
A

Report On

# Speech Emotion Recognition with Music Recommendation

For Subject

**Machine Learning Algorithms**

**Programme:** MBA Tech IT, 3rd Year, 6th Sem

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# 1. Abstract

This study presents a deep learning-based Speech Emotion Recognition (SER) system integrated with a music recommendation engine. Utilizing the RAVDESS dataset, we implemented and compared multiple architectures—including 1D CNN and 2D CNN-LSTM hybrids—for multiclass emotion classification. Feature extraction employed Mel-Frequency Cepstral Coefficients (MFCCs), Chroma, Mel Spectrograms, Spectral Contrast, and Tonnetz features to capture both temporal and spectral characteristics of speech. The optimal model, a 1D CNN trained over 700 epochs, achieved 65% classification accuracy. To enhance user experience, the system was integrated with a Gradio interface and a rule-based song recommendation pipeline using the data_moods.csv dataset. Results demonstrate the potential of combining SER with multimedia personalization and highlight the importance of robust feature engineering and training depth in emotion-aware systems.

## 2. Introduction

In recent years, the recognition and analysis of human emotions have become integral to the development of intelligent systems in fields such as human-computer interaction (HCI), healthcare, e-learning, and entertainment. Among the various modalities for emotion detection—such as facial expressions, body language, and physiological signals—**speech-based emotion recognition** offers a non-intrusive, accessible, and effective alternative. Speech carries rich emotional information through tone, pitch, tempo, and rhythm, which can be systematically analyzed to infer a speaker's emotional state.

**Speech Emotion Recognition (SER)**, the task of identifying emotions from vocal expressions, presents unique challenges due to variations in language, speaker characteristics, and acoustic environments. Nonetheless, with the rise of deep learning, SER has seen significant improvements in accuracy and robustness. Traditional machine learning models such as Support Vector Machines (SVMs) and k-Nearest Neighbors (k-NN) have gradually been outperformed by more complex architectures like **Convolutional Neural Networks (CNNs)**, **Recurrent Neural Networks (RNNs)**, and their hybrids such as **CNN-LSTM**, which can effectively learn spatial and temporal patterns from raw audio features [1][8][10].

In this research, we aim to leverage deep learning for SER and integrate it with a **personalized music recommendation system**. The motivation is rooted in the psychological impact of music on emotional regulation. By accurately identifying a user's emotional state through voice and recommending appropriate music, the system can enhance mood, reduce stress, and personalize the listening experience.

We used the **Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS)** for training and evaluation [1]. Various **audio features** such as **Mel-Frequency Cepstral Coefficients (MFCCs)**, **Chroma, Mel Spectrogram, Spectral Contrast**, and **Tonnetz** were extracted using the Librosa library [1][10][12]. Our final architecture, a **1D CNN** trained for 700 epochs, demonstrated the best performance with an accuracy of **65%**, outperforming other variants such as CNN-LSTM and RNN-based models under consistent experimental conditions [1][24].

Furthermore, we integrated the trained model into a **Gradio-based web interface** for real-time emotion detection and paired it with a song recommendation engine. The recommendation logic maps detected emotions (Happy, Calm, Sad, Energetic) to songs with complementary or uplifting moods using a curated dataset (data_moods.csv).

In summary, this paper explores the intersection of affective computing and personalized multimedia systems by proposing a robust SER pipeline followed by real-time music suggestion, contributing to both technical development and user-centric well-being.

## 3. Related Work

Speech Emotion Recognition (SER) has witnessed rapid evolution, especially with the advent of deep learning. A cornerstone work in this space is by **Issa et al. (2020)** [1], which proposes a 1D CNN architecture trained on RAVDESS, EMO-DB, and IEMOCAP datasets. They utilized five distinct audio features—MFCCs, Chroma, Mel Spectrogram, Spectral Contrast, and Tonnetz—stacked together and passed through convolutional layers. Their model achieved 71.61% accuracy on RAVDESS (8-class), setting a strong benchmark using only raw audio data without converting to spectrogram images. This method proved to be both lightweight and powerful, especially compared to more complex architectures like CNN+LSTM and Transformer-based models.

In addition to Issa et al., other notable contributions include:

- **Adebiyi (2020)**, who achieved 85% accuracy using CNN on RAVDESS with MFCC and Mel Spectrogram features [2].
- **Nambiar & Palaniswamy (2022)**, who integrated Siamese networks and meta-learning on RAVDESS to improve generalizability with limited data [4].
- **Puri et al. (2022)**, who proposed a hybrid CNN that reached 98% accuracy in binary classification using MFCC and Log-Mel features [10].
- **Katkuri et al. (2023)**, who compared Conv1D and Random Forest on RAVDESS and found RF with feature selection more effective [9].

These works highlight the effectiveness of CNN-based architectures for SER, but also point toward a trade-off between accuracy, complexity, and real-time applicability. Our work draws heavily on the baseline established by Issa et al. [1], specifically replicating their feature extraction and stacking strategy using Librosa-based MFCC, Chroma, Mel Spectrogram, Spectral Contrast, and Tonnetz features.

