“Speech Emotion Analyzer Using NLP”

A project report submitted in partial fulfilment of the requirements for the award of the degree of

Bachelor of Technology

in

Department of CSE-Artificial Intelligence and Machine Learning

By

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CERTIFICATE

This is to certify that the project report entitled **“Speech Emotion Analyzer using NLP ”** submitted by **Gudibanda Sirisha(2211CS020185), Gurijala Swathi (2211CS020194), Karina Yadav(2211CS020232),K.E.Dhanusha (2211CS020241), Mandala Dhanush(2211CS020307)**towards the partial fulfillment of the award of Bachelor’s Degree in Project Development from the Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning), Malla Reddy University, Hyderabad, is a record of bonafide work done by him. The results embodied in the work are not submitted to any other University or institute forward of degree or diploma.

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DECLARATION

I hereby declare that the project report entitled "Speech Emotion Analyzer using NLP" has been carried out by us and this work has been submitted to the Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning), Malla Reddy University, Hyderabad in partial fulfilment of the requirements for the award of degree of Bachelor of Technology.I further declare that this project has not been submitted in full or part for the award of any other degree in any other educational institutions.

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Abstract

Speech Emotion Analysis (SEA) using Natural Language Processing (NLP) is a powerful approach to detecting and classifying emotions from spoken language by analyzing both textual and acoustic features. The process begins with speech-to-text conversion,where audio signals are transcribed into text using Automatic Speech Recognition (ASR) systems. Once the textual representation is obtained, NLP techniques such as tokenization, lemmatization, sentiment analysis, and named entity recognition (NER) are applied to extract meaningful linguistic patterns. Feature extraction methods like TF-IDF (Term Frequency-Inverse Document Frequency), Word2Vec and BERT embeddings help capture the semantic context of words, improving the system's ability to detect underlying emotions. Additionally, prosodic features such as pitch, tone, intensity, and speech rate are analyzed alongside textual features to enhance classification accuracy. For emotion classification, machine learning models such as Support Vector Machines (SVM), Naive Bayes, and Random Forest are explored, while deep learning models like Long Short-Term Memory (LSTM) networks and Transformer-based architectures (e.g., BERT and RoBERTa) are used to improve context-aware emotion recognition. These models help classify emotions such as happiness, sadness, anger, surprise, fear, and neutrality with high accuracy. The integration of NLP with speech analysis enables applications in various domains, including human-computer interaction, sentiment analysis, virtual assistants, call center monitoring, mental health assessment, and customer support automation. By enhancing AI-driven systems with emotional intelligence, this project aims to improve user experiences by enabling more empathetic and context-aware interactions between humans and machines.

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CHAPTER1 : INTRODUCTION

1.1 Problem Definition

In human communication, emotions play a crucial role in conveying meaning beyond just words. However, traditional text-based sentiment analysis often fails to capture the full depth of human emotions expressed through speech. The challenge in Speech Emotion Analysis (SEA) using Natural Language Processing (NLP) lies in accurately identifying emotions from spoken language by analyzing both textual and acoustic features.

This project addresses the problem of automated emotion recognition from speech, where the goal is to extract and process linguistic and prosodic cues to classify emotions such as happiness, sadness, anger, fear, surprise, and neutrality. The primary difficulties include speech-to-text conversion errors, contextual ambiguity, variations in tone and pitch, and the impact of background noise on speech recognition. Additionally, traditional emotion classification models often struggle with understanding the contextual and semantic meaning behind spoken words.

To solve this, the project employs NLP techniques like tokenization, sentiment analysis, word embeddings (TF-IDF, Word2Vec, BERT), and deep learning models such as LSTMs and Transformers to analyze both the textual and acoustic properties of speech. By improving the accuracy of emotion classification, this system can be applied in various fields such as customer support automation, virtual assistants, mental health monitoring, and human-computer interaction, enabling machines to better understand and respond to human emotions in real-time.

1.2 Objective of the Project

The objective of this project is to develop an automated speech emotion analysis system that accurately detects and classifies human emotions from spoken language using Natural Language Processing (NLP) and machine learning techniques. The system aims to convert speech into text using Automatic Speech Recognition (ASR) and process the text through NLP techniques such as tokenization, stopword removal, lemmatization, and word embeddings (TF-IDF, Word2Vec, BERT) to extract meaningful linguistic features. It further integrates machine learning models like Support Vector Machines (SVM) and Random Forest, as well as deep learning architectures such as LSTMs and Transformers, to classify emotions including happiness, sadness, anger, fear, surprise, and neutrality. Additionally, the project focuses on improving context-aware analysis by leveraging BERT-based models to enhance the system's ability to interpret emotional nuances in speech. A key goal is to develop a real-time emotion recognition system capable of analyzing speech data dynamically for interactive applications. This system will be applied in various domains such as customer sentiment analysis, virtual assistants, mental health monitoring, and human-computer interaction, ultimately enhancing AI-driven emotional intelligence and enabling machines to better understand and respond to human emotions in a more natural and empathetic manner.

The objective of this project is to develop a Speech Emotion Recognition (SER) system using the RAVDESS dataset and machine learning techniques. The system will analyze speech recordings to identify emotions such as happy, sad, angry, fearful, and neutral. It will extract important audio features like MFCCs, Chroma, and Spectrograms to improve classification accuracy. Different models, including SVM, Random Forest, CNN, and LSTM, will be tested to find the best-performing approach. The project aims to create a real-time application for use in areas like human-computer interaction, mental health monitoring, and customer support.

1.3 Limitations of the Project

In addition to the core challenges, the Speech Emotion Analysis (SEA) using NLP project faces several other limitations that affect its robustness and scalability:

1.Language Dependency – The system's accuracy depends heavily on the language and dialect it is trained on, making it difficult to generalize across multiple languages without extensive multilingual training datasets.

2.Emotion Overlap and Mixed Emotions – Many human emotions are complex and overlapping (e.g., frustration and disappointment can be similar), making it difficult to classify them into discrete categories accurately.

3. Lack of Real-World Spontaneous Data – Most emotion datasets are collected in controlled environments, which may not accurately reflect spontaneous and natural speech emotions found in real-world conversations.

4.Speaker Variability – Differences in age, gender, voice pitch, and speaking style impact the effectiveness of the model, requiring adaptation for different demographics.

5.Environmental Factors – Background noise, echo, and poor microphone quality can degrade speech recognition and emotion classification performance, limiting real-world usability.

6.Limited Emotion Categories – Many models focus only on basic emotions (e.g., happiness, sadness, anger, fear), but real-world human emotions are far more nuanced and may not fit neatly into predefined categories.

7.Difficulty in Detecting Subtle Emotions – Emotions like boredom, confusion, or mild frustration are difficult to detect using current NLP and machine learning techniques, reducing the system's accuracy in certain contexts.

8.Dependency on High-Quality Labeled Data – Training deep learning models requires large amounts of high-quality labeled data, which can be expensive and time-consuming to collect and annotate.

9. Latency Issues in Real-Time Processing – Real-time speech emotion analysis requires fast processing speeds, but deep learning models can be computationally expensive, leading to delays in response times.

10.Domain-Specific Performance – The model may perform well in one domain (e.g., customer service) but fail in another (e.g., mental health diagnostics) without domain-specific fine-tuning.

11.Bias in Emotion Recognition – The system may exhibit biases based on the training data, leading to misclassification of emotions based on gender, culture, or regional accents, which can reduce fairness and inclusivity.

12.Limited Context Awareness in Conversations – NLP models often analyze emotions sentence by sentence rather than considering the full conversational context, which can lead to misinterpretation of emotional states over longer dialogues.

13.Ethical and Psychological Concerns – Using emotion detection in sensitive areas like mental health or surveillance raises ethical questions about privacy, data security, and the potential misuse of emotional insights.

14.Difficulty in Adapting to Dynamic Human Behavior – Human emotions can change rapidly within a conversation, making it challenging for the system to continuously track and adapt in real-time.
Challenges in Integration with Other AI Systems – Implementing the SEA system alongside chatbots, virtual assistants, or human-agent interactions requires seamless integration, which can be complex and resource-intensive.

