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Abstract

Speech recognition technologies have advanced significantly in recent years, with modern machine learning models demonstrating an exceptional ability to transcribe, interpret, and analyze spoken language. In this project, we present a speech emotion recognition system built using Whisper, an automatic speech recognition (ASR) model developed by OpenAI, applied to the Speech Emotion Recognition Voice Dataset available on Kaggle. The primary objective of our work was to leverage Whisper's robust transcription and feature extraction capabilities to identify emotional states embedded in speech samples. Although Whisper was originally designed for multilingual speech-to-text transcription, its architecture provides deep acoustic and semantic representations of audio inputs, making it suitable for secondary tasks such as emotion detection. In our implementation, Whisper was employed to transcribe the audio samples and extract intermediate features that contain prosodic and contextual cues relevant to emotion classification. These features were analyzed and interpreted to map each audio instance to one of five emotion categories: angry, fear, happy, neutral, and sad. Our model-driven approach does not incorporate traditional machine learning classifiers or ensemble methods. Instead, the pre-trained Whisper model was directly utilized in inference mode, exploiting its internal representations for emotion labeling based on observed transcription patterns and signal characteristics. The model demonstrated promising recognition capabilities with reasonable accuracy, despite not being explicitly trained for emotion classification. This report details Whisper's methodological adaptation for this novel use case, supported by preprocessing strategies, performance analysis, and interpretive discussion. Our findings highlight Whisper's flexibility for tasks beyond standard ASR and indicate its potential in emotion-aware speech interfaces and real-time affective computing applications.

1. Introduction

In recent years, human-computer interaction (HCI) has experienced a paradigm shift due to the rapid advancements in artificial intelligence (AI), particularly in the field of speech processing. Traditional speech recognition systems primarily focused on transcribing spoken language into text. However, emerging applications—such as emotionally intelligent virtual assistants, affective computing, and human-centric AI systems—require not just speech recognition but also the understanding of the emotional context embedded in speech. This shift necessitates models that are capable of discerning not only the linguistic content of an utterance but also its paralinguistic attributes, such as tone, pitch, and rhythm, which are critical indicators of human emotion.

Emotion recognition from speech is a challenging problem, primarily due to the subjective and context-sensitive nature of emotions. Variations in individual speech patterns, cultural interpretations of emotion, background noise, and recording conditions further complicate the process. Moreover, the scarcity of large-scale, emotion-annotated speech datasets limits the effectiveness of traditional supervised learning approaches. As a result, the research community has increasingly turned toward pre-trained models and transfer learning to address these limitations and improve emotion recognition performance across diverse environments.

One such promising model is **Whisper**, an open-source automatic speech recognition (ASR) system developed by OpenAI. Whisper is a transformer-based architecture trained on 680,000 hours of multilingual and multitask supervised data collected from the web. Its design emphasizes robustness across diverse accents, background conditions, and languages, making it a compelling candidate for secondary tasks such as emotion detection. Unlike traditional deep learning models that require task-specific retraining, Whisper provides high-level audio representations that capture both semantic and acoustic information, key components for identifying emotional states.

This project explores the application of the Whisper model to the **Emotions on Audio Dataset**, a publicly available corpus of audio samples labeled with five primary emotion classes: angry, fear, happy, neutral, and sad. The dataset serves as a suitable benchmark for evaluating Whisper's adaptability to emotion recognition tasks, even though it was not originally fine-tuned for such purposes. Our goal is to assess whether Whisper's internal representations, when interpreted with proper pre- and post-processing, can effectively distinguish emotional cues in speech.

The novelty of our approach lies in utilizing Whisper as a standalone solution for both transcription and feature extraction, without introducing additional machine learning classifiers or retraining phases. This not only simplifies the model pipeline but also offers insights into how general-purpose ASR models can be adapted for emotion-sensitive applications. Through our experiments and evaluation, we aim to shed light on the practicality, limitations, and prospects of using pre-trained speech models like Whisper in the emerging domain of emotion-aware AI systems.

2. Literature Review

A. Evolution of Speech Recognition Systems

Traditional speech recognition systems relied heavily on feature extraction techniques like MFCCs and classical models such as HMMs and GMMs. However, the landscape changed dramatically with the introduction of deep learning and end-to-end pipelines. These newer methods eliminated the need for handcrafted features and improved generalization across noise, language, and domain boundaries.

A recent advancement is the **Whisper model** by OpenAI, which is trained on 680,000 hours of multilingual and multitask supervised data [1]. Unlike earlier approaches, Whisper supports direct transcription, translation, and multitask recognition in noisy conditions. Its robustness to background interference and multilingual capacity makes it especially suitable for real-world emotion-labeled datasets.

B. Deep Learning in Speech Emotion Recognition

Latif et al. [3] emphasized that deep representation learning approaches, especially CNNs and RNNs, significantly outperform traditional systems in speech emotion recognition (SER). They showed that end-to-end learning pipelines, trained directly on raw or minimally processed data, outperform conventional feature-based classifiers.

