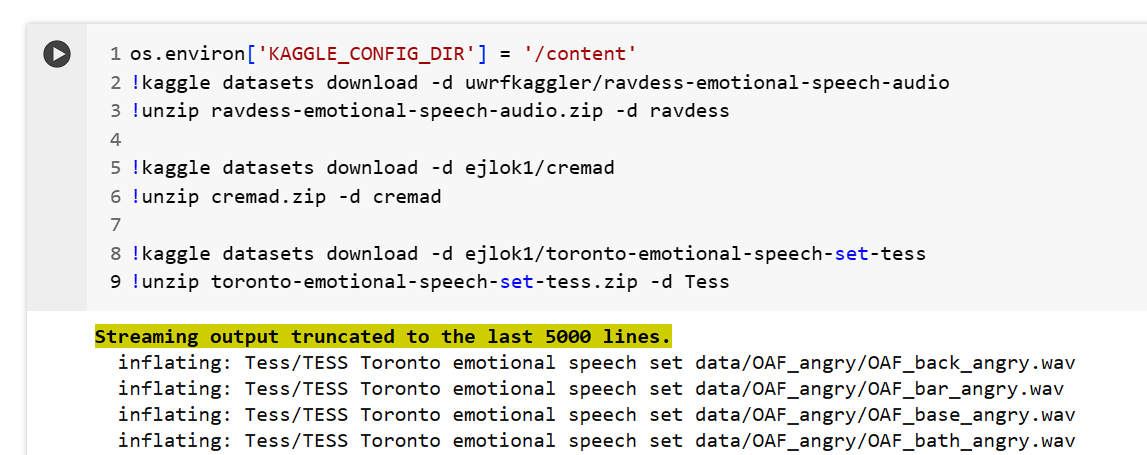
In the phase of model training, we assessed performance by employing diverse metrics and evaluating both training and validation datasets.

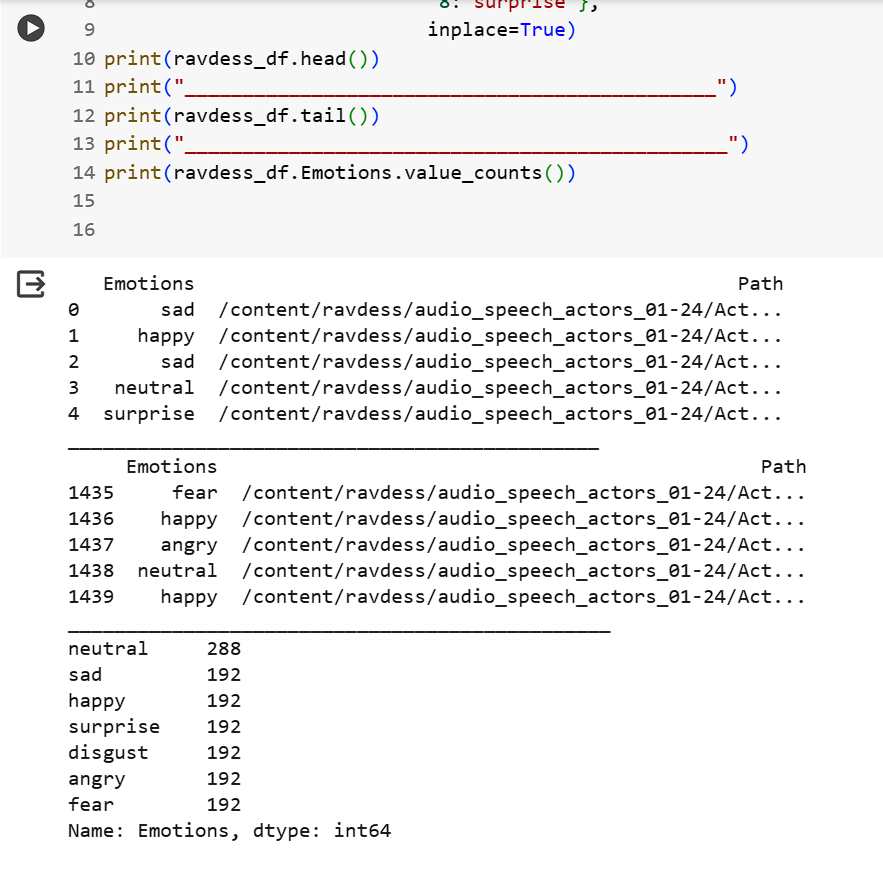
1. **Conclusion**

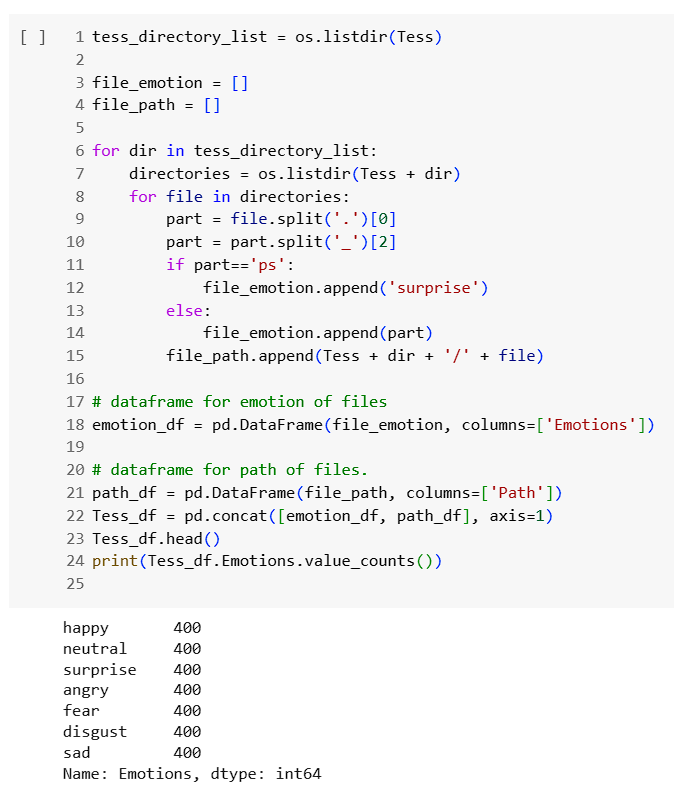
The conclusion was drawn based on the performance of the model on the test dataset.