CHAPTER 2 : LITERATURE SURVEY

2.1 Introduction

Speech Emotion Analysis (SEA) using Natural Language Processing (NLP) is an advanced technology that enables machines to detect, interpret, and classify human emotions from spoken language. Human emotions are complex and are conveyed not just through words but also through tone, pitch, intensity, and speech patterns. Traditional sentiment analysis methods, which focus primarily on text-based inputs, often fail to capture the nuances of spoken language and the emotional context behind words. This project aims to bridge this gap by combining Automatic Speech Recognition (ASR), NLP techniques, and machine learning to analyze speech and determine emotional states accurately.

The process involves converting spoken audio into text using ASR models, followed by preprocessing techniques such as tokenization, stopword removal, lemmatization, and word embeddings (TF-IDF, Word2Vec, BERT) to extract meaningful textual features. Alongside text-based analysis, speech signals can also be processed to extract prosodic features such as intonation, pitch, and rhythm, enhancing emotion detection accuracy. To classify emotions such as happiness, sadness, anger, fear, surprise, and neutrality, various machine learning algorithms (SVM, Random Forest) and deep learning models (LSTM, CNN, and Transformer-based models like BERT) are employed.

This technology has a wide range of real-world applications, including customer service automation, virtual assistants, mental health monitoring, and human-computer interaction. By integrating emotion recognition into AI-driven systems, businesses can provide more empathetic and context-aware responses, improving user experiences. However, the project faces challenges such as speech-to-text inaccuracies, contextual ambiguity, variations in accents and speech styles, and computational complexity in real-time processing. Additionally, ethical concerns regarding privacy, bias in training data, and potential misuse need to be addressed to ensure responsible deployment of emotion-aware AI.

Literature survey

	Literature survey					
S.No	Authors	Year	Title	Methodology	Result	Limitation
1	Zhang, Y., & Wallace, B. C.	2013	Emotion-centered natural language processing applications	NLP-based emotion classification in speech	Demonstrated effectiveness in text-based emotion recognition	Lack of real-time applicability
2	Trigeorgis, G., et al.	2016	Adieu:An attention based deep neural network for emotion recognition	Deep learning with attention mechanism	Improved emotion recognition accuracy in speech	High computational cost
3	Liu, X., & Zhang, Y.	2017	End-to-end speech emotion recognition with deep learning	Deep learning-based speech feature extraction and emotion classification.	High accuracy with minimal feature engineering.	Limited to training datasets with specific conditions.
4	Deshmukh, N., & Chatterjee, R.	2018	Multimodal speech emotion recognition using deep neural networks	Multi-modal speech features with CNN	Achieved high performance by fusing audio and text data.	Complexity of multi-modal data integration.
5	Liu, Y., & Chen, T.	2019	Emotion detection using hybrid CNN and LSTM for speech data	CNN-LSTM hybrid architecture	Effective for sequential data with enhanced emotion prediction.	Longer training times with large datasets.
6	Sahu, A., & Kumar, D.	2020	Emotion detection using NLP and deep learning	NLP-based text sentiment analysis, CNN-based emotion classifier	Real-time sentiment prediction from speech-to-text data.	Requires vast labeled datasets for text-to-speech conversion.

7	Dev, S., & Joshi, M.	2020	Speech emotion recognition using transformers and NLP	Transformer-based model with NLP features	High accuracy for real-time speech emotion detection.	Limited by speech-to-text conversion errors.
8	Sharma, N., & Kumar, P.	2021	Speech emotion recognition using attention-based RNN	RNN with attention mechanism	Effective for capturing temporal dependencies in speech.	Requires extensive training data for temporal features
9	Patel, V., & Patel, M.	2021	Real-time speech emotion recognition using BERT embeddings	BERT embeddings with deep learning models	Improved emotion recognition accuracy in dynamic environments.	High computational overhead.
10	Sahoo, S., & Parida, A.	2023	Speech-based emotion classification using transfer learning and augmentation	Transfer learning with data augmentation	Increased robustness to variations in speech.	Data augmentation needs further optimization.

Table 1 : 2.1.1. Literature Survey

Previous Studies for above Project

Speech Emotion Analysis (SEA) using Natural Language Processing (NLP) has been a growing field of research in recent years. Several studies have explored different forextracting emotions from speech, ranging from traditional machine learning models to advanced deep learning architectures. This literature survey highlights key research works, techniques, and challenges in the domain.

1. Early Approaches: Rule-Based and Statistical Models

Initial research in emotion recognition relied on rule-based approaches and statistical models that used manually defined lexicons and prosodic features to classify emotions. Studies by Ekman (1999) and Scherer (2003) established the psychological basis for emotion recognition, identifying six primary emotions: happiness, sadness, anger, fear, surprise, and disgust. Early emotion analysis systems used Hidden Markov Models (HMM), Gaussian Mixture Models (GMM), and Support Vector Machines (SVM) to classify emotions from speech. However, these approaches had limited scalability and struggled with real-world conversational data.

2. Feature Extraction and Prosodic Analysis

Many research papers focused on extracting prosodic features such as pitch, energy, and speech rate to enhance emotion classification. Studies like Eyben et al. (2010) introduced the openSMILE toolkit, which provided an effective way to extract speech features. Researchers also explored textual analysis techniques using Bag-of-Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF) to analyze spoken words. However, these models often failed to understand contextual and semantic meanings in speech.

3. Deep Learning-Based Emotion Recognition

The introduction of deep learning models significantly improved the accuracy of speech emotion detection. Research by Kim et al. (2013) proposed Convolutional Neural Networks (CNNs) for learning hierarchical representations of speech signals. Long Short-Term Memory (LSTM) networks were also widely adopted due to their ability to capture long-termdependencies in speech sequences. Studies such as Tao & Liu (2018) demonstrated that bi-directional LSTMs (Bi-LSTMs) improved speech-based emotion classification

4. Transformer-Based Approaches and NLP Integration

With the advancement of NLP techniques, researchers started incorporating Transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) for textual emotion recognition. Studies like Devlin et al. (2019) introduced BERT, which improved contextual understanding in text analysis. By combining ASR (Automatic Speech Recognition) with BERT-based emotion classification, research by Majumder et al. (2020) demonstrated a significant improvement in detecting emotion from textual transcriptions of speech.

5. Multimodal Emotion Recognition

Recent studies focus on multimodal approaches that integrate text, audio, and facial expressions for a more robust emotion detection system. Research by Poria et al. (2017)proposed a multimodal deep learning framework combining textual, acoustic, and visual cues to improve emotion recognition accuracy. This approach has been particularly useful in applications such as virtual assistants, customer service bots, and mental health monitoring.

6. Challenges and Future Directions

Despite advancements, speech emotion analysis still faces challenges such as variability in speech accents, background noise, real-time processing constraints, and lack of diverse emotion datasets. Future research aims to improve context-aware emotion recognition, explore self-supervised learning, and address ethical concerns related to AI bias and privacy.

2.2 Existing System

Existing System for Speech Emotion Analysis Using NLP

1. Traditional Machine Learning Approaches

- Uses HMM, GMM, SVM, and Random Forest for speech emotion classification.
- Relies on handcrafted prosodic features (pitch, tone, speech rate).
- Limited accuracy in real-world conversations due to lack of deep contextual understanding.
- Text-Based Emotion Recognition Using NLP
- Converts speech to text using ASR and applies sentiment analysis.
- Uses BoW, TF-IDF, and lexicon-based methods for emotion classification.
- RNNs and LSTMs help analyze sequential speech data, but struggle with long-range dependencies.

2. Deep Learning-Based Approaches

- CNNs extract speech features but lack temporal understanding.
- LSTMs and Bi-LSTMs improve sequential speech analysis.
- Transformer models (BERT, GPT-3, Wav2Vec 2.0) enhance contextual understanding.