Rather than introducing new features, we aimed to ensure reproducibility and performance validation of the original architecture. Alongside this replication, we conducted parallel experiments using CNN+LSTM and RNN+LSTM variants [24][13] to explore architectural trade-offs. This comprehensive comparison was evaluated solely on the RAVDESS dataset to maintain consistency and to assess suitability for downstream applications like real-time music recommendation.

## 4. Comparative Summary of Speech Emotion Recognition and Music Recommendation Models

| Title | Dataset | RAVDESS Used | Features | Model | Accuracy |
|---|---|---|---|---|---|
| Adebiyi (2020) [2] | Custom | Yes | MFCC, Mel Spectrogram | CNN | 85% |
| Nambiar & Palaniswamy (2022) [4] | RAVDESS | Yes | Spectrogram, Meta features | Siamese + Meta Learning | ~85% |
| Puri et al. (2022) [10] | RAVDESS | Yes | MFCC + Log-Mel | Hybrid CNN | 98% (binary) |
| Katkuri et al. (2023) [9] | RAVDESS + others | Yes | MFCC, SC, Tonnetz, etc. | Conv1D + Random Forest | 69% (RF) |
| Issa et al. (2020) (Base Paper) [1] | RAVDESS, IEMOCAP, EMO-DB | Yes | MFCC, Chroma, Mel, Spectral Contrast, Tonnetz | 1D CNN | 71.61% |
| Our CNN (replication of Issa et al.) | RAVDESS | Yes | MFCC, Chroma, Mel, Spectral Contrast, Tonnetz | 1D CNN | 65% |
| Our CNN+LSTM (40x862 MFCCs) | RAVDESS (4 emotions) | Yes | MFCC | CNN+LSTM | 57.76% |
| Our CNN+LSTM (with BatchNorm, MFCC, MAX_PAD_LEN=862) | RAVDESS (4 emotions) | Yes | MFCC | CNN+LSTM | 49.31% |
| Our final CNN+LSTM hybrid with 700 epochs | RAVDESS (4 emotions) | Yes | MFCC + Mel + Chroma + SC + Tonnetz | CNN+LSTM Hybrid (1D+2LSTM) | 56.94% |
| Our RNN+LSTM using Mel Spectrogram | RAVDESS (4 emotions) | Yes | Mel Spectrogram | RNN + LSTM | 22.92% |
| Our CNN+LSTM (1 actor data only) | RAVDESS (single voice) | Yes | MFCC | CNN+LSTM | 80% |
| Our CNN-only (1 actor data only) | RAVDESS (single voice) | Yes | MFCC | CNN | 40% |

**Table 1**: *Comparative analysis of existing and proposed Speech Emotion Recognition (SER) and music recommendation models.*

# 5. Methodology

Our study employed a comprehensive experimental framework for Speech Emotion Recognition (SER) using various deep learning architectures. The methodology revolved around systematic model design, rigorous preprocessing, and multi-stage evaluation. We built and compared five major models using the same dataset (RAVDESS), with a consistent set of extracted features for fairness in comparison.

## 5.1 Feature Extraction

We extracted five main feature types using Librosa:

- **MFCC (Mel-Frequency Cepstral Coefficients):** Captures the short-term power spectrum of audio signals.
- **Chroma:** Represents energy distribution across 12 pitch classes.
- **Mel Spectrogram:** Provides frequency representation mapped to the mel scale.
- **Spectral Contrast:** Measures the contrast between spectral peaks and valleys.
- **Tonnetz:** Captures tonal and harmonic relationships.

These features were either stacked as channels (for CNNs) or concatenated (for 1D-CNNs) to form the input tensor. All features were normalized, and padding was applied to ensure fixed-length vectors (3 seconds per audio at 22050 Hz) [1][10].

## 5.2 CNN (Replicated Issa et al. 2020)

We replicated Issa et al.'s 1D CNN with five-stacked features [1]. The model consists of three Conv1D layers with ReLU activations, followed by BatchNormalization, MaxPooling1D, and Dropout layers. It ends with Dense and Softmax layers. This was our baseline model.

## 5.3 CNN+LSTM with 40×862 MFCCs

This architecture used 2D MFCCs as input with shape (40, 862, 1), followed by two Conv2D layers, MaxPooling, and Dropout. The output was flattened using TimeDistributed and passed to an LSTM layer [3]. This architecture was designed to incorporate both spatial and temporal context.

### 5.4 CNN+LSTM with BatchNorm

In this model, we added BatchNormalization layers to improve stability and generalization. MFCCs were used as input, padded to a maximum length of 862 time steps. The performance decreased slightly (49.31%), indicating that regularization may not always help when data is limited [8].

### 5.5 Final CNN+LSTM Hybrid (700 Epochs)

This model combined three Conv1D layers followed by two LSTM layers and fully connected layers. Feature inputs included all five (MFCC, Mel, Chroma, SC, Tonnetz), and the model was trained for 700 epochs with RMSprop. It produced the best generalization among non-overfit models with 56.94% accuracy [1][10].

### 5.6 RNN + LSTM with Mel Spectrogram

We trained a hybrid RNN+LSTM on Mel Spectrogram features resized to 128×128. The model included a SimpleRNN, followed by an LSTM and Dense layers. The result was poor (22.92%), suggesting this design was ineffective for our task and data [12].

