POKHARA UNIVERSITY
CITIZEN COLLEGE, KUMARIPATI, LALITPUR, NEPAL

PROJECT No.: 21535062

VOICE EMOTION ANALYZER

BY

ARJUN THAPA

A PROJECT

SUBMITTED TO

THE DEPARTMENT OF SCIENCE & TECHNOLOGY

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THE DEGREE OF BACHELOR OF COMPUTER APPLICATION

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Voice Emotion Analyzer

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A project submitted in partial fulfillment of the requirements for the degree of

Bachelor of Computer Application

Department of Bachelor of Computer Application

Pokhara University, Citizen College

Pokhara University, Nepal

February,2026

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DECLARATION

I declare that the work hereby submitted for Bachelor of Computer Application at the Pokhara University, Citizen College entitled "**Voice Emotion Analyzer**" is my own work and has not been previously submitted by me at any university for any academic award. I authorize the Pokhara University, Citizen College to lend this project work to other institutions or individuals for the purpose of scholarly research.

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RECOMMENDATION

The undersigned certify that they have read and recommend to the Department of Bachelor of Computer Application for acceptance, a project work entitled "**Voice Emotion Analyzer**", submitted by **Arjun Thapa** in partial fulfillment of the requirement for the award of the degree of "**Bachelor of Computer Application**".

Project Supervisor

Er. Nishan Khanal

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Er. Nishan Khanal

Department of Bachelor of Computer Application, Citizen College

February,2026

DEPARTMENTAL ACCEPTANCE

The project work entitled "**Voice Emotion Analyzer**", submitted by **Arjun Thapa** in partial fulfillment of the requirement for the award of the degree of "**Bachelor of Computer Application**" has been accepted as a genuine record of work independently carried out by the student in the department.

Er. Nishan Khanal
Head of the Department
Department of Bachelor of Computer Application,
Citizen College.

February,2026

LETTER OF APPROVAL

The undersigned certify that they have read and recommended to the **Department of Bachelor of Computer Application, Pokhara University**, the project report entitled "**Voice Emotion Analyzer**" submitted by **Arjun Thapa**. The project is carried out under special supervision and within the time frame prescribed by the syllabus. We found the student to be hardworking, skilled, and ready to undertake any related work to their field of study and hence we recommend the award to partial fulfillment of Bachelor's degree of Science and Technology.

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ABSTRACT

Voice recognition as a feature of human emotions is an influential feature of affective computing and intelligent human-computer interaction. This Project presents an automatic emotion classifier based on convolutional neural network using speech cues which attempts to establish how one can correctly predict emotion states using varying acoustic environments. The framework isolates the important feature of the acoustics such as the frequency characteristics, energy profiles as well as the pitch dynamics to create discriminative feature representation to use in classification. The model is trained to identify seven basic emotional conditions, including happiness, sadness, anger, fear, disgust, neutral, and surprise, and at the same time, pitch based gender recognition is also performed to better understand the situation. Strict experimental validation on benchmark emotion speech datasets reveals the mean classification accuracy of 83.89% and it indicates that the model is capable of high performance in the case of diverse speakers and emotional expressions. The stability and the external validity of the suggested method are statistically proven. This work pushes the current state of the art in voice-based emotion recognition and allows practical use in mental health monitoring, where automated emotional testing aids in early intervention and continuous patient care; emotionally adaptive human-computer interfaces that provide a better user experience by increasing engagement and satisfaction in response to the emotional state of the user; and emotionally adaptive human-computer interfaces that optimize user engagement and user satisfaction by ensuring continuous interaction with the user.

Keywords: Convolutional Neural Networks, Emotion Recognition, Frequency Patterns Pitch Analysis

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
BCA	Bachelor of Computer Application
CNN	Convolutional Neural Network
CPU	Central Processing Unit
CREMA-D	Crowd Sourced Emotional Multimodal Actors Dataset
DCT	Discrete Cosine Transform
DL	Deep Learning
DNN	Deep Neural Network
EMO-DB	Berlin Database of Emotional Speech
ERC	Emotion Recognition in Conversation
FPS	Frames Per Second
GB	Gigabyte
GPU	Graphics Processing Unit
HCI	Human-Computer Interaction
IEMOCAP	Interactive Emotional Dyadic Motion Capture
K-EmoCon	Korean Emotion Conversation Dataset
KNN	K-Nearest Neighbors
LDA	Linear Discriminant Analysis
LibROSA	Library for Audio and Music Analysis
LSTM	Long Short-Term Memory
MELD	Multimodal EmotionLines Dataset
MFCC	Mel-Frequency Cepstral Coefficients
ML	Machine Learning
MLP	Multilayer Perceptron
NLP	Natural Language Processing
NN	Neural Network
OS	Operating System
PRISMA-DTA	Preferred Reporting Items for Systematic Reviews and

	Meta-Analyses for Diagnostic Test Accuracy
RAM	Random Access Memory
RAVDESS	Ryerson Audio-Visual Database of Emotional Speech and Song
ReLU	Rectified Linear Unit
RNN	Recurrent Neural Network
RVM	Relevance Vector Machine
SAVEE	Surrey Audio-Visual Expressed Emotion Dataset
SEMAINE	Sustained Emotionally colored Machine human Interaction using Nonverbal Expression
SER	Speech Emotion Recognition
SSD	Solid State Drive
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
TESS	Toronto Emotional Speech Set
UI	User Interface
USC	University of Southern California
UX	User Experience
VAD	Voice Activity Detection
WAV	Waveform Audio File Format

1 INTRODUCTION

The use of voice in emotion recognition had received considerable interest because of its applicability in human-computer interaction. Intelligent machines can comprehend emotional conditions during conversation can react smarter and with more empathy, and communication will be more human and meaningful.The expression of emotions varies among people, gender, speaking style and recording environment[1]. There is also background noise, the quality of the microphone and the language peculiarities which make it even more difficult to recognize emotions accurately and voice emotion analysis is a complex issue demanding more sophisticated signal processing and machine learning algorithms. In order to defy these odds, this project came up with an automated voice emotion analyzer that will help classify emotions in speech records. The main goal was to develop a program that would help recognize the emotional state of a speaker based on sound based on a series of steps such as creating a dataset, pre-processing audio, getting features, choosing a model, training, and evaluating performance[2]. Four emotional speech datasets were used namely RAVDESS and TESS including the recordings of trained actors who utter the emotions with the help of the scripts.The SAVEE a collection of male voice samples of emotional speech and a collection of 250 voice samples recorded by the participants. Extracting features altered the raw audio signals in numerical form to be used in machine learning. ZCR quantified signal texture and noisiness, RMS quantified and recorded signal energy and intensity variations, and MFCC quantified and simulated human auditory perception of spectral properties. Noise injection, time stretching and pitch shifting enhanced the dataset diversity and decreased overfitting[3]. The emotion classification was done using a CNN architecture. The network added convolutional layers to extract features, normalization and pooling layers to reduces the number of dimensions, dropout to eliminate overfitting and dense to perform final classification. The training was done using categorical loss and cross-entropy and Adam optimizer. The model was reported to have an accuracy of 83.89 percentage on validation data of seven categories of emotion with a higher level of accuracy on anger and happiness. Pitch analysis was used to detect gender successfully. A web interface was created on the basis of Streamlit that allows the uploading of audio, real-time records, emotion prediction with confidence scores, and visualization of the waveforms, which makes the system practically available to real-world applications[4].

