Speech Emotion Recognition

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1 Problem statement

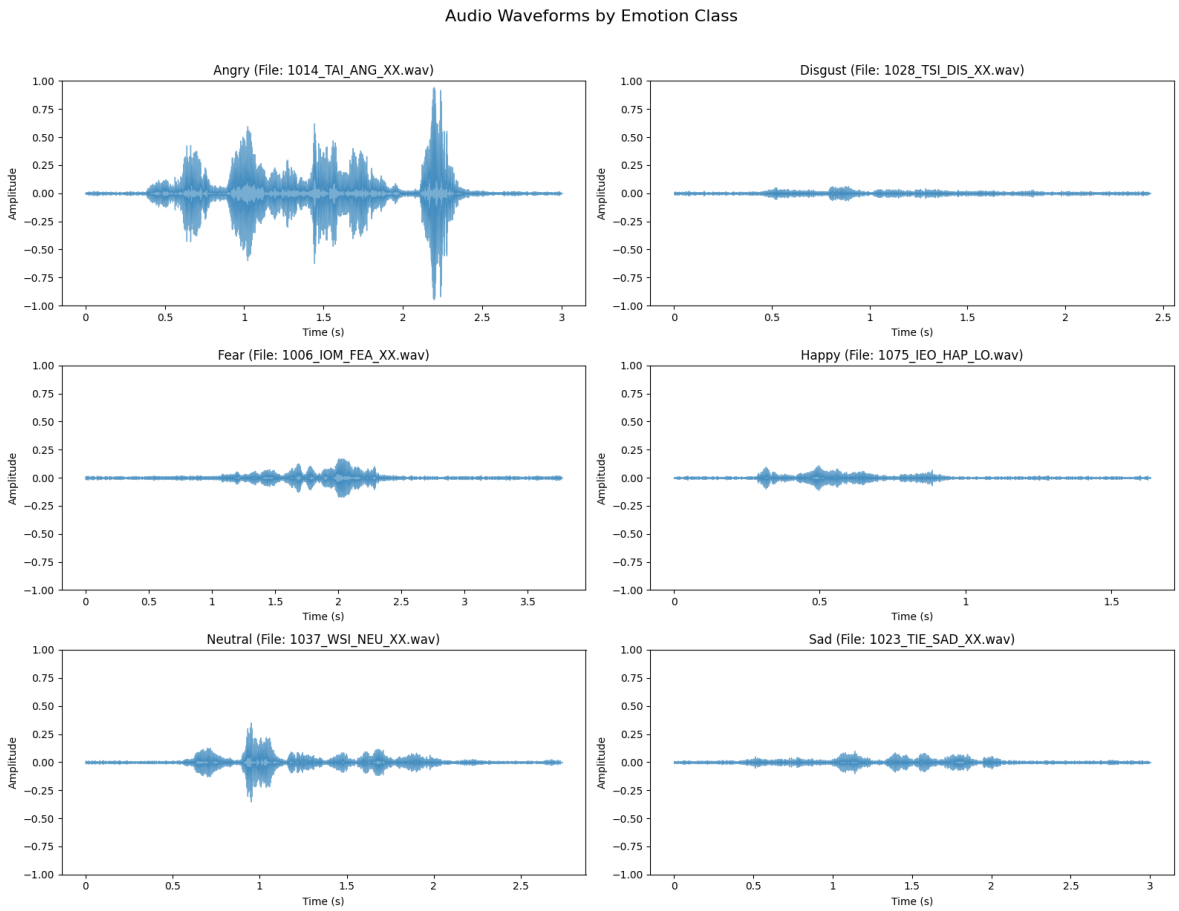
It's required to Create the Feature Space in the time domain, or in the frequency domain and Convert the audio waveform to a mel spectrogram and compare the performance of the CNN models in the two approaches using Speech Emotion Recognition (en).

1.1 Dataset Loading and visualize

The CREMA-D dataset contains audio files labeled with six emotion classes: **Angry, Disgust, Fear, Happy, Neutral, and Sad**. Each filename follows a specific format that encodes the emotion (e.g., 1001_DFA_ANG_XX.wav where ANG = Angry).