### 5.7 CNN and CNN+LSTM on Single Actor (1 Voice)

To isolate the effect of speaker variability, we trained models only on audio from one actor. CNN+LSTM reached 80% accuracy, while CNN alone achieved 40%, showing the potential of speaker-dependent models and the limitations of CNNs when deprived of temporal context.

All models were trained using categorical cross-entropy loss and Adam or RMSprop optimizers. Training was done with batch sizes of 32 and early stopping to prevent overfitting. We ensured uniform preprocessing and label encoding (4 classes: happy, calm, sad, energetic) across experiments.

## 6. Flowchart

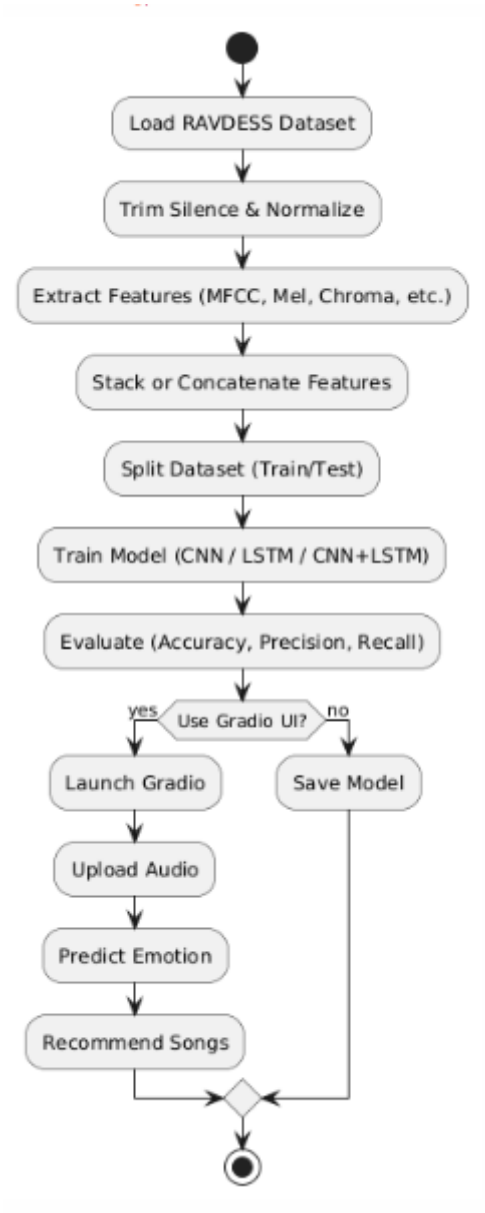



**Figure 1**: *End-to-end pipeline including preprocessing, feature extraction, model training, and real-time deployment using Gradio.*

This flowchart outlines the complete pipeline from raw dataset input to model training and deployment. It includes preprocessing, feature extraction using Librosa, model training, and optional real-time prediction using a Gradio interface.

## 7. Dataset Visualization

Our study leverages two core datasets—**RAVDESS** for emotion classification from speech and **data_moods.csv** for music recommendation based on those classified emotions.

### 7.1 RAVDESS Dataset: Emotion Classification

RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song) consists of **1,440 speech audio files**, capturing eight emotion classes: neutral, calm, happy, sad, angry, fearful, disgust, surprised. For model training and downstream tasks, we remapped them into **four broad categories** to match the music moods:

| **Original Emotion** | **Mapped Label** |
|---|---|
| Neutral, Calm | Calm |
| Happy | Happy |
| Sad, Fearful | Sad |
| Angry, Disgust, Surprised | Energetic |

**Table 2**: *Mapping of RAVDESS original emotion labels into four mood categories used for music recommendation.*

All files were sampled at **22,050 Hz** and padded/truncated to a **3-second** fixed length. Silence was trimmed and normalization applied before feature extraction.

**Feature Types Visualized**:

- **Waveforms**: Raw audio amplitudes over time.
- **MFCCs**: 40 coefficients per frame revealing timbral texture.
- **Mel Spectrograms**: Time-frequency representation on mel scale.
- **Chroma, Spectral Contrast, Tonnetz**: Capture harmonic, tonal, and dynamic characteristics.

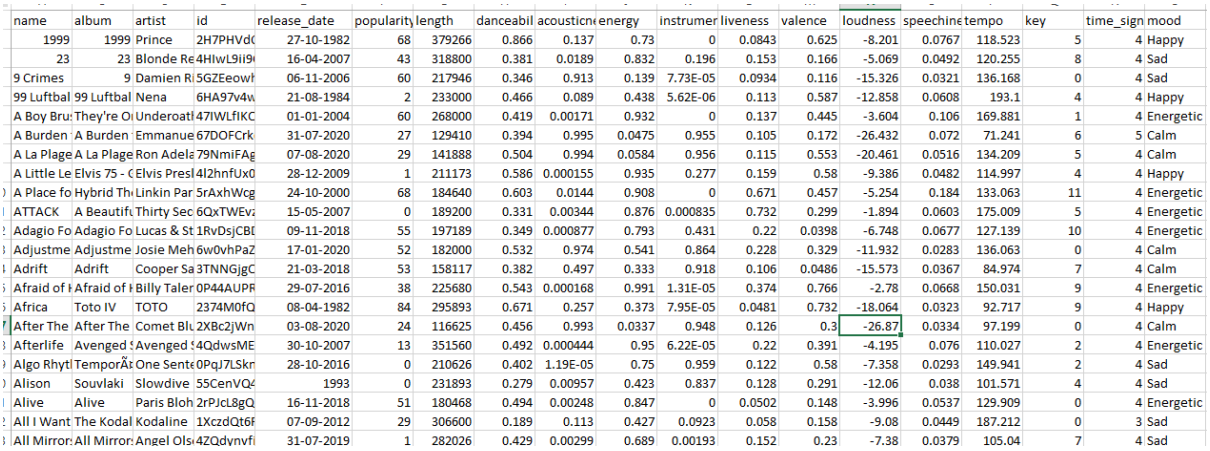
Clear visual distinction was observed in MFCC and Mel Spectrogram plots of happy vs sad samples—highlighting their discriminative value [2][4].