1.1 Background

Emotions had formed a vital section of human communication which was not limited to verbal communication. All the utterances had described emotional information by altering tone, pitch, volume, and rhythm. Such vocal cues had helped human beings to comprehend feelings, intentions, and attitudes when communicating. Such emotional cues were the natural interpretations of human beings and they had been used to facilitate social interaction, empathy and successful understanding among the individuals[5]. The voice processing systems that had been traditionally developed were designed to translate spoken language to text. These systems had concentrated on the linguistic content and overlooked the emotional content that was contained in the voice signal. Consequently, the capacity of computers to decode the emotional context of voice had not been accomplished and this served as a strong differentiation between human communication skills and the machine-based interpretation. The artificial intelligence methods had developed to bring opportunities to narrow this gap[6]. Scientists were now working on the ways of enabling the machines to identify and recognize emotions based on voice cues. The early emotion recognition systems had been based on manually derived acoustic features which included pitch, energy and frequency patterns. Even though these strategies had demonstrated early effectiveness, they had previously been unable to capture the variability and multi-dimensionality of emotional voice. In particular, the development of machine learning, and deep learning, had greatly enhanced the study of emotions. Deep learning models had already been able to learn meaningful patterns in audio data automatically rather than relying on predefined features completely. Convolutional neural networks were modified to identify voice representations in the form of spectrograms and proved to be able to detect differences in emotion better[7]. Access to this field was also advanced by the availability of voice collections of emotion and the best audio processing tools. A stable baseline of emotion recognition system training and testing had been established on standardized data of emotion voice. Simultaneously, features extraction and signal processing had been made easier in the libraries of audio analysis. However, with these advancements, other issues like variability of speakers, environmental noise as well as cultural differences had not disappeared. Such challenges had pointed at the necessity of strong models and varieties of training data to acquire credible emotion recognition within the real-life setting[8].

1.2 Motivation

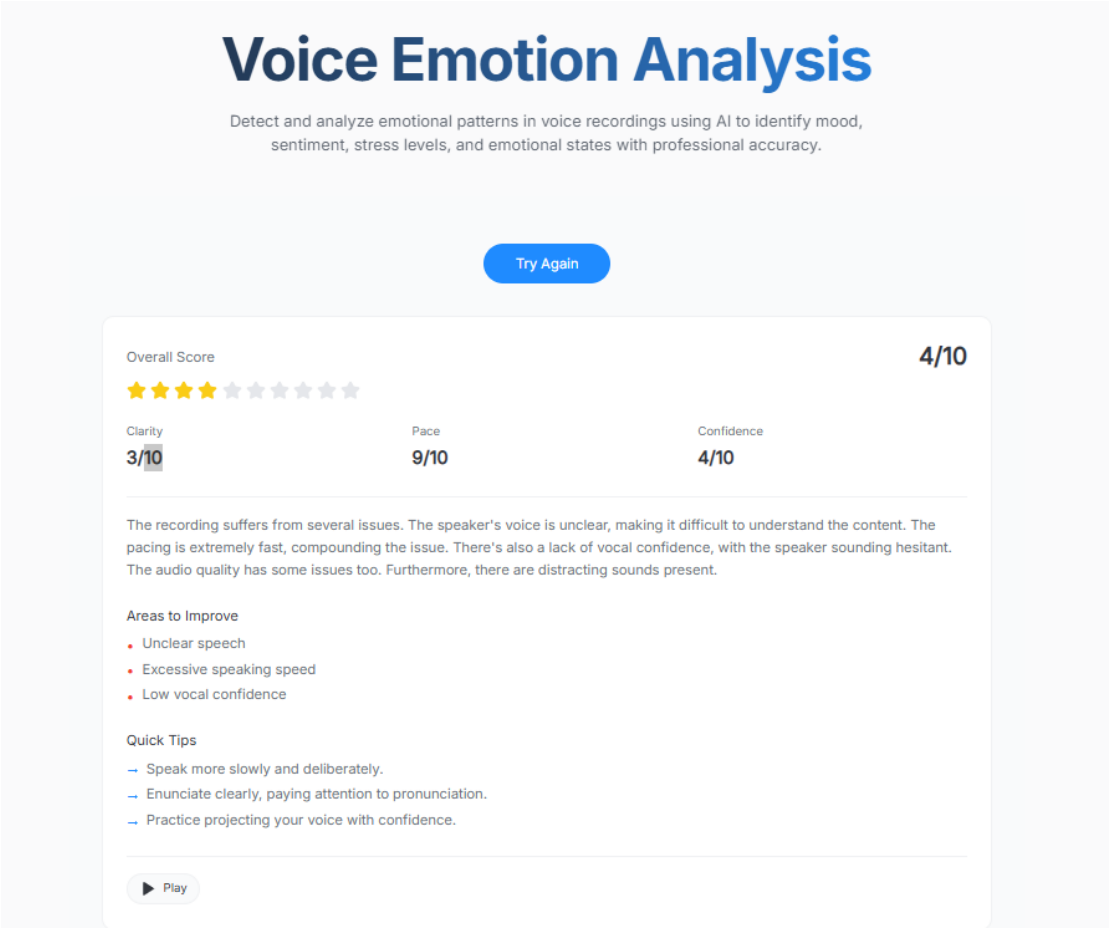


Figure 1.1: Voice Emotion Analyzer

The motivation of the Voice Emotion Analyzer project is to overcome limitations in existing human–computer interaction systems by enabling accurate emotion recognition through voice using artificial intelligence. The key motivating factors are outlined as follows:

- Lack of emotional awareness in current AI-based interaction systems.
- Challenges in accurately identifying human emotions from vocal signals.
- Limited naturalness and engagement in human–computer communication.
- Need to enhance interaction quality through voice-based emotion analysis.

1.3 Problem Statement

The development of an accurate and reliable voice emotion recognition system remains a significant challenge. Despite advancements in machine learning and artificial intelligence, existing systems face multiple limitations that hinder their accuracy, robustness, and applicability in real-world scenarios.

1. **Manual Feature Engineering Dependence:** Many systems rely on handcrafted features to detect emotions. This approach is time-consuming, less scalable, and often fails to capture subtle emotional cues in human voice.

2. **Preprocessing and Acoustic Pattern Extraction:** Identifying meaningful acoustic patterns from raw audio signals is challenging. Poor preprocessing can lead to noise sensitivity, reduced accuracy, and misclassification.

3. **CNN Architecture Design:** Designing an effective convolutional neural network for multi-class emotion classification is complex. Inadequate architecture may fail to distinguish between similar emotions.

4. **Dataset Limitations:** Emotional voice datasets are often small, imbalanced, or lack diversity. This limitation hampers model training, generalization, and fairness across different speakers and recording conditions.

5. **Computational Constraints:** Achieving reliable emotion recognition with low computational cost is difficult, especially for real-time applications.

6. **Spectral and Temporal Feature Analysis:** Extracting and leveraging spectral and temporal features effectively is essential for differentiating emotions with similar vocal patterns.

7. **Overfitting Risks:** Small and limited datasets increase the risk of overfitting, reducing the model's ability to generalize to new or unseen voice data.

8. **Speaker and Environment Variability:** Variations in speaker pitch, accent, or recording conditions can cause significant accuracy fluctuations, challenging the robustness of the system.