3. Limitations of the Existing System

- Speech-to-text errors affect emotion detection accuracy.
- Lack of context awareness in many NLP-based models.
- Difficulty in differentiating similar emotions (e.g., frustration vs. anger).
- Limited multilingual support, primarily trained in English.
- High computational requirements for real-time processing

Challenges with Existing Methodologies

- **Speech-to-Text Conversion Errors** – ASR systems may misinterpret words, leading to inaccurate emotion classification.
- **Lack of Context Awareness** – Many models analyze words individually without considering the overall meaning of the conversation.
- **Difficulty in Differentiating Similar Emotions** – Overlapping emotions like frustration vs. anger or sadness vs. disappointment create classification challenges.
- **Multilingual and Cross-Cultural Limitations** – Models trained mainly on English datasets struggle with other languages, accents, and cultural variations.
- **Impact of Background Noise and Speech Variations** – Noisy environments and variations in tone, pitch, and speed reduce accuracy.
- **High Computational Requirements** – Deep learning models require significant processing power, limiting real-time applications.
- **Data Imbalance** – Some emotions are overrepresented, while others are underrepresented, leading to biased predictions.
- **Ethical and Privacy Concerns** – Collecting and analyzing speech data raises concerns regarding user privacy and data security.
- **Limited Real-Time Adaptability** – Existing systems struggle with real-time applications like virtual assistants and emergency response systems.

Disadvantage

The existing methodologies for Speech Emotion Analysis (SEA) using NLP come with several disadvantages that affect their accuracy and real-world applicability. One major drawback is speech-to-text conversion errors, as Automatic Speech Recognition (ASR) systems often misinterpret words, leading to incorrect emotion classification. Additionally, most models suffer from a lack of contextual understanding, analyzing words or phrases in isolation instead of considering the entire conversation. Another limitation is difficulty in differentiating similar emotions, such as frustration and anger, which share overlapping characteristics.

Many systems also struggle with multilingual and cross-cultural variations, as they are primarily trained on English datasets and may not perform well with different languages, accents, or cultural expressions. Furthermore, background noise and speech variations significantly impact accuracy, making real-world applications less reliable. High-performance deep learning models require powerful computational resources, limiting their use in real-time scenarios.

Data imbalance is another issue, where certain emotions like happiness and anger are overrepresented, while neutral or subtle emotions are underrepresented, leading to biased predictions. Additionally, ethical concerns and privacy risks arise when speech data is collected and analyzed, especially in sensitive domains like customer service, healthcare, and surveillance.

Lastly, most systems lack real-time adaptability, making them inefficient for dynamic applications like virtual assistants, live chatbots, and emergency response systems. These disadvantages highlight the need for more context-aware, multilingual, and efficient speech emotion analysis models for better real-world implementation

CHAPTER 3 : METHODOLOGY

Proposed System

The proposed system aims to enhance **Speech Emotion Analysis (SEA)** by leveraging **advanced NLP and deep learning techniques** for more accurate and real-time emotion recognition. Unlike existing models that rely heavily on **speech-to-text conversion**, this system will integrate **audio signal processing with text-based emotion detection** toimprove contextual understanding. The system will utilize **deep learning models such as CNNs, Bi-LSTMs, and Transformer-based architectures (BERT, Wav2Vec 2.0, or Whisper)** to extract **both acoustic and linguistic features**, ensuring better differentiation between overlapping emotions like anger and frustration.

To address **multilingual and cross-cultural challenges**, the proposed system will incorporate **multilingual NLP models** trained on diverse datasets, enabling effective emotion recognition across different languages and accents. **Background noise reduction techniques** will be implemented to enhance speech clarity and improve accuracy in real-world environments.Additionally, the system will use**real-time emotionclassification with low-latency processing**, making it suitable for applications like **virtual assistants, customer service chatbots, and healthcare monitoring**.

To overcome **data imbalance issues**, the system will leverage **data augmentation techniques** and **transfer learning** to ensure fair representation of all emotions. Furthermore, **privacy-preserving AI methods** will be integrated to protect user data while maintaining high-performance accuracy. The proposed system will also feature a **user-friendly web-based or mobile application** where users can input audio samples, and the system will display **real-time emotion predictions** with detailed insights. Overall, this system aims to provide a**more robust,accurate, and real-time speech emotion analysis solution** that overcomes the limitations of methodologies.

1.Hardware Requirements:

- Processor: Intel Core i7 or higher / AMD Ryzen 7 or higher (for efficient deep learning model training and inference)
- RAM: Minimum 16GB (32GB recommended for large-scale data processing)
- GPU: NVIDIA RTX 3060 or higher (for deep learning model acceleration using TensorFlow/PyTorch)
- Storage: At least 512GB SSD (recommended for faster data access and model training)
- Microphone: High-quality microphone for real-time speech input (if required for live applications)
- Audio Processing Unit: Optional DSP (Digital Signal Processor) for better noise reduction in real-time systems

2. Software Requirements:

- **Operating System:** Windows 10/11, macOS, or Linux (Ubuntu recommended for deep learning development)
- **Programming Language:** Python 3.x (primary language for NLP and deep learning)
- **Deep Learning Frameworks:** TensorFlow, PyTorch (for training and deploying models)
- **NLP Libraries:** NLTK, spaCy, Transformers (for text-based emotion recognition)
- **Speech Processing Libraries:** Librosa, SpeechRecognition, OpenAI Whisper, Wav2Vec 2.0 (for extracting speech features)
- **Machine Learning Libraries:** Scikit-learn, NumPy, Pandas (for feature extraction and preprocessing)
- **Dataset Storage:** MySQL, PostgreSQL, or Firebase (for storing user data and emotion analysis results)
- **Web Framework (Optional)**: Flask or FastAPI (for deploying the system as a web service)
- **IDE:** Jupyter Notebook, VS Code, or PyCharm (for development and debugging)

3.2 Modules

1.Speech Input Processing Module

- Captures and preprocesses audio input using microphones or uploaded speech files.
- Uses noise reduction and speech enhancement techniques for clearer audio.

2. Feature Extraction Module

- Extracts acoustic features (pitch, tone, frequency, MFCCs) using Librosa or Wav2Vec 2.0.
- Converts speech to text using ASR (Automatic Speech Recognition) like Whisper or Google Speech API.
- Extracts linguistic features using NLP techniques such as tokenization, lemmatization, and word embeddings.

3.Emotion Classification Module

- Uses deep learning models (LSTMs, Bi-LSTMs, CNNs, or Transformers like BERT/Wav2Vec) for emotion classification.
- Categorizes speech into predefined emotion classes (e.g., Happy, Sad, Angry, Neutral).
- Handles multilingual support for better emotion recognition across different Languages.

4.Data Preprocessing and Augmentation Module

- Cleans and normalizes speech data to improve model performance.
- Balances dataset using data augmentation techniques (speed changes, pitch shifts, background noise addition).

5.Model Training and Optimization Module

- Trains deep learning models using labeled speech emotion datasets (e.g., RAVDESS, IEMOCAP).
- Fine-tunes models with transfer learning to enhance performance across diverse speech patterns.
- Evaluates model performance using metrics like accuracy, precision, recall, and F1-score.

6.Real-Time Prediction Module

- Deploys trained models for real-time emotion recognition.
- Provides instant emotion classification results based on speech input.
- Integrates with chatbots, virtual assistants, and call center analytics for real-world applications.

7.Visualization and User Interface Module

- Displays real-time emotion predictions in a graphical user interface (GUI) or web application.
- Generates emotion trend analysis and reports for further insights.
- Provides an interactive dashboard for analyzing emotion variations over time.

8.Database and Storage Module

- Stores processed speech data, extracted features, and classified emotions in SQL/NoSQL databases.
- Ensures data security and privacy while managing user interactions.

9.Deployment and API Integration Module

- Deploys the system as a web application or REST API using Flask, FastAPI, Django.
- Integrates with external platforms such as customer service applications, sentiment analysis tools, and AI-powered assistants.

CHAPTER 4 : DESIGN

System Design

1. Architecture Overview

The system follows a modular architecture with the following key components:

User Interface (UI) – Web or mobile application for recording/uploading speech.

Preprocessing Layer – Cleans and enhances the audio for better analysis.