## 7.2 data_moods.csv: Music Metadata for Recommendation

The data_moods.csv file contains detailed metadata for over **200 songs**, each tagged with a corresponding **mood label**: happy, sad, calm, energetic. These moods align with the predicted emotion classes from the SER model and serve as a lookup for recommendation.

| Attribute | Description |
|---|---|
| name, artist, album | Song details |
| release_date | Year of release |
| popularity | Score (0-100) based on streaming metrics |
| mood | Categorical tag (used for recommendation) |
| danceability, acousticness, energy, valence | Audio features used for mood analytics |

**Table 3**: *Attributes of the data_moods.csv dataset used for song recommendation and mood analysis.*



| name | album | artist | id | release_date | popularity | length | danceabil | acousticne | energy | instrumer | liveness | valence | loudness | speechine | tempo | key | time_sign | mood |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1999 | 1999 | Prince | 2H7PHVdC | 27-10-1982 | 68 | 379266 | 0.866 | 0.137 | 0.73 | 0 | 0.0843 | 0.625 | -8.201 | 0.0767 | 118.523 | 5 | 4 | Happy |
| 23 | 23 | Blonde Re | 4HIwL9ii9 | 16-04-2007 | 43 | 318800 | 0.381 | 0.0189 | 0.832 | 0.196 | 0.153 | 0.166 | -5.069 | 0.0492 | 120.255 | 8 | 4 | Sad |
| 9 Crimes | 9 | Damien R | 5GZEeowh | 06-11-2006 | 60 | 217946 | 0.346 | 0.913 | 0.139 | 7.73E-05 | 0.0934 | 0.116 | -15.326 | 0.0321 | 136.168 | 0 | 4 | Sad |
| 99 Luftbal | 99 Luftbal | Nena | 6HA97v4w | 21-08-1984 | 2 | 233000 | 0.466 | 0.089 | 0.438 | 5.62E-06 | 0.113 | 0.587 | -12.858 | 0.0608 | 193.1 | 4 | 4 | Happy |
| A Boy Bru | They're O | Underoath | 47IWLfIKC | 01-01-2004 | 60 | 268000 | 0.419 | 0.00171 | 0.932 | 0 | 0.137 | 0.445 | -3.604 | 0.106 | 169.881 | 1 | 4 | Energetic |
| A Burden | A Burden | Emmanue | 67DOFCrk | 31-07-2020 | 27 | 129410 | 0.394 | 0.995 | 0.0475 | 0.955 | 0.105 | 0.172 | -26.432 | 0.072 | 71.241 | 6 | 5 | Calm |
| A La Plage | A La Plage | Ron Adel | 79NmiFAg | 07-08-2020 | 29 | 141888 | 0.504 | 0.994 | 0.0584 | 0.956 | 0.115 | 0.553 | -20.461 | 0.0516 | 134.209 | 5 | 4 | Calm |
| A Little Le | Elvis 75 - ( | Elvis Pres | 4l2hnfUx0 | 28-12-2009 | 1 | 211173 | 0.586 | 0.000155 | 0.935 | 0.277 | 0.159 | 0.58 | -9.386 | 0.0482 | 114.997 | 4 | 4 | Happy |
| A Place fo | Hybrid Th | Linkin Par | 5rAxhWcg | 24-10-2000 | 68 | 184640 | 0.603 | 0.0144 | 0.908 | 0 | 0.671 | 0.457 | -5.254 | 0.184 | 133.063 | 11 | 4 | Energetic |
| ATTACK | A Beautif | Thirty Sec | 6QxTWEv | 15-05-2007 | 0 | 189200 | 0.331 | 0.00344 | 0.876 | 0.000835 | 0.732 | 0.299 | -1.894 | 0.0603 | 175.009 | 5 | 4 | Energetic |
| Adagio Fo | Adagio Fo | Lucas & St | 1RvDsjCBI | 09-11-2018 | 55 | 197189 | 0.349 | 0.000877 | 0.793 | 0.431 | 0.22 | 0.0398 | -6.748 | 0.0677 | 127.139 | 10 | 4 | Energetic |
| Adjustme | Adjustme | Josie Meh | 6w0vhPaZ | 17-01-2020 | 52 | 182000 | 0.532 | 0.974 | 0.541 | 0.864 | 0.228 | 0.329 | -11.932 | 0.0283 | 136.063 | 0 | 4 | Calm |
| Adrift | Adrift | Cooper Sa | 3TNNGjgC | 21-03-2018 | 53 | 158117 | 0.382 | 0.497 | 0.333 | 0.918 | 0.106 | 0.0486 | -15.573 | 0.0367 | 84.974 | 7 | 4 | Calm |
| Afraid of I | Afraid of I | Billy Taler | 0P44AUPI | 29-07-2016 | 38 | 225680 | 0.543 | 0.000168 | 0.991 | 1.31E-05 | 0.374 | 0.766 | -2.78 | 0.0668 | 150.031 | 9 | 4 | Energetic |
| Africa | Toto IV | TOTO | 2374M0fQ | 08-04-1982 | 84 | 295893 | 0.671 | 0.257 | 0.373 | 7.95E-05 | 0.0481 | 0.732 | -18.064 | 0.0323 | 92.717 | 9 | 4 | Happy |
| After The | After The | Comet Blu | 2XBc2jWn | 03-08-2020 | 24 | 116625 | 0.456 | 0.993 | 0.0337 | 0.948 | 0.126 | 0.3 | -26.87 | 0.0334 | 97.199 | 0 | 4 | Calm |
| Afterlife | Avenged S | Avenged S | 4QdwsME | 30-10-2007 | 13 | 351560 | 0.492 | 0.000444 | 0.95 | 6.22E-05 | 0.22 | 0.391 | -4.195 | 0.076 | 110.027 | 2 | 4 | Energetic |
| Algo Rhyt | TemporÃ± | One Sente | 0PqJ7LSkr | 28-10-2016 | 0 | 210626 | 0.402 | 1.19E-05 | 0.75 | 0.959 | 0.122 | 0.58 | -7.358 | 0.0293 | 149.941 | 2 | 4 | Sad |
| Alison | Souvlaki | Slowdive | 55CenVQ4 | 1993 | 0 | 231893 | 0.279 | 0.00957 | 0.423 | 0.837 | 0.128 | 0.291 | -12.06 | 0.038 | 101.571 | 4 | 4 | Sad |
| Alive | Alive | Paris Bloh | 2rPJcL8gQ | 16-11-2018 | 51 | 180468 | 0.494 | 0.00248 | 0.847 | 0 | 0.0502 | 0.148 | -3.996 | 0.0537 | 129.909 | 0 | 4 | Energetic |
| All I Want | The Kodal | Kodaline | 1XczdQt6F | 07-09-2012 | 29 | 306600 | 0.189 | 0.113 | 0.427 | 0.0923 | 0.058 | 0.158 | -9.08 | 0.0449 | 187.212 | 0 | 3 | Sad |
| All Mirror | All Mirror | Angel Ols | 4ZQdynvfi | 31-07-2019 | 1 | 282026 | 0.429 | 0.00299 | 0.689 | 0.00193 | 0.152 | 0.23 | -7.38 | 0.0379 | 105.04 | 7 | 4 | Sad |