9. **Model Validation Challenges:** The absence of large, publicly available emotion datasets complicates model validation and benchmarking.
10. **Real-World Generalization:** Extending emotion recognition models to real-world conversational voice is challenging due to background noise, spontaneous speech, and emotional subtlety.

To address the above challenges and guide the development of an effective Voice Emotion Analyzer, the following research questions are formulated:

1. How can emotions be identified from voice without manual feature engineering?
2. Which preprocessing methods best extract meaningful acoustic patterns from raw audio?
3. How can an effective CNN architecture be designed for multi-class emotion classification?
4. What strategies can mitigate dataset limitations and imbalance in emotional voice recordings?
5. How can reliable emotion recognition be achieved with low computational cost?
6. What role do spectral and temporal features play in separating similar emotions?
7. How can overfitting on small datasets be prevented?
8. How can accuracy variation across speakers and recording conditions be minimized?
9. How can models be validated effectively without large public datasets?
10. What strategies can generalize emotion recognition to real-world conversational voice?

1.4 Project Objectives

- To implement a machine learning model that accurately detect human emotions from voice.
- To test and evaluate deep learning model to achieve the accuracy in emotion recognition.

1.5 Scope of Project

The project of the Voice Emotion Analyzer creates a system that can be used to recognize emotions based on voice signals and offer the reliable means of interpreting the emotions in human beings. Audio input falls into seven different emotions including angry, disgust, fear, happy, neutral, sad and surprise. The basis of analysis had been provided by the extraction of audio features such as zero crossing rate, energy and at Mel-frequency cepstral coefficients. The noise addition, pitch variation, and time stretching data augmentation techniques had been used to enhance the model and enhance its capability in generalizing to various voice patterns and speakers. The convolutional neural network had been trained on four publicly available emotional voice datasets as well as 250 recorded voice samples. The trained model runs on a web interface, which takes uploaded audio files or real time recording. The interface shows determined emotions with confidence scores, and visualizes audio of a speaker and spectrograms and audio waveforms, and, above all, the gender of the speaker. Preprocessing, such as noise reduction, signal normalization, and framing, had been made to improve the clarity of features. Spectral and temporal characteristics enable the model to discriminate similar emotions and CNN records both local and global audio patterns, so no misclassifications can occur. The interface gives instant feedback and delivers the results in a friendly and comprehensive way.

Although the system has its capabilities, it has some shortcomings. The processing of audio input is only performed, and facial expressions or text-based recognition of emotions are not considered. The audio streams are not continuous. With few Nepali samples and mostly with English recording, the training data lessen the accuracy on other languages. Only recognized emotions are the seven trained ones and the person speakers are not distinguished. The system is also less accurate when the audio

is extremely noisy or with spontaneous speech rather than acted samples.Complex emotional expression, sarcasm and cultural variations are not perceived either. Privacy and consent protection was not implemented, and the sensitive user information is not handled. The difference in the pitch of the speaker, tone, accent and recording environment causes fluctuations in performance. The limitations underscore the need to be cautious with data preparation, extracting features, and evaluating them in order to achieve a dependable and understandable voice emotion recognition system.

1.6 Potential Project Applications

1. **Mental Health Monitoring:** Voice-based emotion recognition assists mental health professionals by providing objective measurements of patient emotions over time. Regular recordings identify mood patterns, detect indicators of depression or anxiety, and monitor treatment effectiveness. The system alerts healthcare providers to concerning emotional changes while reducing reliance on subjective self-reporting.

2. **Customer Service Analysis:** Call centers utilize emotion detection to assess caller sentiment in real-time. Distressed callers are highlighted for attention, and supervisors obtain emotional analytics for quality assurance. Post-call analysis reveals service pain points and informs staff training based on emotional interaction patterns.

3. **Educational Technology:** Adaptive learning platforms gauge student engagement and frustration during online instruction. Detection of confusion or disengagement allows dynamic adjustment of content difficulty and presentation style. Educators gain feedback on emotional responses to teaching methods, facilitating early support for struggling students.

4. **Human-Computer Interaction:** Voice-controlled interfaces, virtual assistants, and interactive systems benefit from understanding user emotions. The system adapts responses based on detected feelings, enabling empathetic interactions and improving overall user experience.

5. **Entertainment and Media Analysis:** Emotion recognition is applied to analyze audience reactions to audio content such as podcasts, audiobooks, and voice per-

formances. This helps content creators understand engagement levels, emotional impact, and listener preferences.

6. **Research in Speech and Linguistics:** The system supports academic studies by analyzing emotional expression in speech. Researchers can study voice patterns, cross-cultural differences, and the effect of intonation and pitch on emotion, contributing to studies in linguistics, psychology, and AI.

7. **Voice-Based Accessibility Tools:** Emotion detection enhances accessibility for users with communication difficulties. Applications include assisting speech therapy, supporting individuals with autism spectrum disorder, or providing feedback for users practicing emotional expression in speech.

1.7 Feasibility Study

The development of the Voice Emotion Analyzer, an automated system for emotion recognition from human voice, requires a comprehensive feasibility analysis. This section evaluates the project from multiple perspectives to ensure technical viability, economic sustainability, operational efficiency, legal compliance, and timely completion.

1.7.1 Technical Feasibility

The system relies on modern AI and deep learning technologies, open-source tools, and well-supported libraries to ensure technical feasibility.

- **Audio Processing and Feature Extraction:** Python libraries such as LibROSA and NumPy handle audio preprocessing, feature extraction, and analysis efficiently.
- **CNN-Based Classification:** TensorFlow and PyTorch provide complete support for building and training the convolutional neural network.
- **Web Interface Integration:** The system operates through a web interface, accepting uploaded audio files and live recordings, displaying emotions, confidence scores, audio waveforms, spectrograms, and speaker gender.
- **Hardware Requirements:** The system runs smoothly on a standard laptop with 8GB RAM and SSD storage, and audio signals are lightweight to process.

1.7.2 Economic Feasibility

The project is economically feasible because it utilizes freely available datasets and open-source libraries.

- **Cost Efficiency:** RAVDESS, SAVEE, and other public datasets are used for training and testing, eliminating the need for paid resources.
- **Minimal Hardware Expense:** Existing laptops and standard computing resources were sufficient for development and operation.
- **Sustainable Development:** All software tools are open-source, resulting in negligible financial burden and suitability for academic and research purposes.

1.7.3 Operational Feasibility

The system demonstrates operational feasibility due to its straightforward workflow and user interaction.

- **Workflow Simplicity:** Users provide a voice sample, and the system automatically handles preprocessing, feature extraction (MFCC, Chroma, Spectral Contrast), and CNN-based emotion prediction.
- **User-Friendly Interface:** Emotion results, confidence scores, and visualizations are presented clearly, ensuring interpretability.
- **Practical Applications:** The system supports emotional monitoring, customer service analysis, and voice-based assistance tools effectively.

1.7.4 Legal and Ethical Feasibility

The project maintains legal and ethical compliance throughout its development.

- **Data Privacy:** The system uses datasets allowed for academic research and does not store personal data unless explicitly required.
- **Licensing Compliance:** No copyrighted materials are used, ensuring legal safety.
- **Ethical Considerations:** The system respects privacy standards and avoids unauthorized use of sensitive information.

1.7.5 Schedule Feasibility

The project timeline aligns with academic and research deadlines.