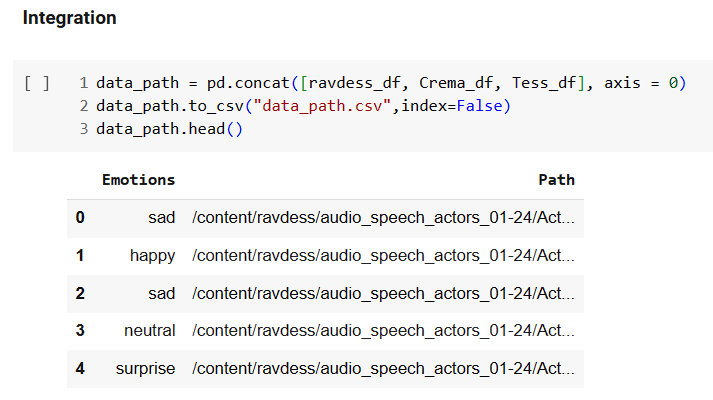
***Data Import and Processing***

The datasets were procured from Kaggle. There were three data sources which were combined for the final dataset.





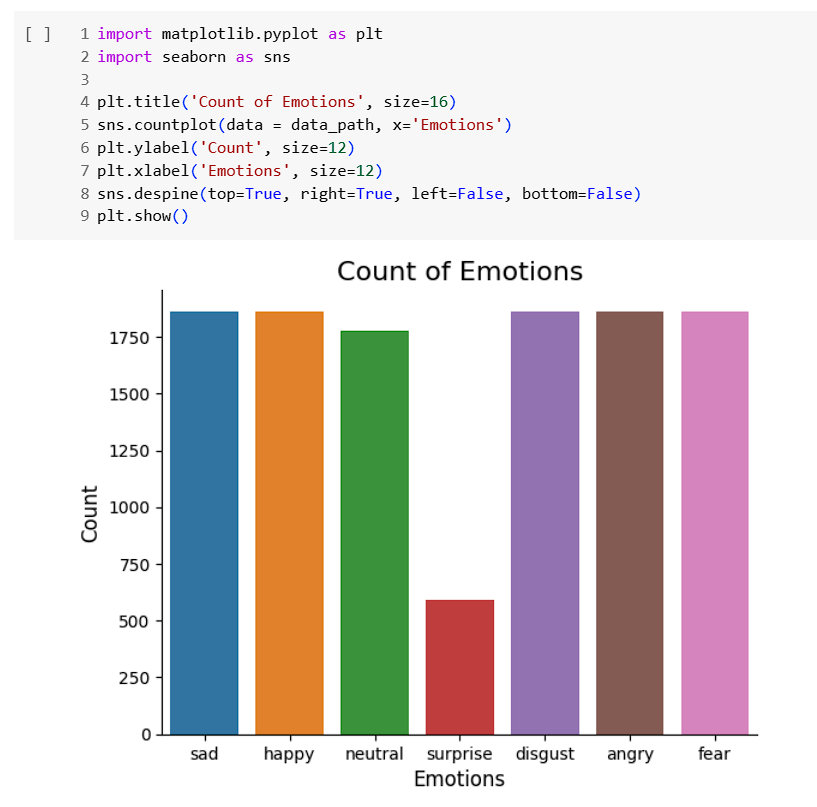


Final data frame creation-  
  


***Data Preprocessing***

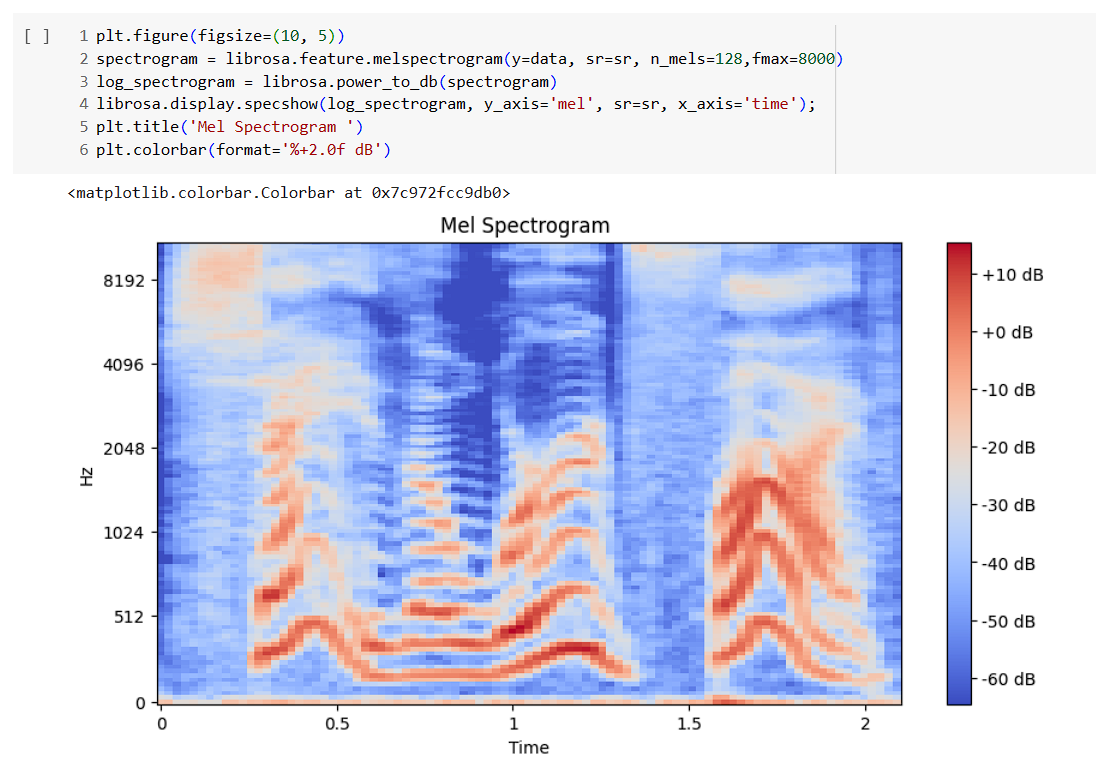
**1**. **Emotion Distribution Visualization**

A count plot was generated to visualize the occurrence of each emotion category within the dataset, offering insights into the distribution of emotions and whether they were balanced or imbalanced.