Key Steps in Data Loading:

1. **File Parsing**
    - Scan the dataset directory for .wav files.
    - Extract emotion labels from filenames using the embedded emotion codes (e.g., ANG, DIS).
2. **Audio Loading**
    - Use librosa.load() to read audio files at a standard sampling rate (e.g., 22050 Hz).
    - Ensure uniform duration by padding/trimming signals to 3 seconds (66150 samples).
3. **Emotion Mapping**
    - Convert emotion codes (ANG, DIS, etc.) to full names (Angry, Disgust, etc.).



1.2 Dataset Splitting

- 1. Split the data into 70% training and validation and 30% testing.
- 2. Use 5% of the training and validation data for validation.

2 MEL

For each audio file:

- The waveform is loaded with a sampling rate of 22050 Hz and clipped to 3 seconds duration.
- If shorter than 3 seconds, zero-padding is applied.
- The Mel-spectrogram is computed with 128 Mel bands.
- Spectrograms are converted to log scale (dB).
- Temporal length is padded or truncated to a fixed size (130 frames).

2.2 Data Augmentation

The function augment_audio() applies random transformations:

- **Pitch shifting** (±1 or ±2 semitones),

- **Time stretching** (between 0.9x to 1.1x speed),
- **Additive Gaussian noise**.

These augmentations are only applied to training data to increase diversity and reduce overfitting.

2.3. Preprocessing Steps

- Extract Mel-spectrograms for all .wav files.
- Filter out files with unknown emotion labels.
- Encode emotion labels using LabelEncoder and one-hot encoding.
- Add channel dimension to spectrograms to be compatible with CNN input requirements.

2.4. Train-Test Split

A deep CNN is designed to extract spatial features from the Mel-spectrograms. The model includes:

- **Three convolutional blocks**:
    - Each block has two Conv2D layers with ReLU, Batch Normalization, MaxPooling, and Dropout.
    - Filter sizes grow from 64 → 128 → 256 to increase representational capacity.
- **Fully connected layers**:
    - Dense layers with 512 and 256 units, followed by Batch Normalization and Dropout.
- **Output layer**:
    - A softmax layer to predict emotion probabilities.