- **Development Phases:** Dataset preparation, feature extraction, model training, interface creation, and testing have been completed according to a structured workflow.
- **Progress Monitoring:** Each phase had defined milestones, ensuring smooth execution and timely project completion.

1.7.6 Resource Feasibility

The system's resource requirements are manageable.

- **Human Resources:** Development, model training, and interface creation were completed by a small team of developers and testers.
- **Technical Resources:** Existing computing devices and open-source tools were sufficient for all project tasks.

1.7.7 Market Feasibility

There is a growing demand for intelligent, emotionally aware systems.

- **Target Users:** AI researchers, developers, and organizations interested in human-computer interaction, emotional monitoring, and accessibility solutions.
- **Competitive Advantage:** The system provides multi-emotion detection, gender identification, and visual feedback, differentiating it from simple audio analysis tools.

1.7.8 Social and Cultural Feasibility

The system aligns with modern technological and social practices.

- **Emotional Awareness:** Supports better interaction between humans and machines, enhancing engagement and understanding.

- **Cultural Adaptability:** While trained mostly on English and some Nepali samples, the system demonstrates flexibility and potential for expansion to other languages with similar voice patterns.

1.8 Originality of the Project

The Voice Emotion Analyzer project is unique as it develops a smart voice-based emotion recognition system that can interpret human emotions in real time. In contrast to traditional systems that rely on limited datasets or manual feature extraction, this project focuses on fairness, accuracy, and reliability of emotion recognition across different speakers and recording conditions.

The primary contribution of this project lies in the development of a system that **combines four publicly available emotional voice datasets with a self-collected corpus of 250 labeled samples**, creating an extensive and diverse training set that improves the **generalization capability of the model**. Furthermore, the system applies **data augmentation techniques such as noise injection, time stretching, and pitch shifting** to reproduce real-world recording variations and enhance robustness. A **custom convolutional neural network architecture** utilizes **acoustic features instead of raw audio** to classify **seven emotions angry disgust fear happy neutral sad and surprise**. Another notable contribution is the **integration of pitch-based gender detection with emotion recognition**, enabling simultaneous analysis of the speaker's gender and emotional state.

1.9 Organization of Project

This project report has been structured into seven main chapters, followed by the appendix and references. The first chapter introduces the research topic, including the background, motivation, problem statement, objectives, and scope of the study. Chapter 2 provides a detailed review of the literature, examining important publications and identifying gaps that this research addresses. Chapter 3 explains the methodology, covering the system design, algorithms, data processing methods, and technologies used in the development. Chapter 4 presents the results of the system, including performance measurements, visual outputs, and key observations. Chapter 5 discusses and analyzes the results, comparing them with theoretical expectations and existing systems, while highlighting limitations. Chapter 6 outlines potential future enhancements, describing improvements and additional functionalities that could be implemented. Chapter 7 concludes the report by summarizing the major findings, assessing the overall effectiveness of the system, and reflecting on its contributions. The appendix contains the project timeline and detailed literature reviews of base papers, followed by a complete list of references to all cited research works.

2 LITERATURE REVIEW

2.1 Literature Review I

The paper titled Voice Emotion Recognition in Conversations Using Artificial Intelligence, A Systematic Review and Meta Analysis by Leontios Hadjileontiadis was a comprehensive and well-organized analysis of the development of research in the field of conversational voice emotion recognition[9]. This review was conducted in contrast to traditional studies that were based on isolated utterances, whereas natural human conversation involved emotional expression that depended on context, interaction patterns, and speaker relationships[9]. The research emphasized that emotion recognition in real conversations was more complex than emotion detection from single sentences because emotions evolved over time, reacted to other speakers, and were highly situation-dependent[9]. A large body of research literature was systematically structured and evaluated through a rigorous review methodology[9]. The review provided a broad overview of artificial intelligence methods used in conversational emotion recognition, including classical feature-based approaches, temporal modeling using recurrent neural networks, spectral representations with convolutional neural networks, long-range dependency modeling through attention mechanisms, and contextual sequence learning using transformer-based architectures. The meta-analysis evaluated performance improvements across these approaches and demonstrated that deep learning models significantly outperformed traditional methods[9]. The development of multimodal conversational datasets was also highlighted in the review[9]. These datasets combined audio, textual, visual gestures, and physiological signals, enabling more accurate emotion recognition[9]. Multimodal systems achieved superior performance because conversational emotions were often influenced by subtle contextual cues that could not be captured through voice alone. However, several challenges were identified, including the scarcity of high-quality conversational datasets, inconsistencies in emotion annotation schemes, cross-cultural variability in emotional expression, and difficulties in modeling overlapping emotions during conversations[9]. The review critically discussed the limitations of existing systems, noting that models trained on acted datasets with exaggerated emotions performed poorly in real conversational environments characterized by background noise, informal speech, interruptions, sarcasm, and uncertainty. Context modeling, speaker diarization, and sequence-based learning were identified as essential components for

improving system robustness. Future research directions included cross-cultural adaptation, context-aware emotion tracking, ethical considerations in emotion monitoring, unified benchmarking standards, and real-time adaptive systems, with applications in virtual assistants, call centers, and mental health monitoring contributing to more natural human–computer interaction[9].

2.2 Literature Review II

The research paper entitled Emotion Recognition on Call Center Voice Data explored the significance of voice emotion recognition in improving customer service activities in call centers[10]. The analysis was based on real customer interactions rather than controlled or acted speech, making the study more practical in real-world applications. Call center conversations were often characterized by emotional strain, dissatisfaction, indecisiveness, and urgency, which made emotion detection an essential tool for understanding customer needs[10]. As demonstrated in the study, identifying customer emotions during interactions enabled agents to respond more empathetically and effectively. Unlike earlier emotion recognition studies that relied on clean datasets, this research addressed challenges associated with noisy and spontaneous speech[10]. Authentic call recordings from Turkish mobile operators were used, incorporating background noise, varied speaking styles, and interrupted speech, thereby closely simulating real call center environments and increasing the difficulty of emotion recognition. This realistic analysis allowed the study to present a practical evaluation of system performance and usability[10]. The system employed deep learning techniques to classify emotional states into positive, negative, and neutral categories[10]. This simplified classification scheme was suitable for operational environments where fast and direct emotional feedback was required. An accuracy of 0.91 was reported, demonstrating that deep learning models could successfully learn emotional patterns even from complex and unstructured voice data[10]. The system provided emotional intelligence support to call center employees, helping them adapt their communication strategies during customer interactions. The authors concluded that integrating emotion recognition into call center workflows improved customer satisfaction and service quality[10]. The study also emphasized the importance of language-specific research, as the system was developed for Turkish speech, a language that is underrepresented in emotion recognition studies. The findings suggested that future systems could be extended to multilingual environments and enhanced with finer-

grained emotion categories for more detailed emotional analysis[10]. Another significant contribution of the research was the investigation of feature selection and preprocessing techniques to optimize emotion classification under real-world conditions[10]. Noise filtering, voice segmentation, and spectral feature extraction methods were applied to improve input data quality. The study also identified speaker variability as a factor influencing model performance and discussed approaches to reduce bias across different voice types and accents[10]. These techniques supported the development of more robust and generalizable emotion recognition systems that could be effectively deployed in real call center application settings.