**2**. **Waveplots and Spectrograms**

Waveplots were utilized to depict the amplitude variations of audio signals over time, showcasing the loudness. Moreover, spectrograms were employed to illustrate the evolution of frequency spectrums over time, offering a holistic view of audio frequency components.



**3**. **Data Augmentation Techniques**

Data augmentation aims to enrich the diversity of the training dataset. In the realm of audio data, various augmentation techniques were investigated using librosa:

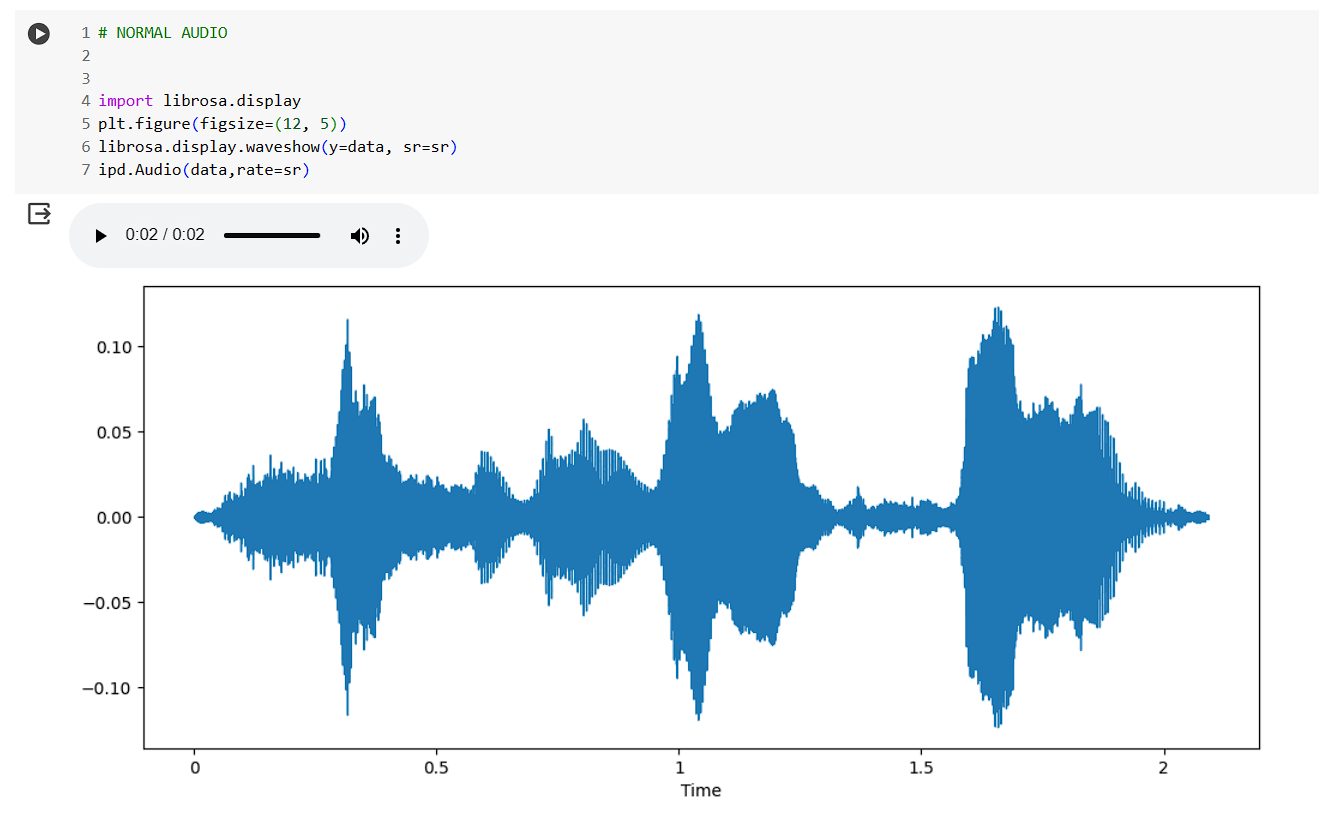
- Noise Injection: Introducing amounts of noise to audio samples.