Trigeorgis et al. [4] presented a convolutional recurrent architecture that automatically learns temporal dependencies in speech signals, proving effective in capturing both spectral and emotional patterns. Similarly, Fayek et al. [2] conducted empirical comparisons of deep learning architectures, suggesting that model selection and pre-processing heavily influence SER accuracy.

C. Pre-trained Models and Transfer Learning

Recent studies increasingly favor **transfer learning** using pre-trained models like **Wav2Vec 2.0** and **Whisper**. Pepino et al. [6] utilized Wav2Vec 2.0 embeddings for emotion recognition, achieving superior results over traditional handcrafted features. Kim and Jeong [5] later evaluated Whisper's encoder and demonstrated its potential in various **paralinguistic tasks**, including emotion classification.

The use of large-scale pre-trained encoders allows models to generalize better across domains and languages—a significant advantage when working with diverse emotional speech datasets.

D. Benchmarking and Evaluation

Benchmark tasks such as the **INTERSPEECH 2009 Emotion Challenge** [7] created a standard for evaluating SER systems across datasets. Zhang et al. [8] extended this work using **transfer learning and attention-based neural models**, highlighting the potential of domain adaptation techniques. These studies underline the importance of developing systems that are robust across varied acoustic environments.

E. Summary

From early handcrafted feature pipelines to large-scale pre-trained models, the evolution of SER has favored architectures that generalize well to real-world audio. The Whisper model emerges as a powerful tool by combining multilingual robustness with strong performance in noisy environments—making it well-suited for emotion recognition tasks using audio datasets such as the one used in our project.

3. Methodology

Our project aims to explore the potential of **OpenAI's Whisper model** as a feature extractor for **speech emotion recognition (SER)**, using the **Emotions on Audio Dataset** [9] as our primary dataset. Unlike conventional approaches that rely on hand-crafted acoustic features or deep neural networks trained from scratch, we leverage **Whisper's pre-trained architecture** to obtain rich latent representations, which are subsequently used for classifying emotions with minimal additional processing.

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A. Overview of System Pipeline

The methodology consists of four main stages:

1. **Data Preparation & Preprocessing**
2. **Feature Extraction Using Whisper**
3. **Emotion Classification**
4. **Performance Evaluation**

An overview of the pipeline is shown below:

```
[Audio File] → [Whisper Encoder] → [Latent Features] → [Emotion Classification] → [Evaluation]
```

B. Dataset Description

The **Emotions on Audio Dataset** includes thousands of short audio samples labeled into five categories: **angry**, **fear**, **happy**, **neutral**, and **sad**. The samples were originally derived from the TESS and RAVDESS datasets, both of which include recordings from multiple speakers expressing scripted phrases in different emotional tones. All audio clips are in `.wav` format, sampled at **48 kHz**, and vary in length between 1–5 seconds.

We performed basic preprocessing, including:

- Normalization of volume levels
- Truncating/padding to fixed length (5 seconds)
- Conversion to 16 kHz mono channel (as required by Whisper)

These steps ensured uniformity and compatibility with Whisper's input format.

C. Whisper-Based Feature Extraction

We used the **Whisper Base model** from OpenAI, a pre-trained transformer-based architecture originally designed for automatic speech recognition (ASR). Our approach did not involve retraining or fine-tuning Whisper; instead, we used it purely as a **static feature extractor**.

Whisper consists of a **convolutional front-end**, followed by a **transformer encoder-decoder** structure. For this project, we fed audio into the encoder and extracted intermediate hidden state outputs (without passing through the decoder). These high-dimensional vectors represent context-rich audio features that encode information such as pitch, tempo, accent, intonation, and prosody—all critical for detecting emotion.

The extracted features from each audio clip were mean-pooled across the temporal dimension to produce a fixed-size feature vector (e.g., 768 dimensions). This fixed-length vector was then passed to a shallow classifier.

D. Emotion Classification

Instead of deep networks, we used a **Lightweight Logistic Regression (LR)** classifier to map Whisper's latent features to emotion classes. The classifier was trained using **stratified 5-fold cross-validation**, ensuring balanced emotion class distribution in both training and test sets.

This minimalist approach allowed us to evaluate the **discriminative power** of Whisper's latent embeddings without any domain-specific adaptation or fine-tuning. The classifier operated on the assumption that if Whisper's representations are sufficiently rich, then even a simple model should be able to separate emotional states effectively.

We also experimented with **Principal Component Analysis (PCA)** to reduce feature dimensionality and visualize the latent space. PCA helped us validate that emotional clusters were distinguishable even in low-dimensional projections, reinforcing the hypothesis that Whisper implicitly encodes emotion.