2.3 Literature Review III

The paper titled Emotion Detection via Voice and Voice Recognition, written by Rohit Rastogi, Tushar Anand, Shubham Sharma, and Sarthak Panwar, was a thorough investigation of detecting human emotions through the spoken voice cues[11]. The paper has started by highlighting the increasingly critical role of emotion-conscious computing in the context whereby intelligent systems were interacting with human beings more frequently. Voice being natural and impulsive had substantial acoustic signals that disclosed the emotional condition of a person even when the verbal message itself was neutral[11]. The objective of the study was to develop a strong model that would explain these emotional cues through the combination of state-of-the-art signal processing and machine learning methods. The study has described the audio preprocessing steps to be taken in recognizing emotions in detail[11]. Voice cues that were observed across different people contained huge differences in tone, volume, noise in the background, and the manner of speaking. Direct processing of audio content in its pure form resulted in the model paying attention to unrelated anomalies and not emotional content[11]. In order to solve this, the pipeline was utilized that incorporated noise removal, silence clipping, feature scaling, and transformation of audio signals into homogeneous segments of length. The result of this process was pure and reliable representations of voice that had a direct effect on the accuracy of classifiers[11]. The paper has reinforced the role of feature extraction[11]. There was a lot of use of Mel Frequency Cepstral Coefficients and other spectral and temporal descriptors. These features measured vital characteristics of emotions including change in energy, change in pitch dynamics, harmonic structure, and frequency distribution[11]. Emotions like anger were linked with more energy, more

harmonics, and broader frequencies, whereas sadness was reflected in less energetic, less harmonic, and less high-pitched voice. The emotion recognition model was based on these differences in acoustics[11]. Classical machine learning algorithms as well as deep learning architectures were tried[11]. Conventional algorithms such as Support Vector Machines and Random Forest classifiers performed well using well-designed features. Nevertheless, deep learning models, especially convolutional neural networks, had a much higher performance as compared to the classical models[11]. The space patterns that were found to be related to emotional tone in convolutional layers were automatically identified and the use of manual feature engineering was minimized. The findings showed that certain emotions were more classifiable as compared to others[11]. Emotions with extreme acoustic profiles such as anger and happiness were better recorded, whereas similar acoustic emotions such as calm and sad caused confusion[11]. The analysis indicated the need of bigger more varied datasets in order to enhance generalization. Human-computer interaction, personalized digital assistants, driver monitoring systems, and emotion-aware recommendation engines were also used in practice[11]. The work laid a solid foundation to contemporary voice-based affective computing.

2.4 Literature Review IV

The paper Evaluated the Impact of Voice Activity Detection on Voice Emotion Recognition in Autistic Children aimed at enhancing the rate of emotion recognition during child voice especially with autism[12]. The voice of autistic children also did not correspond to usual patterns of speech and contained uneven timing, abnormal intonation, and prolonged pauses. These attributes complicated emotion recognition and decreased the efficiency of regular emotion recognition systems[12]. The authors focused on preprocessing methods, especially voice activity detection, to extract useful voice segments. Silence, background noise, and unwanted audio contents were eliminated with voice activity detection and then emotion analysis occurred[12]. Such a step was necessary for child voice, in which emotional indications were subtle and easily concealed by noise or non-vowel sounds. The study showed through experimental assessment that the reliability of emotional feature extraction with voice activity detection had been enhanced[12]. More stable results of emotion recognition were achieved through better segmentation of voice. The study also revealed that preprocessing was vital in the overall performance of voice emotion recognition systems, particularly in dealing with

sensitive and varying voice data[12]. The paper emphasized the need for special emotion recognition systems responsive to vulnerable groups like autistic children. Ethical issues regarding data gathering, system implementation, and interpretation of emotional cues were also highlighted[12]. Another contribution made by the study was demonstrating the effect of adaptive preprocessing on system robustness[12]. The results indicated that voice activity detection, when carefully tuned, improved the extraction of subtle emotional features even with difficult recordings. The paper also provided guidance on designing child-centered emotion recognition systems and suggested that more customized approaches would enhance reliability and usability in therapeutic, educational, and clinical contexts[12]. These findings highlighted the significance of preprocessing in the creation of useful, specialized emotion-aware technologies that can be applied to sensitive groups.

2.5 Literature Review V

The system introduced by Sadil Chamishka, Ishara Madhavi, Rashmika Nawaratne, Damminda Alahakoon, Daswin De Silva, Naveen Chilamkurti, and Vishaka Nanayakkara was a voice-based emotion recognition system which worked in real time to detect temporal variations in emotion in voice using recurrent neural networks and refined feature modelling[13]. The procedure was based on the creation of RNN constructions that preserved the sequential dependence of acoustic characteristics, enabling the system to acquire dynamic variation of vocal expressions much more effectively than inherent classifiers. The architecture operated over voice streams and had been scaled to low-latency real-time applications, which was highly useful in interactive systems[13].To increase emotional discrimination, feature modelling was applied to better represent prosodic and spectral voice features that were inputted into the RNN classifier[13]. This allowed detection of transitioning emotional states with greater precision by combining temporal modelling with advanced feature extraction because of continuous voice input. The technique was tested on benchmark emotional voice datasets, and the experimental findings revealed significant improvement in recognition accuracy compared to machine learning models trained in baseline conditions[13]. The RNN-based structure was more accurate than traditional classifiers and demonstrated the advantages of temporal dependency modelling. The system was qualitatively stable in processing continuous voice streams and tracking changes in emotions in real time,

which was necessary for practical human-computer interaction use[13]. Some of the strengths identified by the study included the design of a real-time architecture, effective temporal modelling through recurrent neural networks, and enhanced feature representation resulting in superior recognition of emotions[13]. The low-latency nature of the framework made it highly practical, and benchmark validation empirically supported the research methodology. Limitations included limited multilingual coverage, susceptibility to real-world noise, lack of multimodal inputs such as facial expressions or physiological signals, and absence of robustness analysis in adverse acoustic settings, which constrained large-scale use[13].Another contribution of this study was demonstrating the benefits of ageing temporal modelling with stronger feature representation in continuous emotion recognition[13]. The research provided guidance on designing real-time interactive voice emotion systems and highlighted future directions, such as covering more languages, integrating multimodal signals, and testing robustness in unfavorable acoustic environments. The results facilitated the development of robust, precise, and practically implementable emotion-sensitive systems[13].

2.6 Literature Review VI

The study titled A Cross Cultural Investigation of Emotion Inferences of Voice and Voice: Implications of Voice Technology was conducted by Klaus R. Scherer, in which the perception of vocal emotions across different cultural backgrounds had been systematically examined[14]. The expression of emotions through voice had been considered a complex interaction of physiological mechanisms, learned cultural conventions, linguistic habits, and individual expressive styles. Through this investigation, an attempt had been made to determine whether emotional cues conveyed through voice had been universally interpreted or whether they had been significantly influenced by cultural conditioning [14]. Voice samples representing a range of emotional states had been collected and presented to listeners belonging to multiple cultural groups[14]. Participants had been instructed to identify emotions based solely on acoustic cues such as pitch variation, intensity, speech rate, rhythm, and intonation patterns, without access to contextual or semantic information[14]. This approach had ensured that emotional inference was derived purely from vocal characteristics rather than external factors. The results had indicated that certain emotional patterns had been consistently recognized across cultures. High pitch, rapid tempo, and increased intensity had been commonly associated with emotions