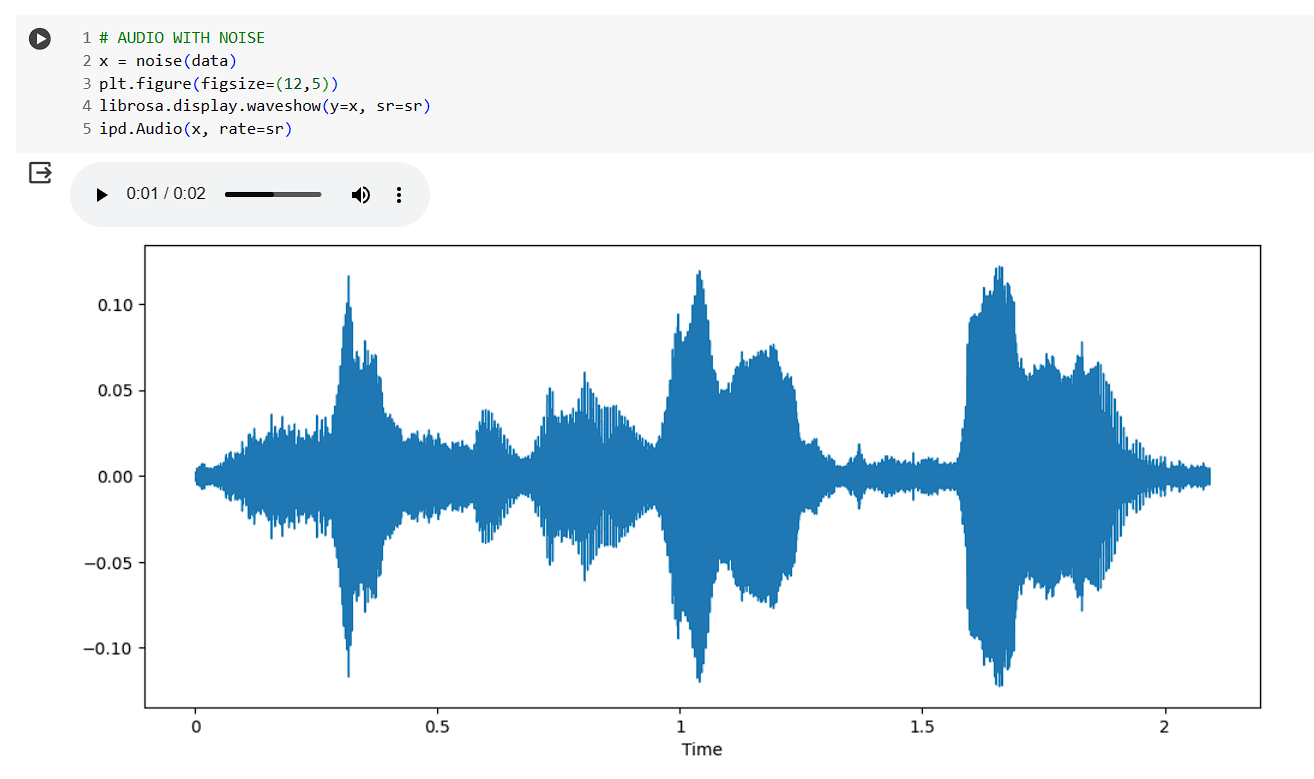
- Stretching: Altering the speed of the audio, thereby modifying its duration without affecting its pitch.

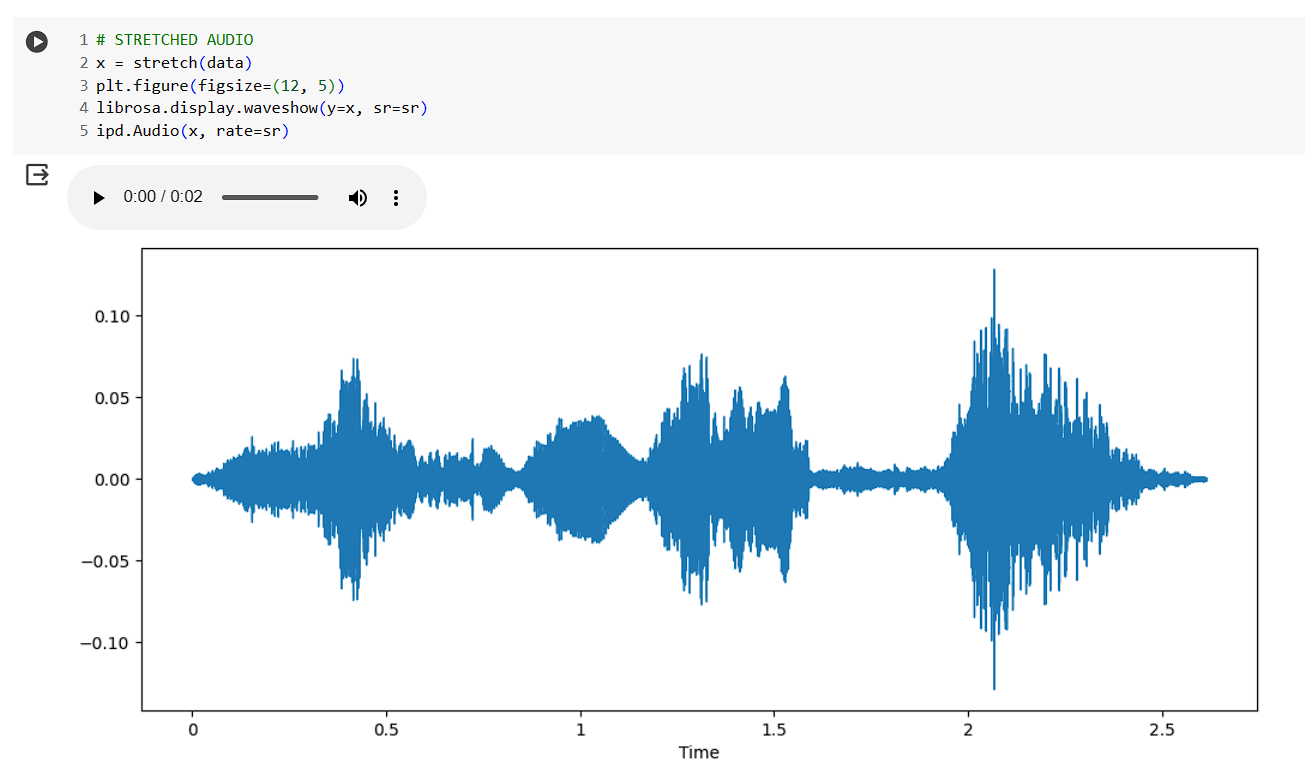
- Shifting: It involves altering the starting point of the audio waveform, effectively changing when the sound begins or ends.