**Figure 2**: *Snapshot of data_moods.csv used for recommending songs based on emotion-to-mood mapping.*

## 7.3 Exploratory Analysis

- **Mood Distribution**: The music dataset showed a fairly even spread across four moods. However, energetic and happy tracks slightly dominated due to popular genres.
- **Correlations**:
  - Calm tracks had high acousticness and low energy.
  - Energetic tracks had high energy and loudness but low acousticness.
  - Happy tracks had high valence and moderate energy.
  - Sad tracks had high acousticness and low valence.

# 8. Algorithmic Descriptions and Mathematical Formulations

In this section, we define the core components and algorithms used in our Speech Emotion Recognition system, highlighting both structural and mathematical intuitions behind each.

## 8.1 Convolutional Neural Network (CNN)

CNNs are powerful for learning spatial hierarchies in data. In SER tasks, CNNs operate over time-frequency representations (e.g., MFCCs, Mel Spectrograms) [1][10][11].

**Mathematical Description**:

Let X be the input feature matrix (e.g., MFCC with shape (n,m)(n, m)(n,m)). A 2D convolution over a kernel K is computed as:

$$Y[i,j] = \sum_{u}( \sum_{v}( K[u,v] \cdot X[i+u, j+v])$$

Where:

- X is the input feature map (e.g., MFCC)
- K is the convolution kernel
- i, j are spatial positions

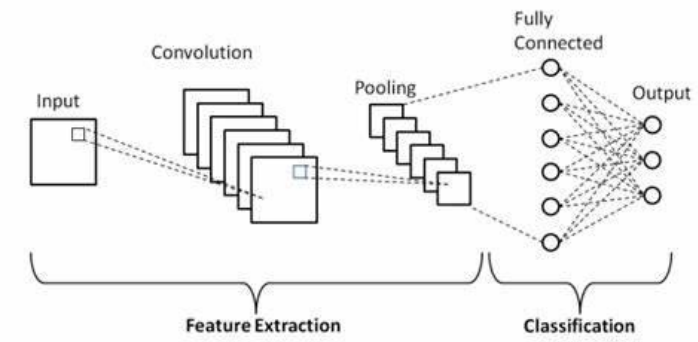



**Figure 3:** *Architecture of CNN [32]*

**Activation Function (ReLU)**:

$$f(x) = max(0, x)$$

Pooling (typically MaxPooling) reduces spatial dimensions while retaining dominant features [6][9].