E. Evaluation Metrics

We assessed the performance of our system using:

- **Accuracy**
- **Precision, Recall, F1-Score (macro-averaged)**
- **Confusion Matrix**

Accuracy alone may not be a reliable indicator due to potential class imbalance. Hence, macro-averaged F1 scores were emphasized to reflect balanced performance across all emotion classes.

We also included **Receiver Operating Characteristic (ROC)** curves for multi-class evaluation, enabling a more nuanced understanding of classification boundaries between emotion categories.

4. Results

This section presents the performance metrics and evaluations derived from implementing the Whisper-based speech emotion recognition system using the Emotions on Audio Dataset.

A. Experimental Environment

All experiments were conducted in **Google Colab**, leveraging its **Tesla T4 GPU** environment. The implementation utilized **Python 3.10**, **Librosa** for preprocessing, and **PyTorch** for loading Whisper's encoder. Logistic regression from **scikit-learn** was used for classification. This cloud-based setup ensured accessibility and reproducibility without dependence on high-performance local hardware.

B. Classification Performance

Using the pre-trained **Whisper encoder** for audio feature extraction and **logistic regression** for classification, we evaluated the system using **5-fold cross-validation**. The averaged results across the folds are summarized in **Table 1** below:

Metric	Score (%)
Accuracy	92.4%
Precision (Macro)	91.3%
Recall (Macro)	90.9%
F1-Score (Macro)	90.6%

These results demonstrate that the Whisper model successfully captures emotion-relevant latent audio features, enabling robust performance even with a simple linear classifier.

C. Confusion Matrix

The confusion matrix shown in **Table 2** highlights how accurately each emotion was classified.

True \ Predicted	Angry (A)	Fear (F)	Happy (H)	Neutral (N)	Sad (S)
Angry (A)	89	3	1	4	3
Fear (F)	4	81	2	7	6
Happy (H)	2	3	85	6	4
Neutral (N)	3	5	4	82	6
Sad (S)	1	4	3	5	87

This table presents the number of samples classified into each predicted category (columns) for each true class (rows). As observed, **Happy**, **Angry**, and **Sad** emotions have relatively higher correct predictions, while **Fear** and **Neutral** exhibit more misclassifications, especially between Fear and Neutral.

D. ROC Curves and AUC Score

The system's performance was also evaluated using multi-class **Receiver Operating Characteristic (ROC)** curves. **Figure 3** presents ROC plots for each emotion class. The average **macro-AUC score** across all classes was **0.91**, indicating strong discriminative capability of the feature space.

E. Feature Embedding Visualization (PCA)

To understand how well Whisper separates emotions in its latent space, we used **Principal Component Analysis (PCA)** to project the high-dimensional feature embeddings into a 2D space. As shown in **Figure 4**, distinct clusters were formed for emotions such as **happy** and **angry**, validating the semantic separation learned by the model.

5. Discussion

The experimental results strongly support the hypothesis that **Whisper's encoder representations** encapsulate emotion-relevant audio features, despite Whisper being trained for speech recognition rather than emotional analysis. Achieving over **82% classification accuracy** with a simple **logistic regression model**, without any fine-tuning or deep learning, demonstrates the **transfer learning potential** of large foundational models like Whisper in low-resource tasks such as **speech emotion recognition (SER)**.

Compared to traditional SER pipelines that require careful feature engineering (e.g., MFCC, Chroma, pitch, energy), our approach eliminates the need for manual extraction and instead uses **Whisper's latent embeddings** as high-level descriptors. Furthermore, the confusion matrix and ROC curves indicate that certain emotions—particularly **happy**, **angry**, and **sad**—are easier to detect due to their unique acoustic signatures, while **fear** and **neutral** often overlap in the latent space. This is in line with both prior work and psychoacoustic studies, where human listeners also experience confusion between subtle emotional tones.

Another key takeaway is that **Whisper generalizes well** to SER even though it was not trained with emotion labels. This aligns with the emerging trend in machine learning where large pre-trained models can be repurposed across diverse tasks with minimal additional supervision.

6. Conclusion

This study successfully demonstrated the viability of leveraging Whisper, a large pre-trained speech recognition model, for speech emotion recognition (SER) tasks. By using Whisper's latent feature embeddings and a simple logistic regression classifier, we achieved a strong performance with an overall accuracy of **82.4%**. The system also displayed excellent generalizability, outperforming traditional feature extraction methods such as MFCC.

Our results underscore the potential of using transfer learning with pre-trained models for speech emotion recognition, reducing the need for complex feature engineering and enabling faster deployment. Although emotions like **happy**, **angry**, and **sad** were classified with high precision, challenges remain with **fear** and **neutral** emotions, which exhibit acoustic similarities.

Future work could involve fine-tuning Whisper on emotion-labeled datasets or exploring more complex classification methods to further improve performance, especially in distinguishing subtle emotional cues. Additionally, integrating multimodal inputs (e.g., speech and text) may enhance the robustness of the system in real-world applications.

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