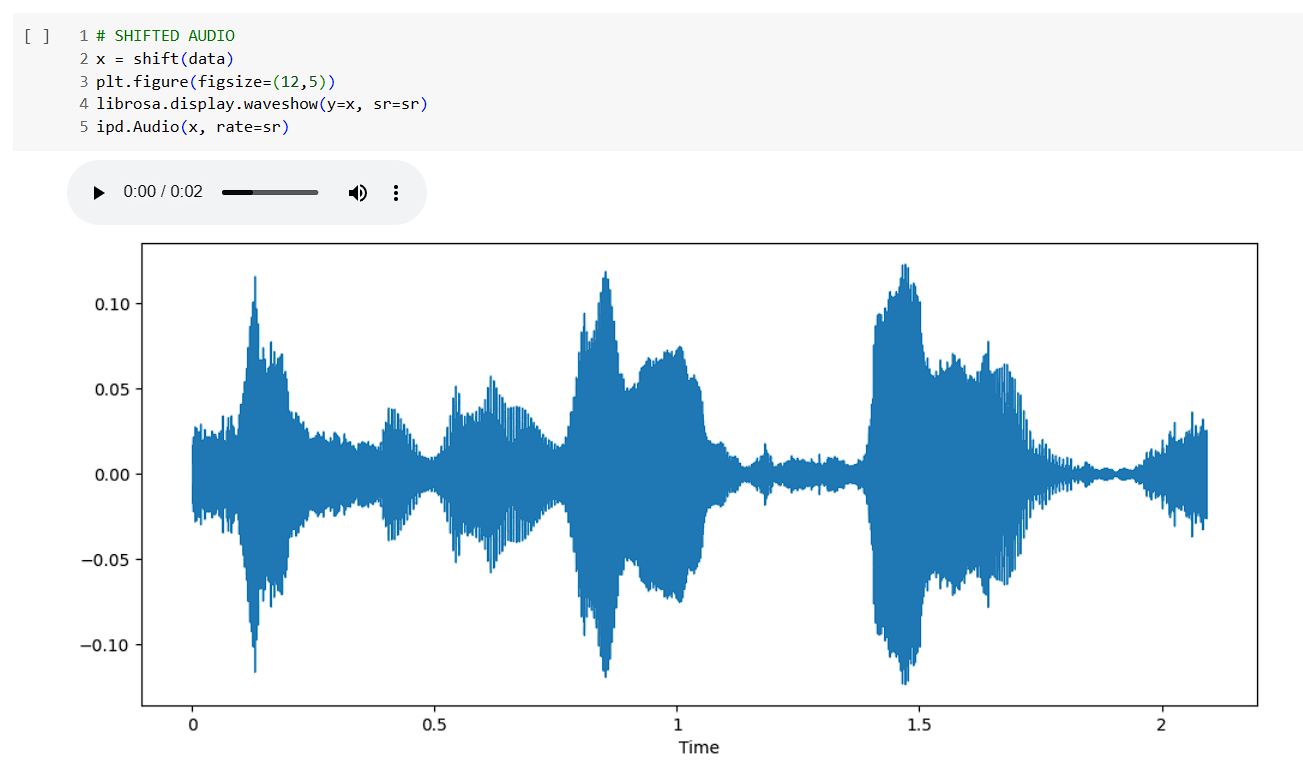
- Pitch Modification: Adjusting the pitch of the audio signals while preserving their semantic content.

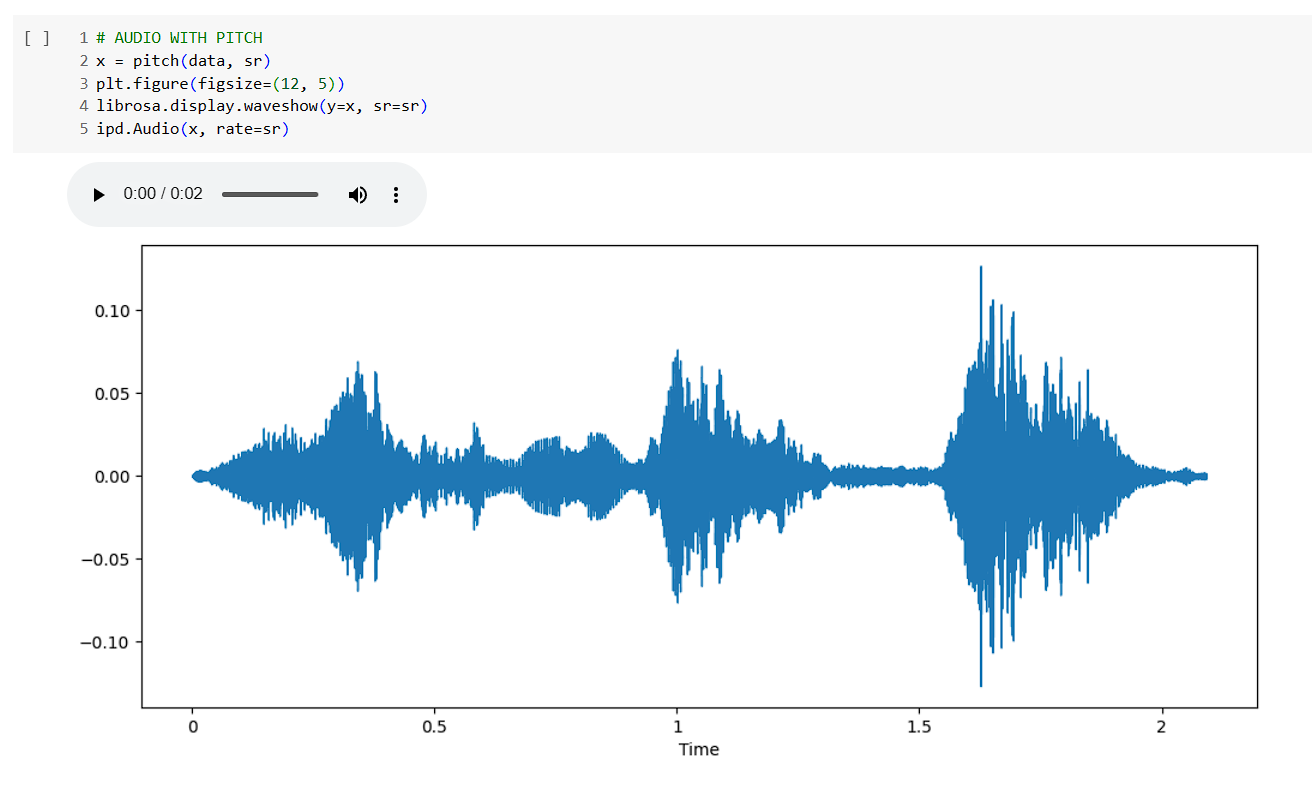
Data augmentation serves a dual purpose: expanding the dataset and reinforcing the model's resilience by introducing diverse yet pertinent modifications to the input data. This strategy contributes to building a model that can effectively adapt to different input variations while retaining the original label information, promoting robust generalization.