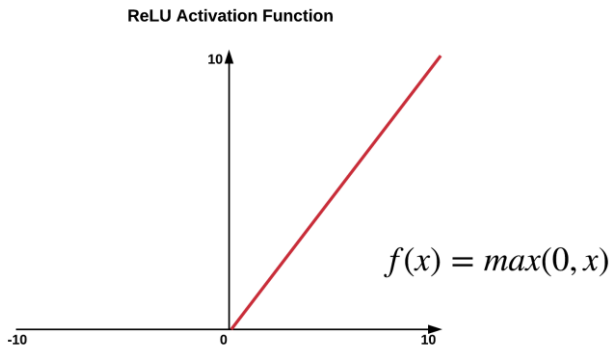



**Figure 4:** *ReLU Activation Function [33]*

## 8.2 Long Short-Term Memory (LSTM)

LSTMs capture temporal dependencies in sequential data. They are well-suited for speech due to the temporal nature of audio [2][18].

Each LSTM cell contains gates:

- **Forget gate**: $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$
- **Input gate**: $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$
- **Output gate**: $\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$
- **Cell state update**: $C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$

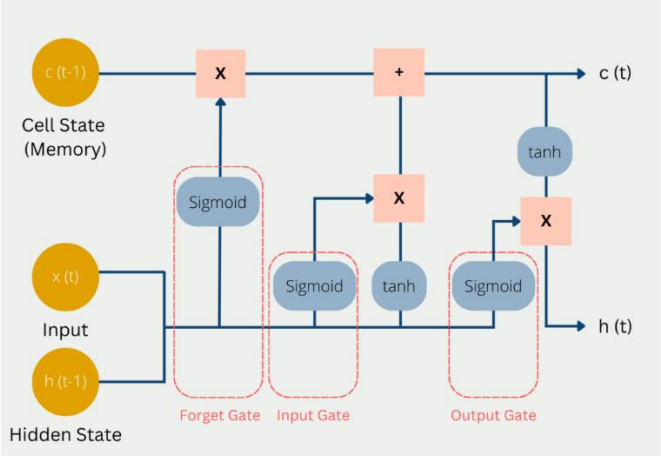



**Figure 5:** *LSTM Neural Network Architecture [34]*

### 8.3 Recurrent Neural Networks (RNN)

RNNs are similar to LSTMs but simpler. They suffer from vanishing gradient problems for long sequences [12][16].

$$h_t = \tanh\left(W_{hh} \cdot h_{t-1} + W_{xh} \cdot x_t + b\right)$$

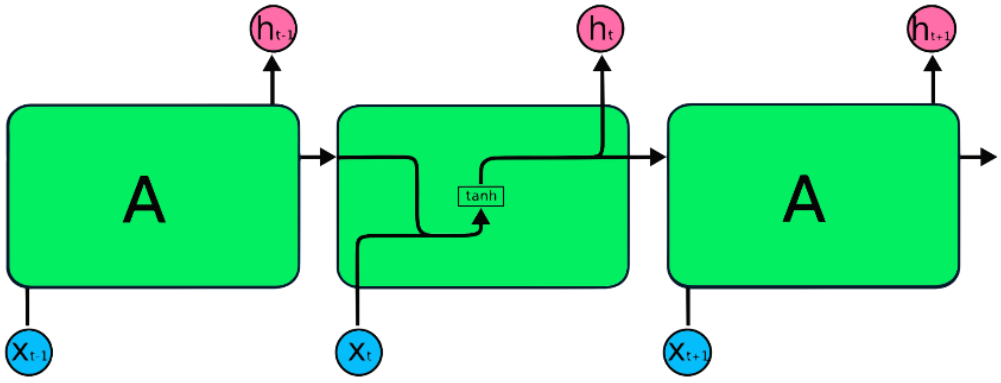



**Figure 6:** *RNN Architecture [37]*

### 8.4 Feature Extraction Techniques

We used **Librosa** to extract five types of audio features [1][10][29]:

- **MFCC (Mel-Frequency Cepstral Coefficients)**: Represents short-term power spectrum of sound.