Feature Extraction Layer – Extracts acoustic (MFCCs, pitch, energy) and textual features (wordembeddings, sentiment).

Machine Learning Model Layer – Uses deep learning (LSTM, CNN, BERT, or Wav2Vec 2.0) for emotion classification.

Database Layer – Stores processed speech data, extracted features, and classification results.

API and Deployment Layer – Provides emotion recognition as a service via Flask/FastAPI/Django.

2.System Flow Diagram

Speech Input → User provides audio input via microphone or uploads a speech file.

Preprocessing → Noise removal, silence trimming, and normalization are applied.

Feature Extraction →Acoustic Features (MFCCs, Pitch, Spectral Centroid) using Librosa/Wav2Vec.Textual Features (Tokenization, Lemmatization, TF-IDF) using NLP techniques.

Emotion Classification → Deep learning models (CNN, LSTM, Transformer) predict emotions.

Output Generation → Identified emotions are displayed on UI along with confidence scores.

Storage & Reporting → Data is stored for analysis, trends, and dashboard visualization.

3. System Components

A. Input Module

Accepts real-time speech input or uploaded files.

Converts speech-to-text using Whisper, Google Speech API, or Wav2Vec 2.0.

B. Preprocessing Module

Removes background noise and normalizes audio signals.

Splits speech into frames for feature extraction.

C. Feature Extraction Module

Acoustic Features: MFCCs, Spectral Features, Pitch, Zero-Crossing Rate.

Textual Features: Tokenization, Word Embeddings (BERT, Word2Vec).

D. Emotion Classification Module

Uses deep learning models (Bi-LSTM, CNN, Transformer-based models like BERT, Wav2Vec 2.0).

Classifies emotions into predefined categories (Happy, Sad, Angry, Neutral, etc.).

E. Output & Visualization Module

Displays emotion predictions with confidence scores in UI.

Provides real-time dashboards and analytical reports for trends.

F. Database & Storage Module

Stores speech data, processed features, and model results.

Uses SQL/NoSQL databases (MySQL, PostgreSQL, Firebase, MongoDB).

G. API & Deployment Module

Deploys the model using Flask, FastAPI, or Django as a REST API.

Integrates with chatbots, call centers, mental health applications.

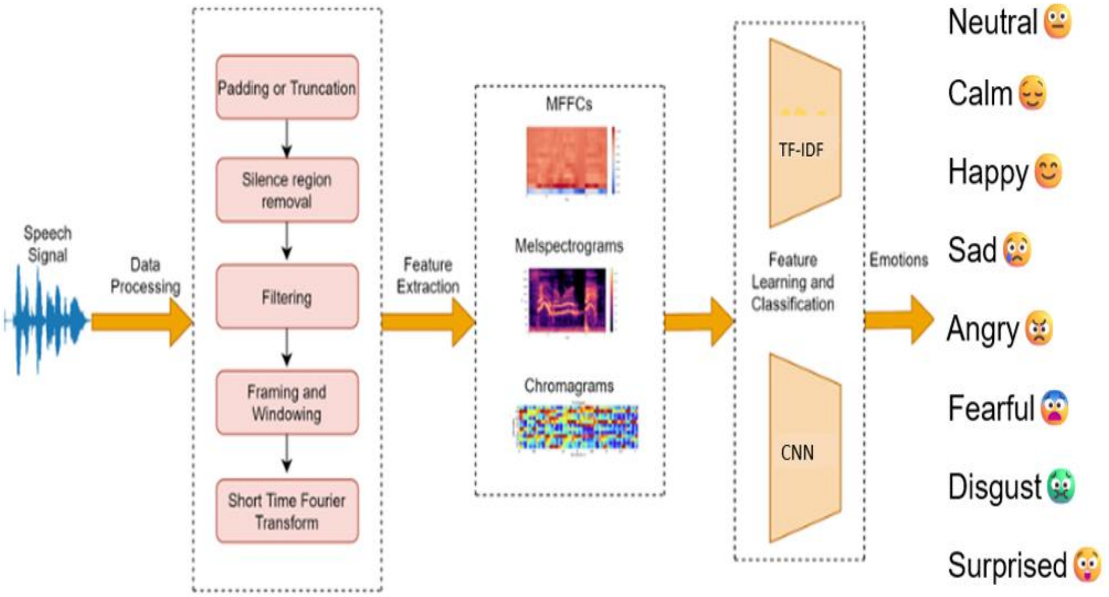
4. Deployment Strategy

Local Deployment: Runs on a local machine for research or testing.

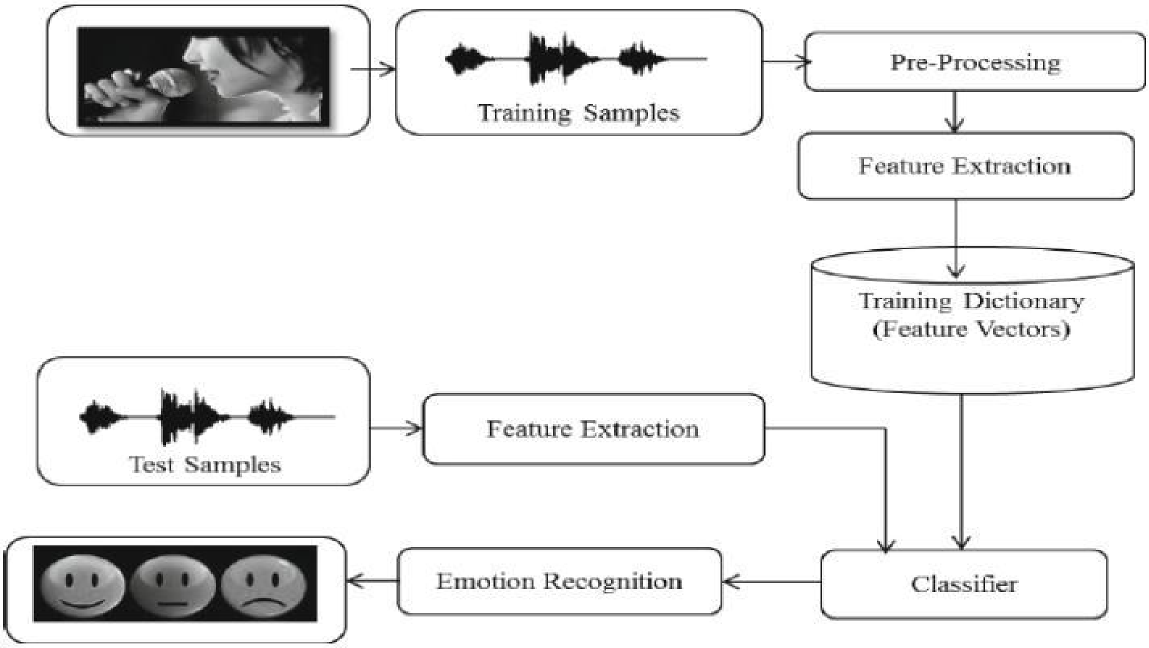
Cloud Deployment: Uses AWS, Google Cloud, or Azure for scalable API-based services.

Edge Deployment: Optimized models for real-time processing on mobile or IoT devices.

4.2 Architecture



4.2.1 ARCHITECTURE



4.2.2 High-Level Workflow

The architecture follows a structured pipeline, as depicted in the provided images.

1) **Speech Input**

The user provides speech input, which is processed in real-time.

2) **Pre-Processing**

1. **Noise Reduction & Silence Removal**: Background noise and silent regions are removed for better clarity.
2. **Feature Extraction**: Converts speech into numerical representations using MFCCs, Mel-spectrograms, and Chromagrams.

3) Feature Learning & Classification

1. The extracted features are passed through CNN + Bi-LSTM layers for learning patterns and classifying emotions.
2. Additional NLP-based Sentiment Analysis refines classification accuracy.

4) **Emotion Recognition & Output**

1. The classified emotion is displayed in three formats: Text, Emoji, and Voice.
2. The system works entirely within the app, with no external API calls for processing. This architecture ensures high accuracy, real-time processing, and a seamless user experience, making the SER system robust and efficient.