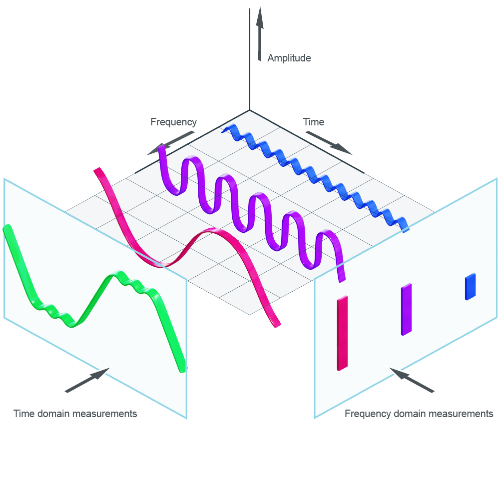






***Feature Extraction***

Feature extraction plays a crucial role in analyzing and establishing relationships between various elements. Given that audio data isn't inherently understandable to models, it requires conversion into an interpretable format, achieved through feature extraction.

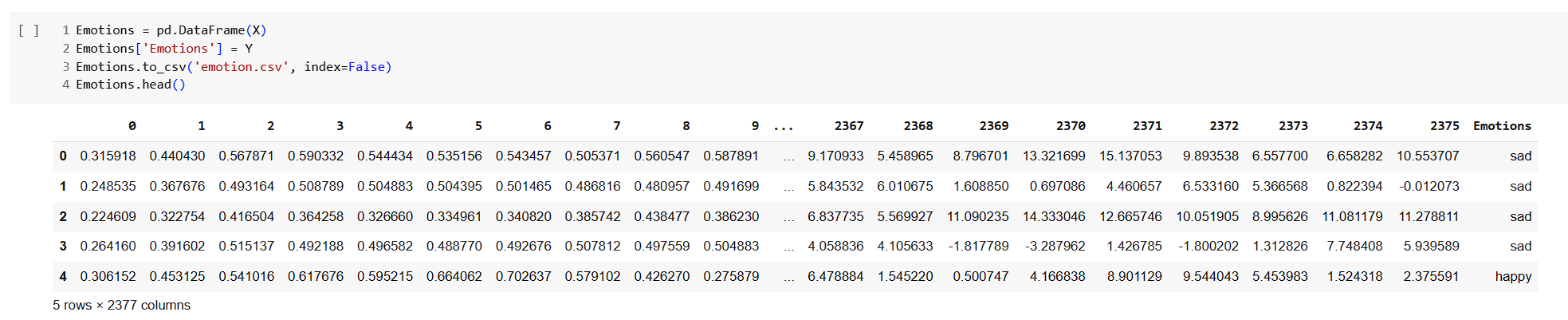


With the help of the sample rate and the sample data, one can perform several transformations on it to extract valuable features:

1. Zero Crossing Rate: The rate at which the audio signal changes sign (from positive to negative or vice versa). It indicates the number of times the waveform crosses the zero horizontal axis.
2. Energy: Represents the total energy in the signal. It's computed by summing the squared values of the audio samples.
3. Entropy of Energy: Measures the distribution or randomness of energy values in the signal.
4. Spectral Centroid: Represents the center of mass of the power spectrum of the audio signal. It signifies where the "center of gravity" of the spectrum is located.
5. Spectral Spread: Measures the width or spread of the spectrum. It indicates how the energy is distributed across frequencies.
6. Spectral Entropy: Reflects the spectral complexity or randomness of the signal's power spectrum.
7. Spectral Flux: Represents the change in spectral shape between consecutive audio frames. It quantifies how much the spectrum changes over time.
8. Spectral Roll-off: Defines the frequency below which a certain percentage (typically 85-95%) of the total spectral energy is concentrated.
9. Mel-frequency Cepstral Coefficients (MFCC): These coefficients represent the spectral envelope of the audio signal. They are derived from the Fourier transform of the log power spectrum on a mel-scale of frequency.
10. Chroma Vector: Represents the intensity of each of the 12 different pitch classes (C, C#, D, D#, E, F, F#, G, G#, A, A#, B) in the audio signal.
11. Chroma Deviation: Measures the variation or deviation of the chroma vectors, reflecting the change in pitch class intensity over time.

Features used for our implementation-

* *Zero Crossing Rate*
* *Mel-frequency Cepstral Coefficients (MFCC)*
* *RMS(root mean square) value*

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***Data Preparation***

**Encoding Labels**

To ensure the model effectively processes categorical labels, one-hot encoding was employed. This conversion method, facilitated by Scikit-Learn's OneHotEncoder, transformed the categorical labels in Y into a binary matrix format.

**Data Splitting**

The dataset was divided into training and testing sets using the `train\_test\_split` function from Scikit-Learn. This process helps in evaluating the model's performance on unseen data. Test Size = 0.4

**Data Scaling**

To ensure uniformity and prevent certain features from dominating the learning process due to their scale, the `StandardScaler` from Scikit-Learn was employed to scale the features to bring them on the same scale.

These preprocessing steps were crucial in ensuring that the data was appropriately formatted, scaled, and split for training and evaluation of the machine learning models. By encoding labels, splitting data into training and testing sets and scaling features, the dataset was made ready for further model development and assessment.

***Neural Network***

**Model Architecture**:

The implemented neural network architecture is a sequential model using TensorFlow's Keras API. This model is designed for speech emotion recognition, aiming to classify audio data into seven distinct emotional categories.