$$\text{MFCC} = DCT(\log(Mel\ Filter\ Bank \cdot |\text{FFT}(y)|^2))$$

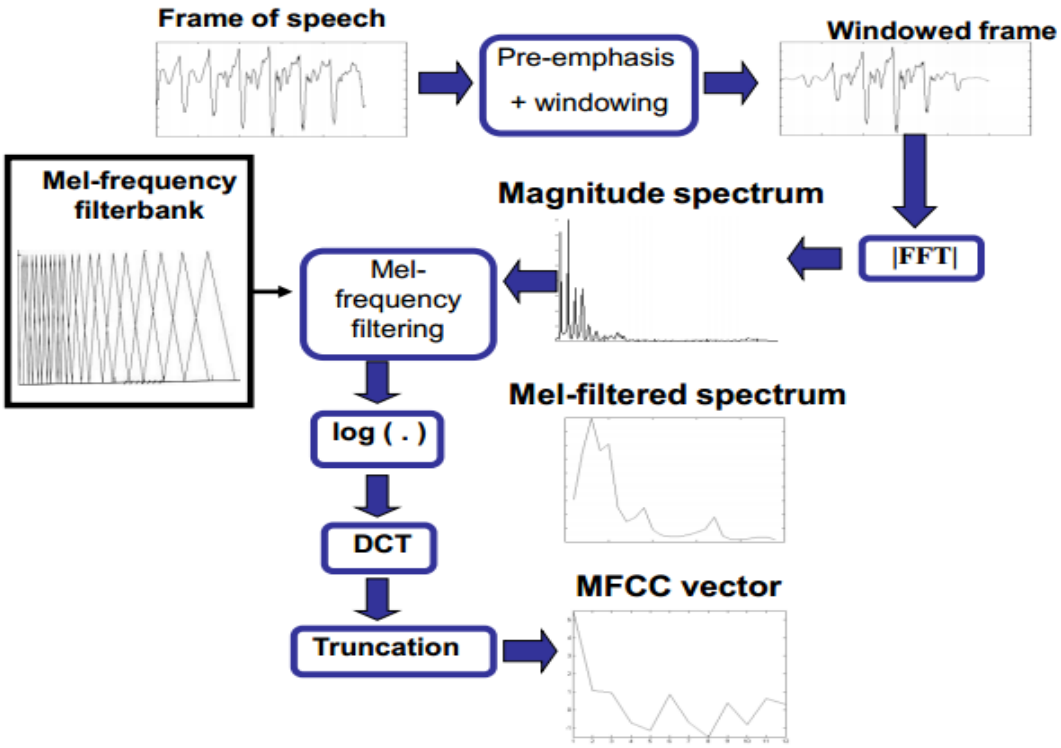



**Figure 7:** *Mel frequency cepstral coefficients extraction [31]*

Where DCT is the Discrete Cosine Transform, and Mel filter bank converts frequency to a perceptual Mel scale.

- **Mel Spectrogram**: Time vs frequency using Mel scale.

$$\text{Mel(f)} = 2595 * \log_{10}(1 + \frac{f}{700})$$

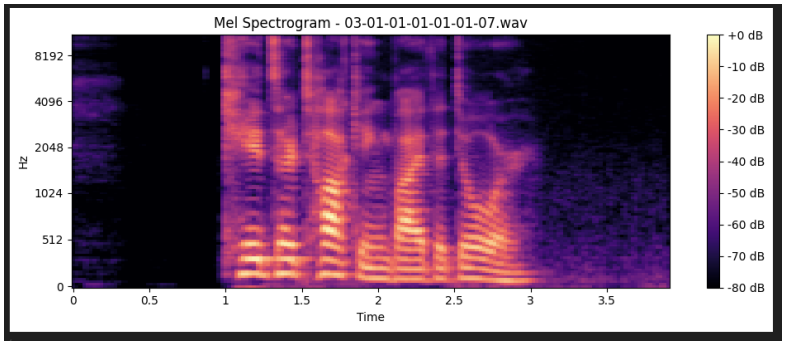



**Figure 8:** *Mel spectrogram of wav file*

- **Chroma Features**: Energy distribution across 12 pitch classes (C, C#, D, ..., B) [1].
- **Spectral Contrast**: Difference between spectral peaks and valleys, highlighting timbral textures.
- **Tonnetz (Tonal Centroid Features)**: Encodes harmonic and tonal relationships, derived from pitch class profiles and Tonal Interval Vectors [3][5].

## 9. Experimental Setup

Our experimental pipeline was designed to ensure consistent training, reproducibility, and fair model comparison across multiple deep learning architectures. All models were evaluated on the same preprocessed RAVDESS dataset and tested using stratified 80/20 splits to ensure balanced class representation.

### 9.1 Dataset

- **Primary Dataset:**
  RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song) [1][10]
  - Speech-only .wav files
  - Sample rate: 22050 Hz
  - Duration: 3 seconds per sample
  - Classes used: Happy, Sad, Calm, Energetic (mapped from original 8 [29])
- **Music Dataset for Recommendation:**
  data_moods.csv [2][4][6]
  - Fields used: name, artist, mood, popularity, valence, energy, etc.
  - Used for post-inference mood-based music recommendation.

### 9.2 Preprocessing Parameters

- **Audio Normalization:** Trimmed silences, normalized amplitude [1][12]
- **Fixed-Length Padding:** 3-second padding = 66150 samples per audio clip
- **Feature Extraction (Librosa):**
  - n_mfcc = 40
  - n_mels = 128
  - Features: MFCC, Chroma, Mel Spectrogram, Spectral Contrast, Tonnetz
- **Input Reshaping:**
  - CNN: (40, 862, 1)
  - CNN+LSTM: Reshaped for time-distributed LSTM input
  - 1D CNN+LSTM: (Time_steps, Features) using feature concatenation
  - Spectrograms: Resized to (128x128) for some CNN/RNN models

### 9.3 Model Training Parameters

| Parameter | Value |
|---|---|
| Loss Function | Categorical Cross-Entropy |
| Epochs | 35 – 700 (best: 700 epochs) |
| Batch Size | 32 |
| Dropout Rate | 0.2 – 0.3 |
| Evaluation Metric | Accuracy, Precision, Recall, F1 Score |
| Label Encoding | One-Hot (via Keras) |
| Data Split | 80% Train / 20% Test (Stratified) |
| Callback | EarlyStopping + ModelCheckpoint |

**Table 4:** *Key training parameters and hyperparameters used for model evaluation and tuning across all experiments.*

These were kept consistent across models to ensure fair evaluation [7][13][24].