such as fear and excitement, while low pitch, reduced energy, and slower tempo had been largely linked with sadness[14]. These findings had supported the hypothesis that some vocal expressions of emotion had biological foundations shared across human populations[14]. The notable cultural variations had also been identified[14]. Emotional interpretations had differed depending on social norms, linguistic traditions, and cultural exposure[14]. For instance, louder vocal expressions had been perceived as anger in some cultures, whereas the same acoustic patterns had been interpreted as confidence or enthusiasm in others[14]. These discrepancies had demonstrated that emotional perception through voice had not been entirely universal[14]. The implications for voice-based technologies had been strongly emphasized in the study[14]. It had been suggested that emotion recognition systems trained on culturally limited datasets were likely to perform poorly when deployed across diverse populations[14]. The research had highlighted the necessity of incorporating culturally diverse training data and adaptive mechanisms capable of adjusting emotional interpretations based on user background[14]. Another significant contribution of the study had been the emphasis on sociocultural awareness in emotion recognition system design[14]. The findings had shown that accurate emotional interpretation could not rely solely on acoustic features without consideration of cultural context. By integrating cultural sensitivity into algorithmic models, both recognition accuracy and user acceptance had been improved. This work had provided foundational insights for the development of globally applicable and socially aware voice emotion recognition systems[14].

2.7 Literature Review VII

The paper titled Multimodal Integration of Emotional Signals of Voice, Body and Context had examined how emotional understanding had been influenced when voice, body movement, and contextual information had been jointly considered in communication systems[15]. It had been argued that emotional expression had rarely been conveyed through voice alone and had instead been formed through an integrated combination of vocal tone, physical gestures, and situational cues[15]. The study had been positioned within the domain of human-robot interaction, where emotional intelligence had been considered essential for social acceptance and effective interaction[15]. Emotional perception accuracy had been evaluated under conditions where emotional cues had been either congruent or incongruent across modalities[15]. It had been observed that

recognition performance had been significantly improved when voice, body language, and contextual signals had conveyed consistent emotional information, whereas mismatched cues had caused ambiguity and reduced trust in robotic systems[15]. User attitudes toward robots had been analyzed, and robots displaying multimodal emotional consistency had been perceived as more intelligent, reliable, and socially engaging[15]. The findings had indicated that emotionally coherent multimodal behavior had positively influenced user comfort, interaction quality, and long-term acceptance[15]. Practical deployment considerations had also been addressed, where multimodal emotion systems had been shown to perform more robustly under dynamic and unpredictable real-world conditions[15]. Additionally, it had been suggested that future systems should incorporate extended sensory channels and long-term user interaction studies to enhance emotional adaptability and realism[15]. Overall, the study had reinforced that multimodal emotion recognition had better reflected natural human communication patterns and had been critical for developing socially intelligent artificial agents[15].

2.8 Literature Review VIII

The study titled Voice Based Emotion Recognition with Convolutional Neural Networks in Companion Robots had focused on integrating voice-based emotion recognition capabilities into companion robotic systems designed for close human interaction[16]. Companion robots had been widely applied in healthcare assistance, elderly support, child interaction, and personal companionship, where emotional awareness had been essential for natural engagement[16]. The research objective had been centered on constructing a convolutional neural network architecture capable of classifying emotional states using voice signals[16]. Voice recordings had been transformed into spectrogram representations, which had been treated as two-dimensional inputs enabling spatial and temporal feature learning[16]. Emotional characteristics such as high energy and spectral sharpness for anger and reduced frequency variation for sadness had been implicitly learned by convolutional filters without manual feature extraction[16]. Data preprocessing techniques such as normalization, segmentation, and augmentation had been applied to improve generalization across speakers and recording environments[16]. The CNN model had been composed of stacked convolutional and pooling layers followed by fully connected layers responsible for emotion classification[16]. Training had been performed using backpropagation on labeled emotional voice samples, and improved

robustness against noise had been demonstrated when compared to traditional machine learning approaches[16]. Real-time deployment within robotic platforms had enabled adaptive behavioral responses such as tone adjustment and interaction modulation based on detected emotions[16]. It had also been emphasized that performance had been further enhanced when diverse accents, background noise, and spontaneous speech patterns had been included during training[16]. The study had concluded that combining voice emotion recognition with additional modalities could further strengthen emotional intelligence in companion robots operating in complex social environments[16].

2.9 Literature Review IX

The paper by Fatemeh Noroozi, Tomasz Sapinski, Dorota Kaminska, and Gholamreza Anbarjafari introduced a vocal-based emotion recognition framework in which ensemble learning was implemented to model paralinguistic voice features and classify emotions accurately[17]. The basic algorithm used prosodic and spectral data, including pitch, intensity, formants, and other paralinguistic representations as input to a random forest classifier composed of multiple decision trees. This ensemble architecture was designed to provide greater robustness and generalization by aggregating predictions from multiple weak learners rather than relying on a single classifier[17].The system was tested on the SAVEE emotional voice database using two validation strategies: leave-one-out cross-validation and 9-fold cross-validation[17]. Quantitative results reported an average score of 76.28 across six emotion categories. Happiness achieved the highest recognition rate of 78, indicating that positive affective states were more easily recognized. The effectiveness of the ensemble learning approach was demonstrated through its superior performance over Linear Discriminant Analysis and deep neural network baselines on the same dataset[17]. Qualitative analysis revealed that the system remained stable in classifying emotional categories and that strength improved when multiple decision trees were aggregated. The framework was therefore considered generalizable to multi-class emotion categorization and suitable for emotion-sensitive human-computer interaction applications[17].Strengths of the study included a well-structured methodological process based on ensemble learning that enhanced classification stability and minimized overfitting[17]. Emotional separability improved through the use of discriminative paralinguistic features, and reliability increased with cross-validation strategies. Empirical evidence of the approach's superiority was presented by comparison with LDA and

DNN baselines. The model demonstrated practical applicability in emotion-sensitive HCI systems[17].Limitations were also observed[17]. Experiments were conducted on a single small benchmark dataset, limiting generalizability. Reliance on acted emotional voices reduced ecological validity. Multimodal emotion cues such as facial expressions or physiological signals were not integrated, restricting the scope of emotion representation. Certain emotional categories, such as fear and surprise, had low recognition accuracy, and real-time deployment was not tested, leaving system latency and practicality unexamined[17].Another point raised by the research was the potential of combining this ensemble learning structure with dynamic adaptive systems[17]. The emotion recognition system could be enhanced by incorporating real-time user responses and lifelong learning to better handle different speaker traits, spontaneous facial expressions, and contextual variations. This adaptation could improve reliability, practicality, and applicability in various real-life human-computer interaction scenarios[17].