**Layers and Configuration**:

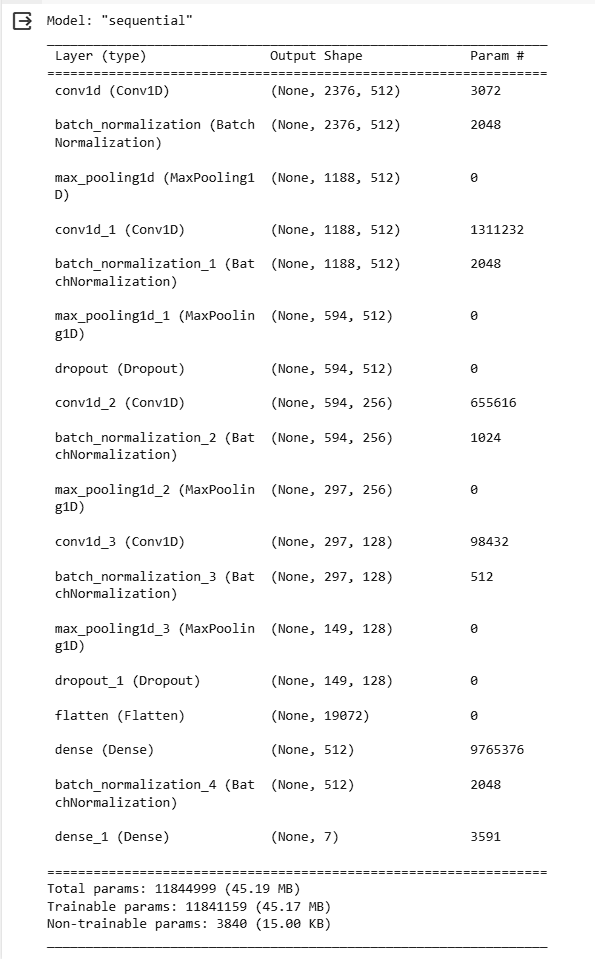
1. **Input Layer:**  
     
   Type: Conv1D  
   Parameters:   
    512 filters  
    Kernel size: 5  
    Strides: 1  
    Padding: 'same'  
    Activation: ReLU  
    Input Shape: (X\_train.shape[1], 1)
2. **Batch Normalization Layer:**  
   Applied after the first Conv1D layer.
3. **MaxPooling1D Layer:**  
   Pool size: 5  
   Strides: 2  
   Padding: 'same'
4. **Conv1D Layers (2nd to 4th):**  
   Configurations: Similar to the initial Conv1D layer, with varying filter numbers (512, 256, 128), kernel sizes (5, 5, 3), and strides (1, 1, 1).  
   Batch Normalization: After each Conv1D layer.  
   MaxPooling1D: Employed after the second and fourth Conv1D layers.  
   Dropout: Applied with a 20% dropout rate after the second and fourth MaxPooling1D layers to prevent overfitting.
5. **Flatten Layer:**  
   Converts the output of the last MaxPooling1D layer into a one-dimensional array.
6. **Dense Layers (Fully Connected Layers):**  
   Dense Layer 1: 512 units with ReLU activation.  
   Batch Normalization: Follows the first Dense layer.
7. **Output Layer:**  
   Dense Layer 2: 7 units (equal to the number of emotional categories) with softmax activation, producing probabilities for each emotion category.

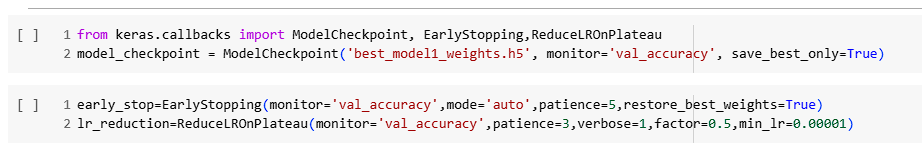
**Model Compilation:**

The model was compiled using the Adam optimizer, categorical cross-entropy as the loss function (suitable for multi-class classification), and 'accuracy' as the metric to monitor during training.

**Model Summary:**

The model comprises a total of 11,844,999 parameters, which are split between trainable and non-trainable parameters. This detailed architecture is aimed at effectively capturing and learning features from audio data to classify emotions with accuracy.