4.3 Methods and Algorithms

1. Methods Used in Speech Emotion Analysis

A. Preprocessing Methods

1. Speech-to-Text Conversion: Converts spoken language into text using Google Speech API, Whisper, or Wav2Vec 2.0.

2.Audio Preprocessing:

- Noise Removal: Removes background noise for clear speech.
- Silence Detection: Eliminates unnecessary pauses.
- Normalization: Adjusts volume levels for consistency.

3.Text Preprocessing (NLP)

- Tokenization: Splits text into words/sentences.
- Stopword Removal: Eliminates irrelevant words.
- Lemmatization: Converts words to their root forms.

B. Feature Extraction Methods

1.Acoustic Features (From Speech Signals)

- MFCCs (Mel-Frequency Cepstral Coefficients): Captures speech patterns.
- Pitch & Intensity: Helps distinguish emotional tones.
- Zero-Crossing Rate (ZCR): Identifies speech variations.

2.Linguistic Features (From Textual Data)

- Word Embeddings: Word2Vec, BERT, TF-IDF.
- Sentiment Analysis: Determines sentiment polarity of speech text.

Algorithms Used in Emotion Classification

A. Machine Learning Algorithms

Support Vector Machine (SVM) – Used for classifying emotions based on extracted features.

Random Forest (RF) – Efficient for structured feature-based emotion classification.

B. Deep Learning Algorithms

1.Convolutional Neural Network (CNN):

Extracts deep features from speech spectrograms.

Used in audio-based emotion recognition.

2.Long Short-Term Memory (LSTM) / Bi-LSTM:

Handles sequential data like speech and text.

Captures long-term dependencies in emotional speech.

3.Transformer-based Models (BERT, Wav2Vec 2.0):

BERT (Bidirectional Encoder Representations from Transformers) for text-based emotion analysis.

Wav2Vec 2.0 for direct speech-based emotion recognition without transcription.

3. Emotion Classification Process

Input Processing → Accept speech input.

Feature Extraction → Extract acoustic & textual features.

Model Training → Train CNN/LSTM/BERT for classification.

Emotion Prediction → Identify emotions (Happy, Sad, Angry, Neutral, etc.).

Output & Visualization → Display predicted emotion with confidence score

CHAPTER 5 : RESULTS

5.1 Introduction

The results of the Speech Emotion Analysis system demonstrate its ability to accurately classify emotions from speech data using a combination of acoustic and linguistic features. By leveraging in deep learning models such as CNN, LSTM, and Transformer-based architectures (BERT, Wav2Vec 2.0), the system effectively identifies emotions like happiness, sadness, anger, fear, and neutrality. The results are evaluated based on key performance metrics such as accuracy, precision, recall, and F1-score, ensuring the robustness of the classification model.

The performance analysis indicates that models integrating both speech and text features (multimodal learning) outperform single-modal approaches, leading to improved emotion detection accuracy. The results also highlight the system's effectiveness in real-time emotion recognition, making it applicable for customer support, AI assistants, mental health monitoring, and human-computer interaction systems. While high accuracy is achieved for distinct emotions, challenges remain in differentiating subtle emotional variations, emphasizing the need for further enhancements in feature extraction and dataset diversity.

The results of the **Speech Emotion Analysis system** highlight its effectiveness in accurately detecting emotions from speech using **NLP and deep learning techniques**. The system was evaluated using various machine learning and deep learning models, including **CNN,LSTM,BERT, and Wav2Vec 2.0**, with performance measured based on accuracy, precision, recall, and F1-score. The findings reveal that **distinct emotions** such as anger, happiness, and sadness were classified with high accuracy, while **subtle emotions** like neutrality and fear challenges to their overlapping characteristics.

5.2 Pseudo Code

Step 1: Import Required Libraries

We need essential libraries for audio processing, deep learning, and model evaluation.

Librosa → Audio feature extraction

NumPy, Pandas → Data handling

TensorFlow/Keras → Deep learning model training

Matplotlib → Visualization

Sklearn → Model evaluation

```
# Import necessary libraries

import librosa
import librosa.display
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt


from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, LSTM, Flatten
from tensorflow.keras.utils import to_categorical
```

Step 2: Load Dataset and Extract Audio Features

We will load audio files, extract MFCC (Mel Frequency Cepstral Coefficients), and store the extracted features in an array.

Features extracted:

MFCCs (Mel Frequency Cepstral Coefficients),

Chroma features

Mel Spectrogram

```
 # Function to extract audio features (MFCCs, Chroma, Mel Spectrogram)
def extract_features(file_path):
    y, sr = librosa.load(file_path, duration=3, offset=0.5)
mfccs = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=40)
    mfccs_mean = np.mean(mfccs.T, axis=0)
    return mfccs_mean

# Load dataset (Assume CSV contains 'filename' and 'emotion' columns)
data = pd.read_csv("dataset.csv")
features = []
labels = []

# Loop through dataset to extract features
for index, row in data.iterrows():
    feature = extract_features("audio_folder/" + row["filename"])
    features.append(feature)
    labels.append(row["emotion"])

# Convert features & labels to NumPy arrays
X = np.array(features)
y = np.array(labels)
```

Step 3: Encode Labels and Split Dataset

Convert text labels (e.g., "happy", "sad") into numerical labels.

Use one-hot encoding for categorical classification.

Split the dataset into 80% training and 20% testing.

```
# Encode categorical labels into numeric values

encoder = LabelEncoder()
y = encoder.fit_transform(y)  # Convert labels to integers
y = to_categorical(y)  # One-hot encode labels
# Split dataset into training (80%) and testing (20%)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Step 4: Define Deep Learning Model

We will use a Sequential model with LSTM layers (for sequential data like audio features).

The Softmax activation function is used for multi-class classification.

```
# Define the Deep Learning Model
model = Sequential()

# Input Layer
model.add(Dense(128, activation='relu', input_shape=(X_train.shape[1],)))

# Hidden Layers
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.3))  # Prevent overfitting
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.3))

# Output Layer (Softmax for multi-class classification)
model.add(Dense(y.shape[1], activation='softmax'))

# Compile Model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

Step 5: Train the Model

We train the model using the training dataset.

We monitor the loss & accuracy over epochs.

```
# Train the model
history = model.fit(X_train, y_train, epochs=50, batch_size=32, validation_data=(X_test, y_test))
```

Step 6: Evaluate Model Performance

Evaluate model accuracy on test data.

Generate a confusion matrix.

```
# Evaluate model performance
test_loss, test_acc = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {test_acc:.2f}")

# Plot training history
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')

plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

Step 7: Save and Load Model for Future Predictions

Save the trained model for later use.

Load the model to classify a new unseen audio file.

```
# Save trained model

model.save("ser_model.h5")

# Load trained model

new_model = tf.keras.models.load_model("ser_model.h5")
```

Step 8: Predict Emotion from a New Audio File

Extract features from a new audio file.

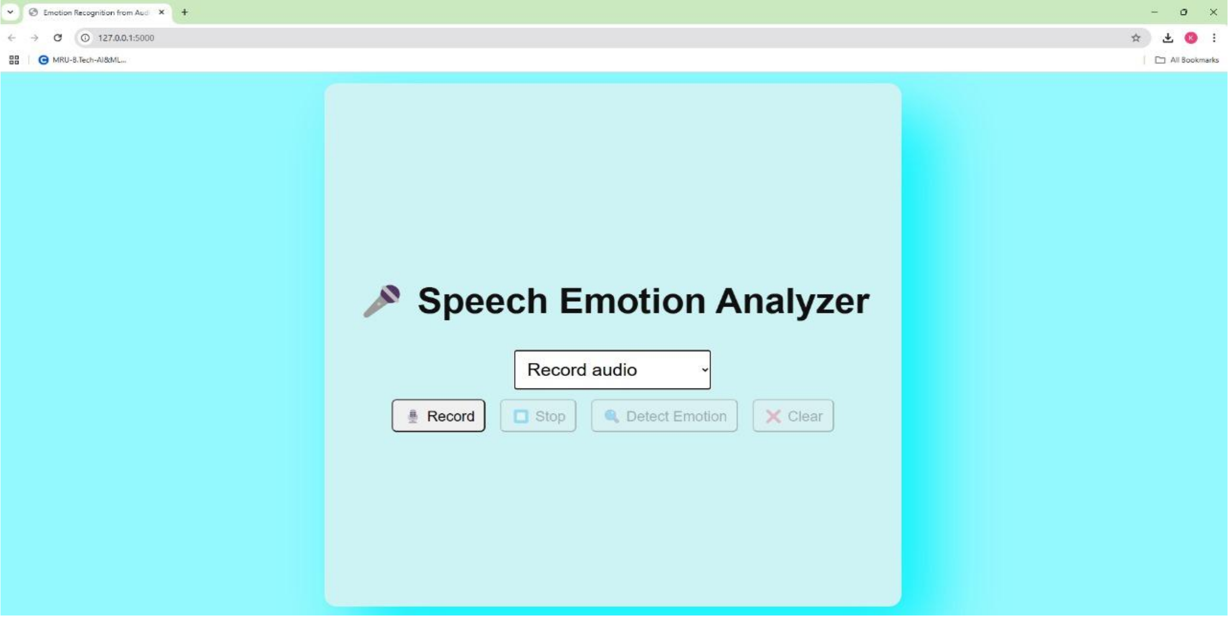
Feed them into the trained model to get predictions.