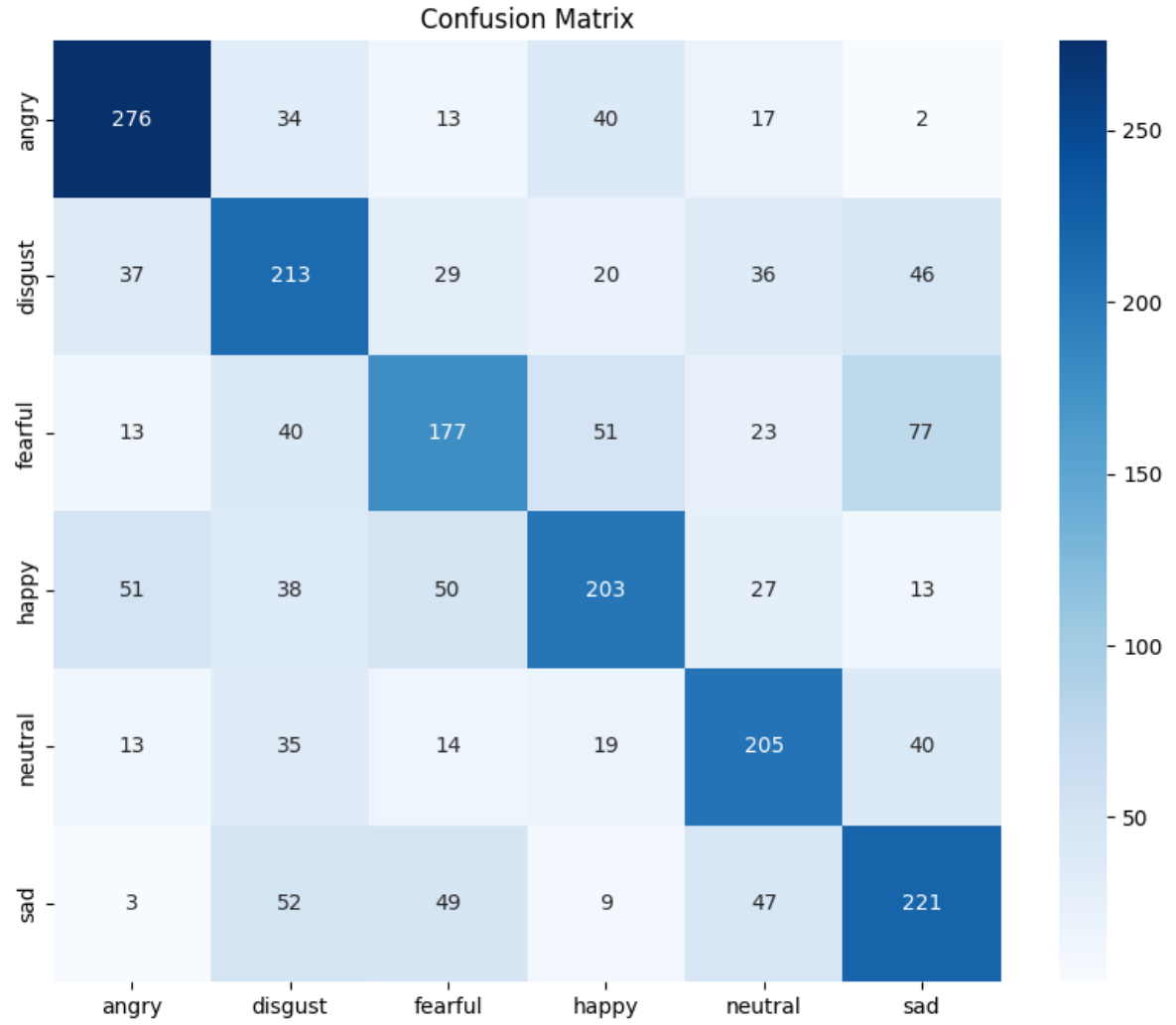
Model Characteristics

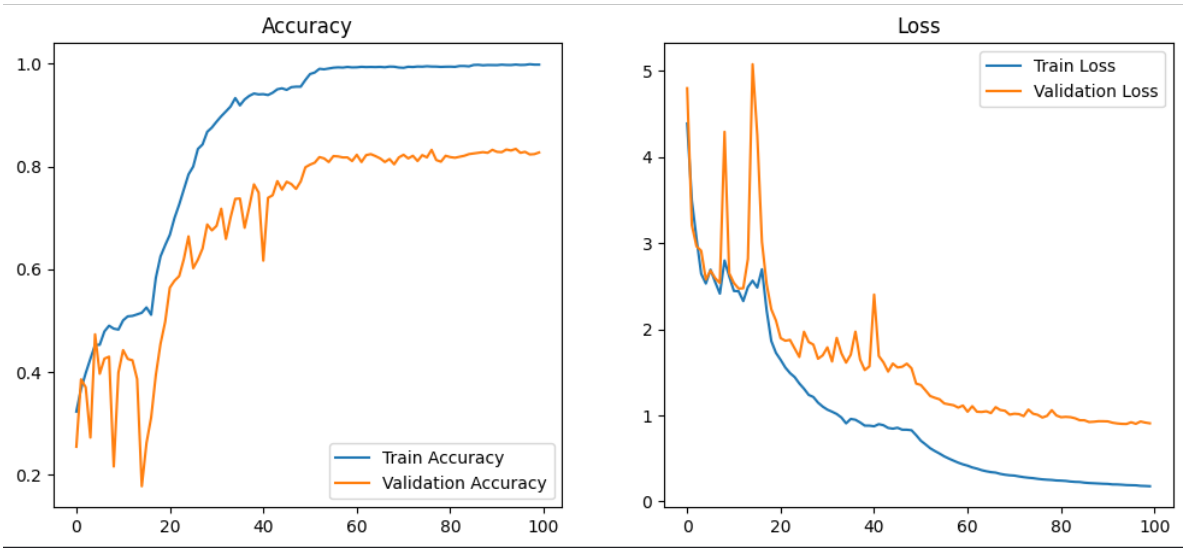
- Strong regularization via L2 penalties and Dropout.
- Batch Normalization accelerates convergence and stabilizes training.
- Designed to be robust against overfitting.