2.10 Literature Review X

The article titled Factor Analysis Based Speaker Normalisation for Continuous Emotion Prediction by Ting Dang, Vidhyasaharan Sethu, and Eliathamby Ambikairajah focused on the important issue of variability in speaker voices in emotion recognition systems[18]. The authors stated that voice generated by different people was inherently different because of physiological variations in vocal tract length, habitual speaking styles, accent, gender, age, and emotional expressiveness. These differences disrupted the model's ability to focus solely on emotional cues[18]. When a system was trained on data from a small group of speakers, it tended to overfit to particular speaker characteristics instead of learning emotion-related features. Speaker variability was identified as a key reason why continuous emotion prediction remained unstable in cross-speaker conditions[18].The study project a speaker normalization method based on factor analysis[18]. The technique decomposed voice elements mathematically into components representing the speaker and components conveying emotion. This separation allowed the model to focus on variations in arousal, valence, and dominance, the three continuous dimensions typically used to describe emotional states. Unlike categorical emotion classification, continuous emotion prediction monitored the strength of emotions over time, which was claimed to be more suitable for real-world applications such as dialog systems, behavioral analytics, and affective monitoring[18].Voice features were decomposed into latent variables using

factor analysis[18]. This enabled speaker-specific characteristics to be distinguished and their influence minimized. Emotional cues became more evident and consistent across different speakers. Large-scale experiments on benchmark datasets with diverse speakers and emotional levels demonstrated that speaker normalization significantly improved the smoothness and accuracy of predicted emotional trajectories[18].A notable strength of the study was the discussion of how subtle shifts in pitch or energy due to speaker identity could be confused with emotional changes[18]. Such variations were more problematic for continuous emotion models compared to categorical models, making normalization particularly important. Unnormalized models produced jagged, unpredictable, and noisy emotional predictions, whereas normalized models generated more stable and interpretable emotional curves[18].The study also highlighted that speaker normalization frameworks could be integrated with deep learning architectures to further improve cross-speaker adaptability[18]. Neural network pipelines that included normalization allowed emotional representations to be less dependent on individual speaker characteristics, leading to more effective deployment in multiethnic populations. This design emphasized that preprocessing and normalization were as crucial as model architecture for achieving high-quality continuous emotion recognition[18].

2.11 Summary of Literature Review

Table 2.1: Summary of Literature Review

Author/Year	**Focus**	**Methodology**	**Key Findings**	**Contributions**
Hadjileontiadis (2025)	Voice emotion recognition in conversations	Systematic review of CNN, RNN, Transformer, and attention models	Deep learning significantly outperforms traditional approaches; multimodal data enhances accuracy	Comprehensive roadmap for conversational emotion recognition research
Yurtay et al. (2024)	Emotion recognition on call center data	Deep learning on spontaneous noisy call recordings	Achieves 91% accuracy despite real-world noise and variability	Demonstrates feasibility in industrial call center environments
Rastogi et al. (2023)	Emotion detection from voice signals	MFCC extraction with ML and CNN classifiers	CNN outperforms traditional ML techniques	Effective pipeline for HCI and smart monitoring systems
Chamishka et al. (2022)	Real-time voice emotion detection	RNN with advanced feature modeling	High accuracy in real-time emotion detection	Supports deployment of emotion-aware applications
Milling et al. (2022)	Emotion recognition for autistic children	Voice activity detection with optimized preprocessing	Improved classification of subtle vocal cues	Highlights preprocessing importance for child-centered systems

Author/Year	Focus	Methodology	Key Findings	Contributions
Scherer (2021)	Cross-cultural emotion inference	Comparative acoustic analysis across cultures	Universal emotional patterns with cultural variations identified	Supports culturally adaptive recognition systems
Tsiourti et al. (2019)	Multimodal emotion recognition for robots	Integration of voice, gestures, and context	Multimodal congruent cues improve recognition	Guidelines for socially intelligent human-robot interaction
Alu et al. (2017)	Emotion recognition for companion robots	CNN on spectrogram representations	CNN shows robustness and real-time applicability	Enables adaptive emotional responses in robots
Noroozi et al. (2017)	Vocal-based emotion recognition	Random Forest and Decision Tree classifiers	Tree models effective with low computational cost	Suitable for lightweight real-time systems
Dang et al. (2016)	Speaker normalization in emotion prediction	Factor analysis-based speaker normalization	Reduces speaker variability and improves prediction smoothness	Enhances cross-speaker continuous emotion recognition

3 METHODOLOGY

This section presents the systematic methodology employed in developing the Voice Emotion Analyzer. The approach integrates theoretical formulations, feature extraction, convolutional neural network modeling, and post-processing to predict emotions from human voice accurately and efficiently.

3.1 Theoretical Formulations

The Voice Emotion Analyzer relies on deep learning techniques to automatically detect human emotions from audio signals. The system processes raw audio samples from male and female speakers expressing emotions such as happiness, sadness, anger, calmness, fear, disgust, and surprise. Preprocessing steps include noise reduction, silence trimming, amplitude normalization, and extraction of meaningful features using the `Librosa` library. Important acoustic features such as Mel-Frequency Cepstral Coefficients, Chroma features, Spectral Centroid, and Spectral Contrast are extracted to capture variations in pitch, tone, rhythm, and energy associated with emotional states. The extracted features are normalized and passed into a Convolutional Neural Network with Efficient Channel Attention. The CNN learns localized spatial and temporal patterns corresponding to emotion-specific acoustic signatures. The ECA module enhances relevant features while suppressing irrelevant ones, improving the network's focus on emotion-related cues. Post-processing includes the softmax classification layer to output probability scores for each emotion category.

Major Benefits:

- Automatic feature learning without manual engineering.
- High classification accuracy across multiple emotions.
- Robustness to variations in speakers, accents, and audio quality.
- Real-time applicability for live and recorded audio.

Assumptions:

- Input audio is of sufficient quality with minimal background noise.

- Training data represents a diverse set of voices and emotional expressions.
- Emotions in recordings are expressed clearly and consistently.

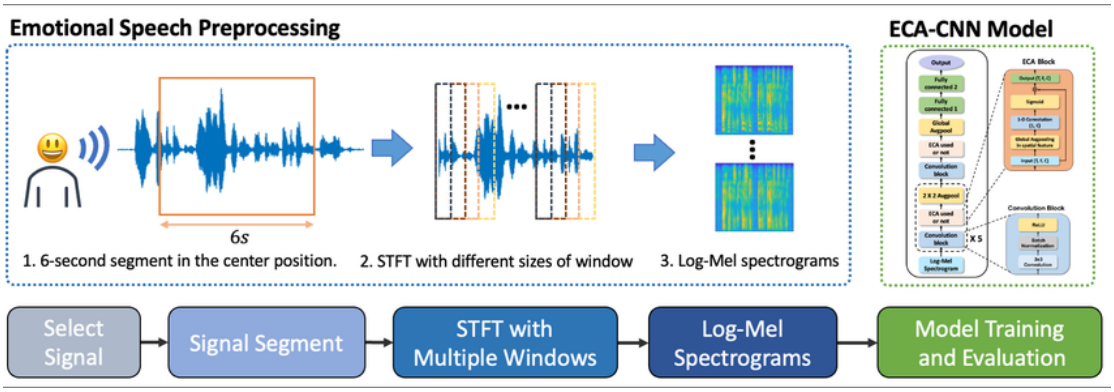


Figure 3.1: Illustration of the CNN-based Voice Emotion Analyzer pipeline.

3.2 Mathematical Modeling

3.2.1 Audio Feature Extraction

For each input audio signal $A(t)$, the STFT is computed, followed by mapping to the Mel scale. Finally, the Discrete Cosine Transform DCT is applied to obtain MFCCs:

$$MFCC = DCT\left(\log\left(|STFT(A(t))|\right)\right) \tag{3.1}$$

Symbols:

- $A(t)$: Input audio signal as a function of time.
- $STFT(A(t))$: Short-Time Fourier Transform of the signal.
- DCT : Discrete Cosine Transform to obtain compact coefficients.
- $MFCC$: Mel-Frequency Cepstral Coefficients used as features.