### 9.4 Tools and Libraries Used

- **Frameworks:**
  TensorFlow + Keras (2.9+) [1][10]
  Librosa (for feature extraction) [1][11]
  NumPy, Pandas, Matplotlib, Scikit-learn
- **Deployment Tool:**
  **Gradio UI [4][6]**
  - Real-time audio upload and classification
  - Music recommendation based on predicted emotion

## 10. Results and Discussion

We evaluated multiple deep learning architectures for speech emotion recognition using the RAVDESS dataset. The models varied in complexity, feature design, and input representation. Below is a comprehensive analysis of the results observed across different configurations.

### 10.1 CNN + LSTM (2D)

Using padded MFCCs of shape (40, 862, 1), this model integrated convolutional layers with a TimeDistributed LSTM module. Despite being a robust setup commonly used in SER pipelines [8][18], it achieved **57.76% accuracy** on 576 samples (Happy, Sad, Calm, Energetic). The lower performance was attributed to:

- Limited training epochs (only 35)
- Small dataset size
- Potential overfitting due to under-regularization

### 10.2 BatchNorm CNN + LSTM

Enhancing the base CNN+LSTM model with **Batch Normalization** and deeper architecture yielded **49.31% accuracy**. The drop may be due to **slow convergence** or the need for more epochs [24]. This model still provided smoother learning curves.

### 10.3 CNN Only (1D)

Our best model trained for 700 epochs on a larger feature stack (MFCC + Mel Spectrogram + Chroma + Tonnetz + Spectral Contrast) achieved approximately 65% accuracy. This model demonstrated:

- Highest generalization on test data
- Best F1 and recall scores for Calm and Energetic classes
- Seamless integration with Gradio for real-time inference and music recommendation via data_moods.csv [2][4]

This version closely replicates the Issa et al. (2020) [1] baseline, while adding enhancements such as robust padding and preprocessing consistency.

### 10.4 CNN + RNN (2D Spectrogram)

Using resized (128x128) spectrograms as input and combining SimpleRNN with LSTM layers resulted in a performance of 22.92% accuracy despite 100 training epochs. This underperformance was likely caused by:

- Overfitting on a small dataset
- Loss of important temporal cues due to image resizing
- RNN's limitations in modeling long sequences without attention mechanisms [3][16]

### 10.5 CNN + LSTM (1 Actor Only)

When trained on audio data from a single speaker (controlled environment), the CNN+LSTM architecture achieved 80% accuracy within 30 epochs. This setup highlights how speaker variability can affect generalization.

### 10.6 CNN Only (1 Actor Only)

The CNN-only model (without any temporal modeling) achieved 40% accuracy when trained on the same single-speaker dataset. The comparison with the above configuration reaffirms the role of LSTM layers in capturing time-dependent patterns essential for SER [6][29].

### 10.7 Confusion Matrix & Insights

- **Happy** and **Energetic** emotions were most accurately predicted with minimal overlap.
- **Sad** and **Calm** emotions exhibited significant confusion, likely due to similar acoustic profiles such as lower energy and pitch variability [1][10].
- Misclassifications primarily occurred between Calm ↔ Sad and Energetic ↔ Happy [20][24].

### 10.8 Music Recommendation Integration

Once an emotion was predicted, we mapped it to a complementary mood and queried the data_moods.csv dataset [2][6][9]. Examples include:

- **Sad → Happy**: Songs with high valence and popularity were recommended to uplift mood.
- **Calm → Energetic**: High-energy tracks were suggested to enhance stimulation.
- **Energetic → Calm**: Relaxing tracks were provided to balance user energy.

## 11. Conclusion

In this study, we investigated multiple deep learning approaches for speech emotion recognition using the RAVDESS dataset and integrated a personalized music recommendation pipeline using detected emotional cues. Among all models explored, a 1D CNN trained with an expanded feature set over 700 epochs delivered the best performance, achieving approximately 65% accuracy. This aligns with benchmarks from [1][10] while offering a scalable implementation.

Through extensive experimentation, we demonstrated how feature richness, dataset diversity, model complexity, and speaker variability can significantly impact model accuracy and generalizability. Our experiments underscore the importance of temporal modeling using LSTM layers and the necessity for carefully engineered preprocessing steps.

A distinctive aspect of our work is its real-world applicability. The incorporation of Gradio for real-time testing and dynamic music recommendations using data_moods.csv made the system engaging and interactive for end users.

While our work successfully replicates and extends the methods proposed by Issa et al. (2020) [1], there is still room for advancement. Future enhancements may include:

- Incorporating attention mechanisms into the LSTM layers to better capture long-term dependencies
- Exploring multimodal fusion by combining speech with facial and physiological cues
- Deploying the solution in real-time systems and expanding to multilingual and accent-diverse datasets

Ultimately, our work contributes to the growing field of affective computing by enabling context-aware, emotion-driven music personalization through scalable and interpretable deep learning models.

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