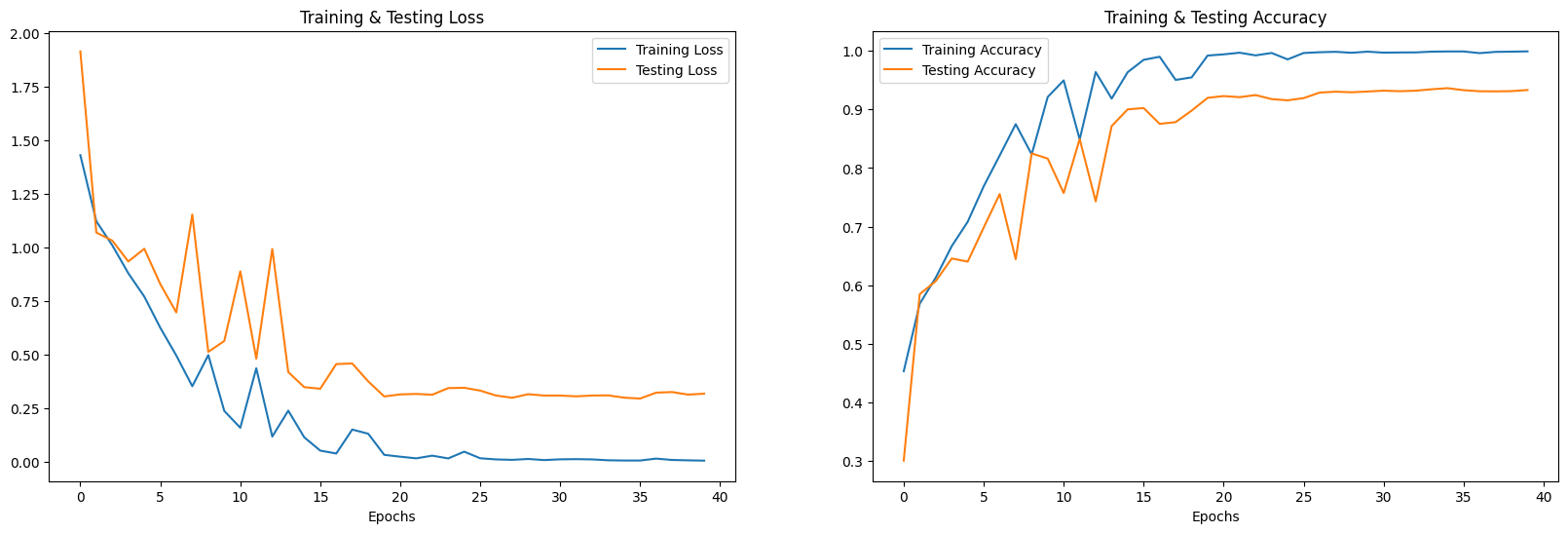


**Measure for preventing Overfitting:**  
 

1. **Model Checkpoint:**ModelCheckpoint was used to save the weights of the best-performing model based on a specified metric, in this case, 'val\_accuracy' (validation accuracy). It ensures that the weights are saved only if the validation accuracy improves from the previous best. This prevents overfitting by allowing the retention of the model state at its best performance on the validation set.
2. **Early Stopping:**  
   EarlyStopping is applied to monitor the 'val\_accuracy' metric. The training process halts if there is no improvement in validation accuracy after a specified number of epochs (patience=5). Additionally, it restores the model's weights to the best-performing epoch when training concludes, preventing overfitting by stopping the process when the model's performance plateaus.
3. **Learning Rate Reduction:**ReduceLROnPlateau reduces the learning rate when the model's validation accuracy stops improving. It monitors 'val\_accuracy' and reduces the learning rate by a factor of 0.5 if no improvement is observed for a certain number of epochs (patience=3). Lowering the learning rate helps the model navigate out of local minima and fine-tune the weights, potentially preventing overfitting.

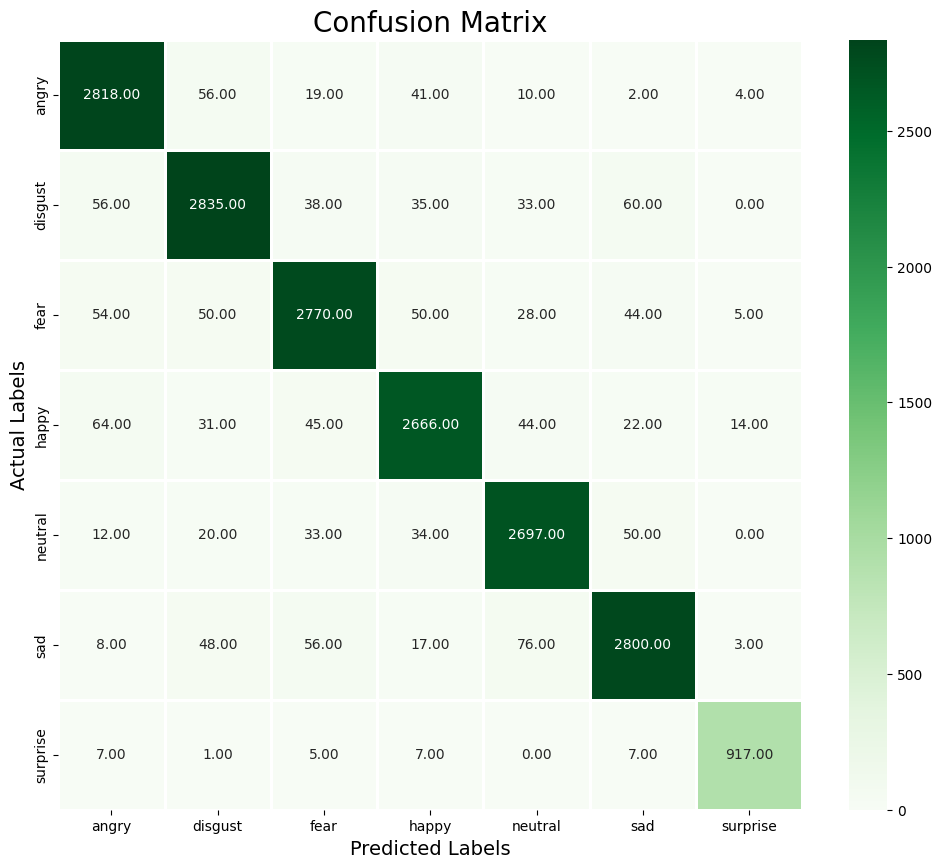
These measures collectively contribute to preventing overfitting by regularly assessing the model's performance on a separate validation dataset and making adjustments to the learning process accordingly. They facilitate the retention of the best-performing model state while avoiding excessive training that might lead to overfitting on the training data.

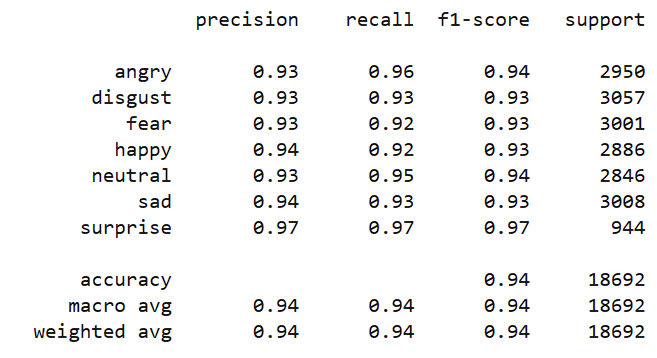
***Training:***The model was trained on the train data for 50 epochs with the parameter early\_stopping enabled to reduce over fitting.



***Model Evaluation***

The trained model was then evaluated on the test data using metrics like accuracy, precision, recall and F1-score.





The model yielded an accuracy of 94% but it overfit on the train set as evident from the training graph.

***Conclusion***

The model demonstrates higher accuracy in predicting surprise, neutral and angry emotions, which aligns with the diverse characteristics of audio files representing these emotions, such as varying pitch and speed. The achieved 94% accuracy on the test data is respectable. However, to further evaluate the model’s robustness, exploring additional datasets and alternative features could be beneficial.

***Future Work***

The exploration into speech emotion recognition has uncovered promising avenues for future research and development. The following areas present opportunities for extending and refining the current study:

**Data Diversity:** Expanding the dataset with more diverse samples might enhance the model's ability to generalize across different variations of emotions, accents, or recording conditions.

**Transfer Learning:** Exploring transfer learning from pre-trained models in speech or audio-related domains might provide insights into leveraging existing knowledge for improved performance and might also help in reducing training time.

**Feature Engineering:** Experimenting with different or more sophisticated features derived from audio data could capture richer representations, potentially boosting accuracy.

***References***

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