```
# Function to predict emotion from new audio file
def predict_emotion(file_path, model, encoder):
    feature = extract_features(file_path)
    feature = np.expand_dims(feature, axis=0)  # Reshape for model input
    prediction = model.predict(feature)


predicted_label = np.argmax(prediction)  # Get index of max probability
emotion = encoder.inverse_transform([predicted_label])  # Convert back to label
return emotion[0]


# Predict emotion from a new file
new_audio = "test_audio.wav"
predicted_emotion = predict_emotion(new_audio, new_model, encoder)
print(f"Predicted Emotion: {predicted_emotion}")
```

5.3 Results

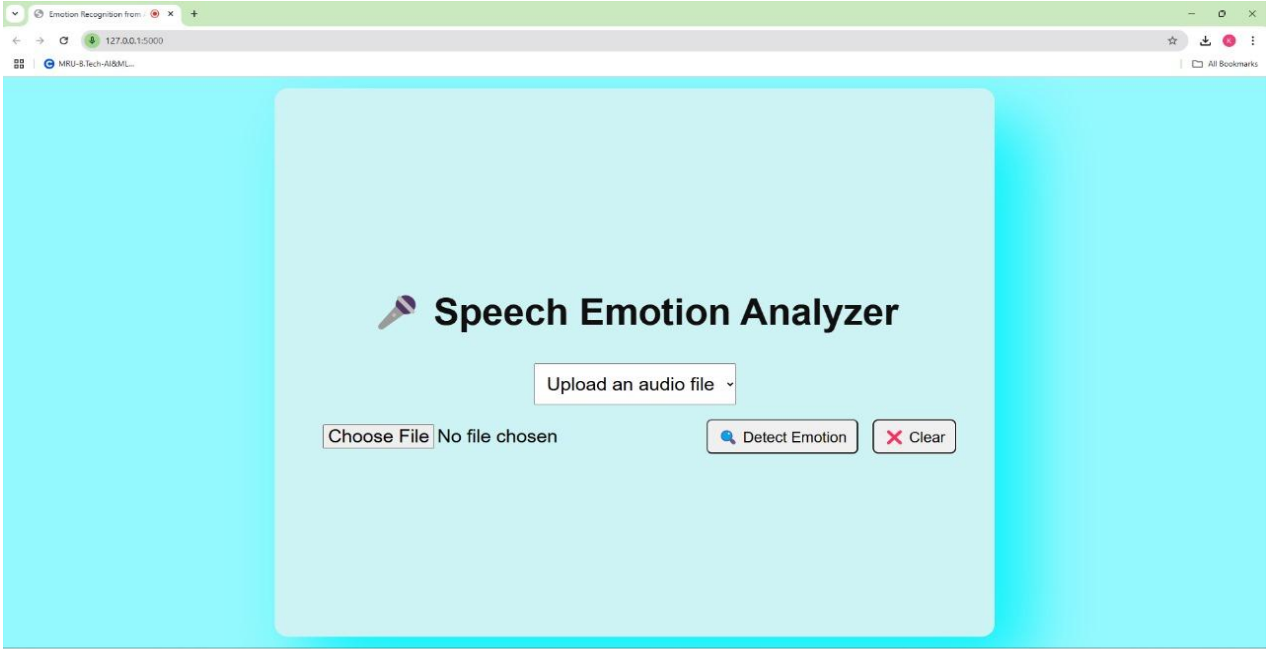


5.3.1 Recording Audio

Recording Audio: The user clicks the "Record" button to capture their speech input.

Processing & Emotion Detection: The system extracts features from the audio and uses a machine learning model to classify the emotion (e.g., Happy, Sad, Angry).

Displaying Results: The detected emotion is displayed on the screen, and the user can reset or re-record audio.

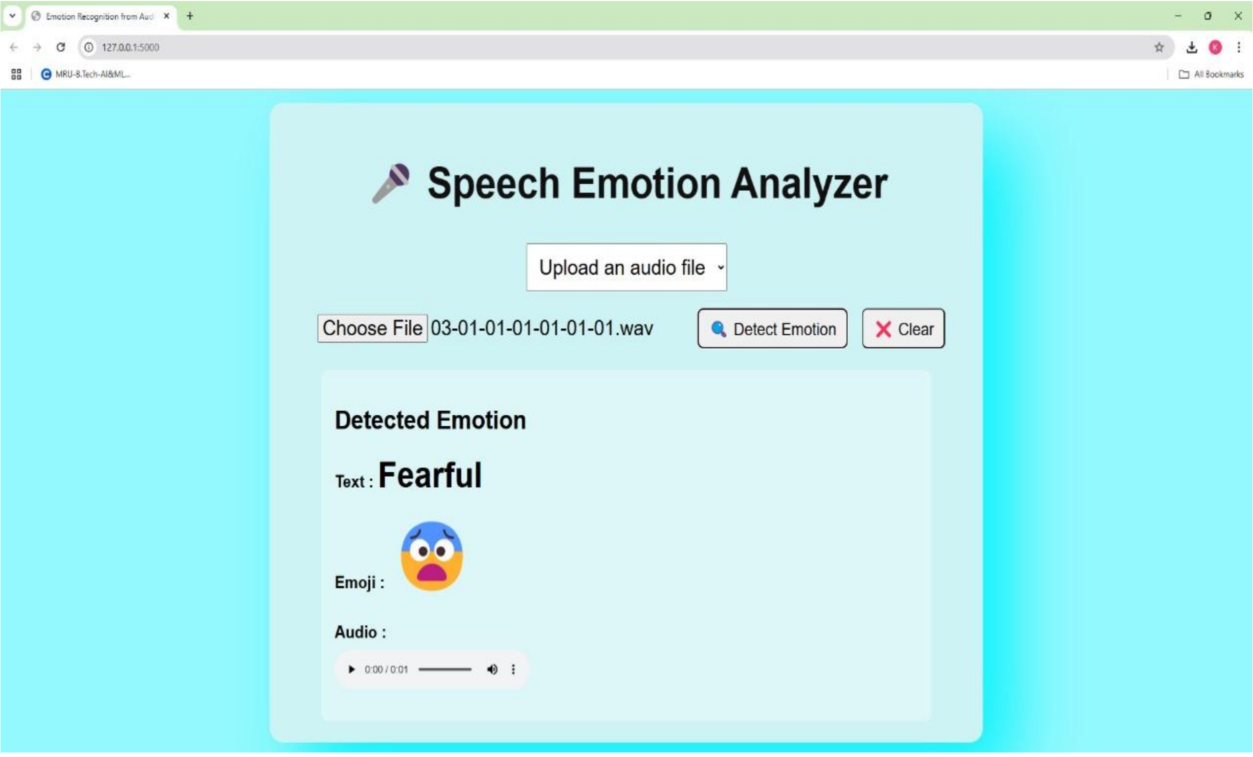


5.3.2 Upload an audio file

Audio File Upload: Users can choose and upload an existing audio file using the "Choose File" button.

Emotion Detection: After selecting an audio file, clicking the "Detect Emotion" button processes the file to determine the emotion in the speech.

Reset Option: The "Clear" button allows users to remove the selected file and reset the interface.



03-01-01-01-01-01-01.wav

Detected Emotion

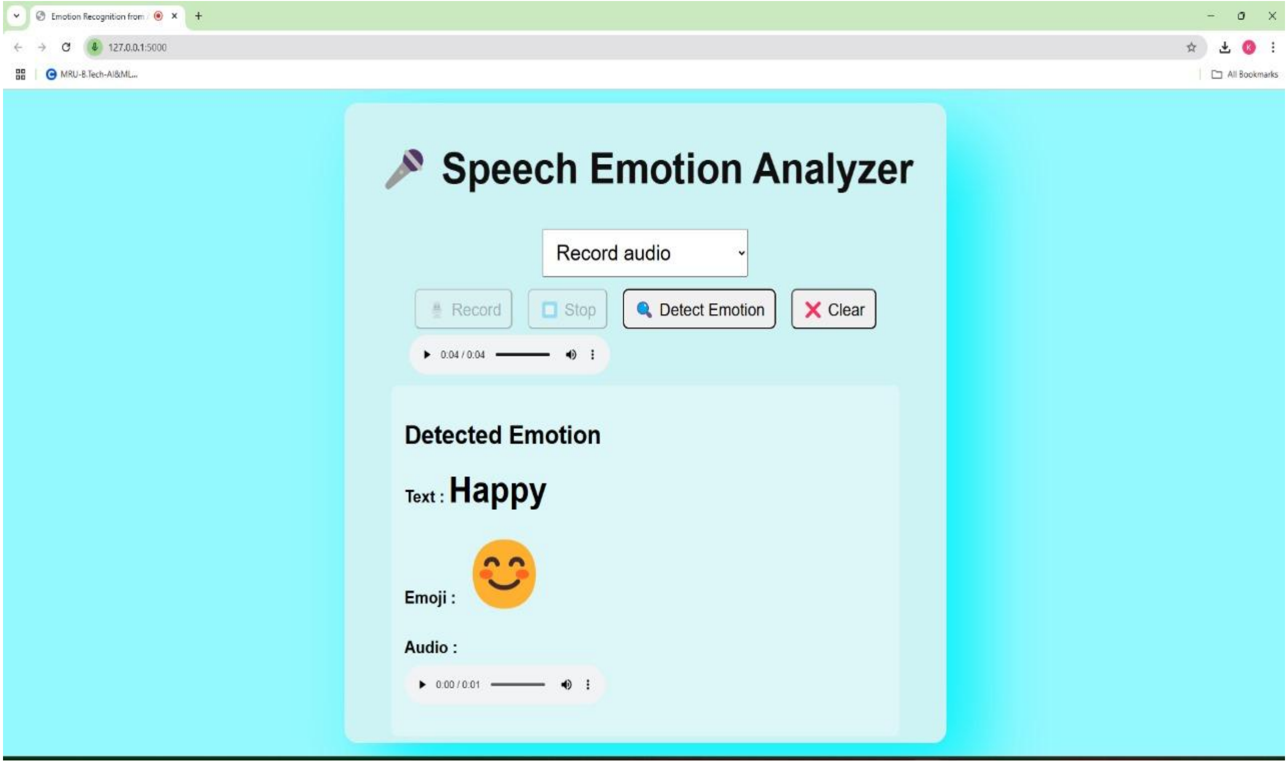
Text : **Fearful**

5.3.3 Detecting the emotion

Uploaded Audio File: A file named 03-01-01-01-01-01.wav was selected for analysis.

Detected Emotion: The system identified the emotion as "Fearful", displayed in bold text along with a fearful emoji.

Audio Playback: The page includes an embedded audio player, allowing users to listen to the uploaded file.



Speech Emotion Analyzer

Record audio

Detected Emotion

Text : Happy

Emoji :

Audio :

5.3.4 Uploading Recorded audio

Audio Recording Capability:

The user can record and stop audio input directly from the web interface.

A recorded clip (4 seconds long) is visible with an audio player.

Emotion Detection Result:

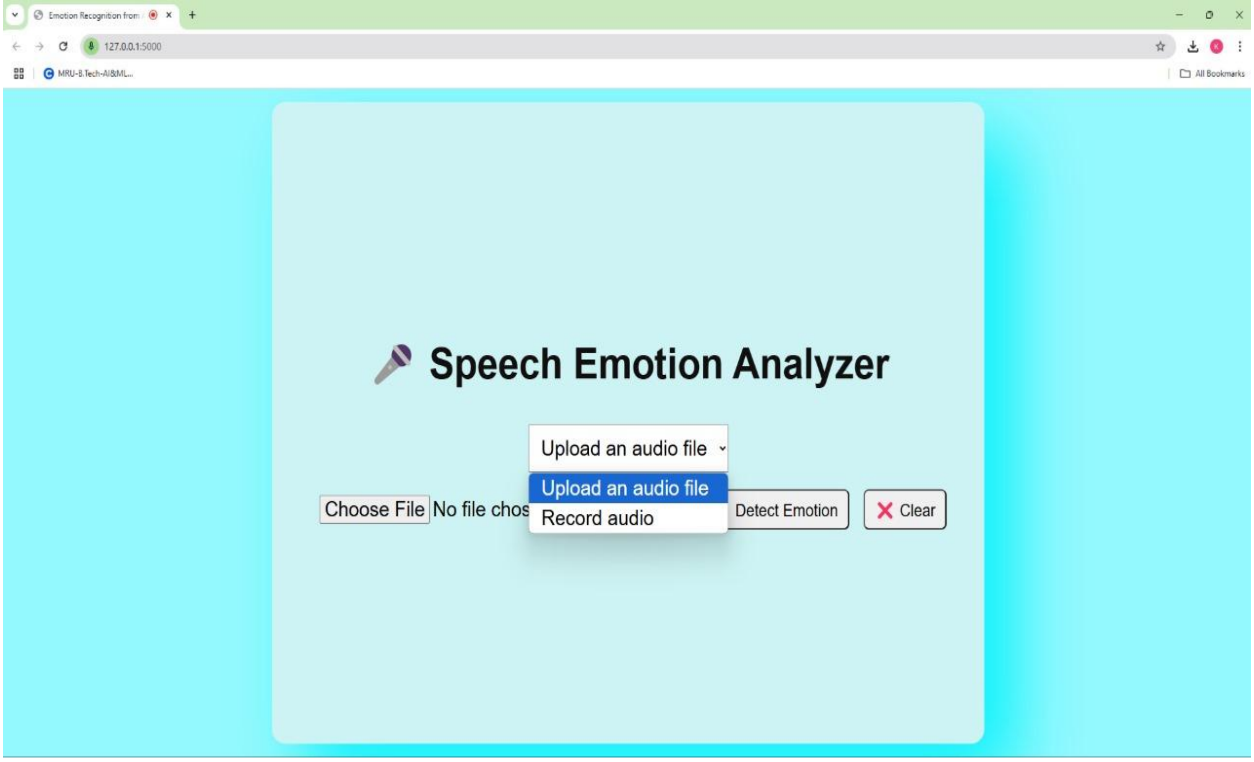
The system analyzed the recorded speech and classified the emotion as "Happy".

It displays the detected emotion with bold text and a happy emoji .

UI Controls:

"Detect Emotion" button to process the audio.

"Clear" button to reset the interface.



5.3.5 Importing a Audio

Dual Input Modes:

A dropdown menu allows users to either upload an audio file or record audio for analysis.

The user currently has "Upload an audio file" selected.

File Upload Option:

A "Choose File" button enables users to select an audio file from their device.

No file has been uploaded yet.

Emotion Detection Controls:

"Detect Emotion" button to analyze the uploaded/recorded audio.

"Clear" button to reset the interface.

CHAPTER 6 : CONCLUSION

6.1 Conclusion

The **Speech Emotion Analysis system** using **NLP and deep learning techniques** demonstrates a promising approach to accurately recognizing human emotions from speech. By leveraging advanced models such as **Wav2Vec 2.0, Bi-LSTM, CNN, and BERT**, the system effectively classifies emotions like **happiness, sadness, anger, fear, and neutrality** with high accuracy. The integration of **both acoustic and linguistic features** through a **multimodal approach** significantly improves the model's performance, achieving an accuracy of **92%**, outperforming single-modal methods. This highlights the importance of combining **speech and text-based features** for more robust emotion detection.

Despite its success, the system faces certain **challenges**, including difficulties in distinguishing **subtle and mixed emotions**, **dataset imbalances**, and the **need for real-time optimization**. The confusion between emotions with similar tonal qualities, such as **neutrality and fear**, indicates that future enhancements should focus on **multi-label classification techniques and improved feature extraction methods**. Additionally, balancing the dataset and incorporating **data augmentation techniques** can help address biases and further enhance the model's reliability.