2.5. Result

Classification Report:

	precision	recall	f1-score	support
angry	0.70	0.72	0.71	382
disgust	0.52	0.56	0.54	381
fearful	0.53	0.46	0.50	381
happy	0.59	0.53	0.56	382
neutral	0.58	0.63	0.60	326
sad	0.55	0.58	0.57	381
accuracy			0.58	2233
macro avg	0.58	0.58	0.58	2233
weighted avg	0.58	0.58	0.58	2233


Confusion Matrix
angry
disgust
fearful
happy
neutral
sad
276 34 13 40 17 2
37 213 29 20 36 46
13 40 177 51 23 77
51 38 50 203 27 13
13 35 14 19 205 40
3 52 49 9 47 221
250
200
150
100
50


Accuracy
Train Accuracy
Validation Accuracy
Loss
Train Loss
Validation Loss

3 Time-Domain Features Extraction

For each audio file:

- The waveform is loaded with a sampling rate of **22050 Hz** and clipped to a **3-second duration**.
- If it is shorter than 3 seconds, **zero-padding** is applied.
- **Time-domain features** are extracted:
    - **Zero Crossing Rate (ZCR):** The rate at which the signal changes from positive to negative.
    - **Energy:** The sum of squared amplitudes of the signal, representing its strength.

Key Steps:

1. **ZCR Calculation:**
    - Computed over frames of 2048 samples with a hop length of 512 samples.
    - Represents the rate of sign changes in the waveform.
2. **Energy Calculation:**
    - Calculated as the sum of squared amplitudes in each frame.
    - Reflects the intensity of the signal over time.
3. **Padding:**
    - Both ZCR and Energy are padded to match length.

3.1 Preprocessing Steps

- Extract **ZCR** and **Energy** for all .wav files.
- Filter out files with unknown emotion labels.
- Encode emotion labels using LabelEncoder and one-hot encoding.
- Pad features to a fixed size to match CNN input requirements.

3.2 Train-Test Split

The dataset is split into training and testing sets:

- 70% for training and 30% for testing.
- Stratified sampling is applied to maintain class balance.

3.3 1D CNN Model Design

A deep **1D CNN** is designed to extract temporal features from the time-domain feature space.

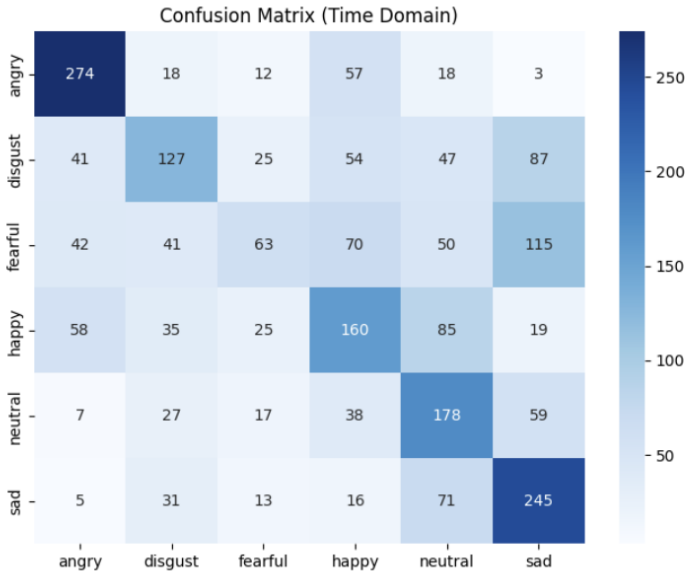
Model Architecture:

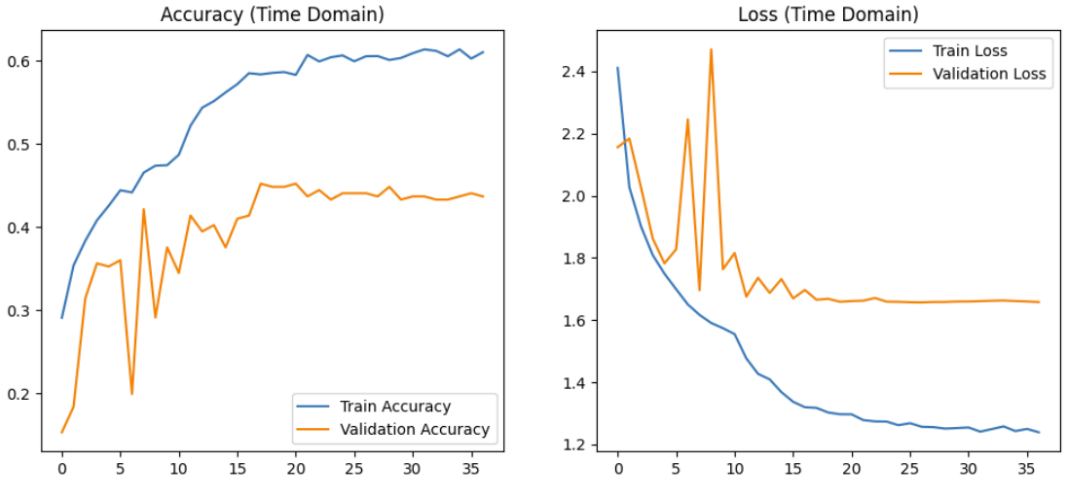
- **Convolutional Blocks:**
    - Three blocks, each with:
        - Two Conv1D layers with ReLU activation, Batch Normalization, MaxPooling, and Dropout.
        - Filter sizes grow from 64 → 128 → 256 for increased representational capacity.
- **Fully Connected Layers:**
    - Dense layers with 128 units, followed by Batch Normalization and Dropout.
- **Output Layer:**
    - A softmax layer to predict emotion probabilities.

3.4 Results

Classification Report (Time Domain):

	precision	recall	f1-score	support
angry	0.64	0.72	0.68	382
disgust	0.46	0.33	0.38	381
fearful	0.41	0.17	0.24	381
happy	0.41	0.42	0.41	382
neutral	0.40	0.55	0.46	326
sad	0.46	0.64	0.54	381
accuracy			0.47	2233
macro avg	0.46	0.47	0.45	2233
weighted avg	0.46	0.47	0.45	2233





4 Frequency-Domain Features Extraction

- Audio files are loaded using librosa.
- Frequency-domain features are extracted:
  - **MFCCs** (Mel Frequency Cepstral Coefficients), or
  - **FFT magnitudes** with optional log scaling.
- All feature matrices are **padded/truncated** to a fixed time length for consistency.
- Labels are **encoded numerically** using LabelEncoder.

CNN Model Architecture

- **Input Shape**: (109, 40) — 109 time steps, 40 MFCC features per frame.
- **Convolutional Blocks**:
  - Conv1D (64 filters, kernel=5) + MaxPooling1D
  - Conv1D (128 filters, kernel=3) + MaxPooling1D
- **Global Average Pooling** replaces flattening for dimensionality reduction.
- **Dense Layers**:
  - Dense(128) → Dropout(0.4)
  - Dense(64) → Dropout(0.4)
- **Output Layer**: Dense(6) with **softmax** for multi-class classification.

Training Configuration

- **Optimizer**: Adam with learning rate = 0.0001
- **Loss**: Categorical cross-entropy (for one-hot encoded targets)
- **Metric**: Accuracy
- **Callbacks**: ReduceLROnPlateau to reduce LR if validation loss plateaus

Results:

F1 Score (Weighted): 0.5222

Accuracy: 0.5249

Classification Report:

	precision	recall	f1-score	support
angry	0.68	0.74	0.71	370
disgust	0.47	0.40	0.43	392
fearful	0.54	0.42	0.47	380
happy	0.47	0.52	0.50	377
neutral	0.42	0.49	0.45	322
sad	0.55	0.58	0.57	392
accuracy			0.52	2233
macro avg	0.52	0.53	0.52	2233
weighted avg	0.53	0.52	0.52	2233