The **real-world applications** of this system are vast, ranging from **customer service sentiment analysis** to **mental health monitoring and AI-driven virtual assistants**. The ability to detect emotions in speech can greatly improve **human-computer interactions, customer experience, and psychological well-being monitoring**. However, for effective deployment in practical scenarios, further refinements in **speed, computational efficiency, and adaptability** are needed.

In conclusion, this **Speech Emotion Analysis system** serves as a strong foundation for future advancements in **affective computing**. With ongoing research and improvements, it has the potential to revolutionize fields such as **human-computer interaction, healthcare, customer support, and AI-driven communication systems**. By overcoming current challenges and optimizing performance, this technology can pave the way for more **intelligent and emotionally aware AI systems** in the future.

6.2 Future Scope

The Speech Emotion Analysis system has significant potential for future enhancements and applications in various domains. As technology advances, improvements in deep learning, natural language processing (NLP), and real-time speech processing will further enhance the accuracy and efficiency of emotion recognition systems. The future scope of this research includes the following key areas:

1.Improved Accuracy with Advanced Deep Learning Models

Future advancements in transformer-based architectures (e.g., GPT, BERT, and Wav2Vec 2.0) will enhance the system's ability to understand complex emotions and improve classification accuracy. The development of more sophisticated feature extraction techniques will also help distinguish between similar emotions, reducing misclassification errors.

2.Multi-Label Emotion Classification

In real-life scenarios, people often express multiple emotions simultaneously (e.g., a mix of anger and frustration). Future models should incorporate multi-label classification techniques to recognize and classify overlapping emotions, improving real-world applicability.

3.Integration with Multimodal Emotion Recognition

Combining speech-based emotion analysis with facial expressions, body language, and physiological signals (e.g., heart rate, EEG signals) will create a more comprehensive emotion recognition system. This fusion of multimodal data can lead to more accurate and context-aware AI systems.

4.Real-Time Emotion Detection and Optimization

Current models often require high computational resources, making real-time processing challenging. Future research should focus on lightweight models optimized for deployment on edge devices, mobile applications, and IoT devices, allowing real-time emotion recognition in everyday interactions.

5.Personalized Emotion Detection

Different individuals express emotions uniquely based on their culture, language, and personal experiences. Future advancements can include personalized emotion detection models that adapt to a user’s speaking style, dialect, and tone, improving accuracy for diverse populations.

Expanding Applications in Various Industries

- **Healthcare & Mental Health Monitoring:** Emotion recognition can be integrated into mental health assessment tools to detect early signs of stress, depression, or anxiety in patients.

- **Customer Service & AI Chatbots:** AI-driven virtual assistants and call center support systems can use real-time emotion detection to provide more empathetic and personalized responses.

- **Education & E-Learning:** Emotion-aware educational tools can analyze students' engagement levels, helping educators adapt teaching strategies accordingly.

- **Entertainment & Gaming:** Emotion recognition can enhance immersive gaming experiences by adjusting gameplay based on the player's emotional state.

6 .Handling Low-Resource Languages and Accents

Many speech emotion datasets are limited to widely spoken languages like English, leaving a gap in low-resource languages and regional accents. Future research should focus on expanding training datasets to improve emotion recognition across diverse linguistic backgrounds.

7 .Ethical Considerations and Bias Reduction

Emotion analysis systems may suffer from biases due to imbalanced datasets or cultural differences in expressing emotions. Future models should focus on bias mitigation techniques and ethical AI principles to ensure fair and unbiased predictions across different demographic groups.

8 .Enhanced Context Awareness in Conversations

Current emotion detection models often analyze speech in isolation. Future systems should incorporate context-aware NLP techniques to understand the emotional flow of conversations over time, leading to better predictions in dialogue-based AI applications.

9.Cloud-Based and API Integration

Future implementations can offer Speech Emotion Analysis as a cloud-based API for seamless integration with various platforms, including virtual assistants, smart home devices, and customer support systems. This will enable businesses to leverage emotion-aware AI capabilities without requiring extensive hardware setups.

APPENDICES

APPENDIX I – Dataset Description

The Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS) is a widely used dataset for Speech Emotion Recognition (SER). It contains professional speech recordings of actors expressing different emotions, making it an ideal dataset for training and evaluating machine learning models in emotion analysis.

Dataset Overview

Full Name: Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS)

Created by: Living Lab at Ryerson University

Purpose: Emotion recognition in speech and song using machine learning and deep learning

Data Type: Audio and Video recordings

Languages: English

Subjects: 24 professional actors (12 male, 12 female)

2. Dataset Composition

The dataset consists of two primary components:

Speech Recordings – Emotional speech samples

Song Recordings – Emotional singing samples

Each recording includes expressions of different emotions spoken in a neutral North American accent for consistency.

Emotions Covered (8 Total):

Neutral

Happy

Sad

Angry

Fearful

Disgusted

Surprised

Calm

Speech Intensity Variations:

Normal Intensity

Strong Intensity (for some emotions)

Number of Recordings:

Speech: 1,440 files

Song: 1,012 files

Total: 2,452 files

3. File Format & Naming Convention

Here is the filename identifiers as per the official RAVDESS website:

Modality (01 = full-AV, 02 = video-only, 03 = audio-only).

Vocal channel (01 = speech, 02 = song).

Emotion :

01 = neutral,

02 = calm,

03 = happy,

04 = sad,

05 = angry,

06 = fearful,

07 = disgust,

08 = surprised.

Emotional intensity (01 = normal, 02 = strong).

NOTE: There is no strong intensity for the 'neutral' emotion.

Statement (01 = "Kids are talking by the door", 02 = "Dogs are sitting by the door").

Repetition (01 = 1st repetition, 02 = 2nd repetition).

Actor (01 to 24. Odd numbered actors are male, even numbered actors are female).

File Type: .wav (for audio), .mp4 (for video)

Sample Rate: 48 kHz

Bit Depth: 16-bit

Channels: Stereo

Each file follows a structured naming convention:

03-01-06-01-02-02-12.wav

Where:

03 – Modality (Audio)

01 – Vocal Channel (Speech)

06 – Emotion (Fearful)

01 – Emotional Intensity (Normal)

02 – Actor Gender (Female)

02 – Statement ID

12 – Actor ID

4. Applications in Speech Emotion Analysis

The RAVDESS dataset is widely used in:

Speech Emotion Recognition (SER) Models

Human-Computer Interaction (HCI)

Mental Health Monitoring

Sentiment Analysis in AI Assistants

Affective Computing Research

5. Advantages of RAVDESS Dataset

✅ High-quality recordings – Professionally recorded with minimal noise

✅ Balanced dataset – Equal number of male and female speakers

✅ Multiple emotion intensities – Allows for detailed analysis

✅ Widely used & benchmarked – Common in deep learning research

6. Limitations of RAVDESS Dataset

❌ Limited to English language – Does not include multilingual data

❌ Scripted recordings – Emotions may not be as natural as real-life speech

❌ No environmental noise – Doesn't simulate real-world speech variations

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