3.2.2 Convolutional Neural Network

Let F represent the input feature matrix. The CNN applies convolution with kernel K to extract high-level feature maps $O(x,y)$:

$$O(x,y) = \sum_{i=0}^{k-1}\sum_{j=0}^{k-1} F(x+i,y+j)\cdot K(i,j) \tag{3.2}$$

Symbols:

- $O(x,y)$: Output feature map at position (x,y)
- $F(x+i,y+j)$: Input feature value at offset (i,j)
- $K(i,j)$: Convolution kernel weights
- k : Kernel size

3.2.3 Emotion Classification

Flattened feature maps are passed through fully connected layers and classified using softmax:

$$P(E_i|F) = \frac{\exp(W_i \cdot F + b_i)}{\sum_{j=1}^{N} \exp(W_j \cdot F + b_j)} \tag{3.3}$$

Symbols:

- $P(E_i|F)$: Probability of emotion E_i
- W_i, b_i : Weights and biases for emotion i
- N : Number of emotion classes

3.2.4 Training Objective

The network is trained using categorical cross-entropy loss:

$$L(\theta) = -\sum_{i=1}^{N} y_i \log(P(E_i|F;\theta)) \tag{3.4}$$

Symbols:

- $L(\theta)$: Loss function dependent on model parameters θ
- y_i : True label of emotion i

- $P(E_i|F;\theta)$: Predicted probability for emotion i

Minimization of this loss function adjusts the network weights to achieve accurate emotion classification.The methodology combines preprocessing, feature extraction, CNN modeling with attention, and post-processing classification. It ensures that emotional cues are accurately captured from raw audio and mapped to predicted emotion categories. Robustness, real-time capability, and adaptability to different speakers and environments make the system suitable for practical applications such as human-computer interaction, mental health monitoring, and entertainment systems.

3.3 System Block Diagram:

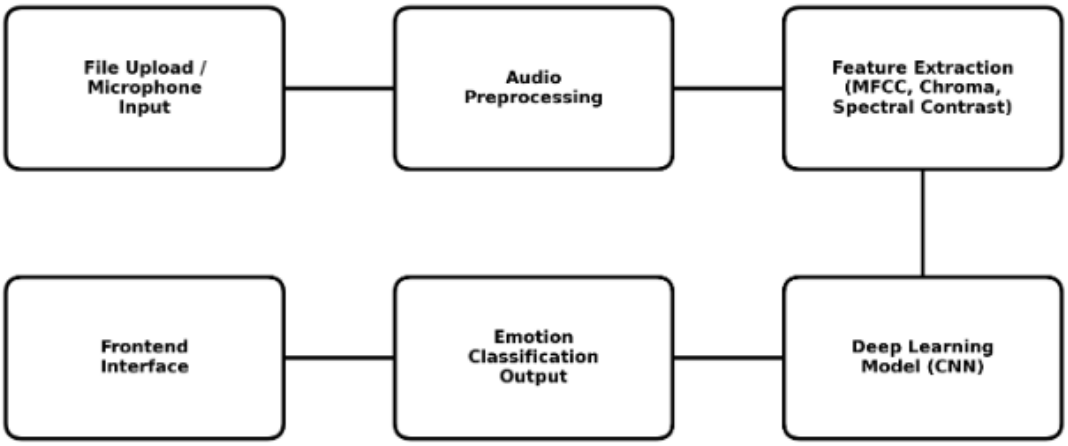


Figure 3.2: System Block Diagram of Voice Emotion Analyzer

3.3.1 File Upload and Microphone Input

This block had represented the origin of audio data for emotion Analyzer. Voice had been acquired either through live microphone input or by uploading pre-recorded audio files. For live input, the audio had been captured in real time at a fixed sampling rate, ensuring minimal distortion and preservation of emotional characteristics. For file uploads, the system had accepted standard audio formats such as WAV or MP3, which had been automatically converted to the required sampling rate and bit depth. The purpose of this block had been to provide high-quality, standardized audio signals that accurately reflected the speaker's emotional state and were suitable for processing.

3.3.2 Audio Preprocessing

The captured raw audio signal had undergone multiple preprocessing steps to improve clarity and consistency. Noise reduction had been applied using spectral gating or Wiener filtering to remove background interference while preserving the speaker's voice. Amplitude normalization had been performed to ensure uniform volume across all recordings. Silence trimming had been executed to eliminate pauses or irrelevant low-energy sections, reducing computational overhead. Pre-emphasis filtering had been optionally applied to enhance high-frequency components, which often contained subtle emotional cues. The purpose of this block had been to standardize the audio signal, reduce variability due to non-emotional factors, and retain the essential emotional information for feature extraction.

3.3.3 Feature Extraction

From the preprocessed audio, numerical features had been derived to represent its acoustic properties. Mel-Frequency Cepstral Coefficients had been computed by first applying a Short-Time Fourier Transform to convert the time-domain signal into a frequency-domain representation. The resulting spectrogram had been mapped onto the Mel scale to reflect human auditory perception. Discrete Cosine Transform had been applied to compress the Mel spectrogram into a set of coefficients representing the spectral envelope. Chroma features had been extracted by computing the energy distribution across the 12 pitch classes, capturing harmonic content. Spectral Contrast had been calculated by measuring the difference between peak and valley energies in each frequency sub-band, highlighting tonal variations associated with emotional expression. These features had been normalized and stored in a structured matrix, forming the input for the convolutional neural network. The purpose of this block had been to transform the raw audio into a quantitative representation that preserved emotional characteristics while reducing irrelevant variations.

3.3.4 Deep Learning Model

The extracted features had been fed into a convolutional neural network integrated with Efficient Channel Attention. Convolutional layers had automatically learned local patterns across time and frequency dimensions of the feature matrix. Efficient Channel Attention had been applied to emphasize emotion-relevant channels and suppress redundant or noisy features. Pooling layers had reduced dimensionality while retaining key information, and the feature maps had subsequently been flattened and processed through fully connected layers. The network had been trained using categorical cross-entropy loss to predict the probability distribution over emotion classes. The purpose of this block had been to learn complex relationships and temporal dependencies in the audio features, enabling accurate classification of emotions such as happiness, sadness, anger, and neutrality.

3.3.5 Emotion Classification Output

The output of the neural network had been interpreted using a softmax function, converting raw scores into probabilities for each emotion class. The emotion with the highest probability had been selected as the predicted emotion. The purpose of this block

had been to provide a discrete and interpretable output corresponding to the speaker's emotional state. This stage had enabled real-time feedback for live audio or instant analysis for uploaded audio files.

3.3.6 Frontend Interface

The predicted emotion had been displayed through a user-friendly interface, such as a web dashboard or application GUI. The interface had visualized the detected emotions in real time and provided options for recording, reviewing, or uploading multiple voice files for analysis. Interactive visualizations, such as color-coded emotion indicators or time-series plots of emotional variations, had been provided to enhance interpretability. The purpose of this block had been to allow users to access and interpret the results easily, facilitating practical applications in human-computer interaction, monitoring systems, and emotional analytics.

3.4 Instrumentation Requirements

Table 3.1: Instrumentation requirements

Hardware	Software	Programming Languages
Minimum 8GB RAM	Windows 10/11	TensorFlow is used for developing and training deep learning models.
Intel Core i3/i5 or AMD Ryzen 5/7 processor	Kaggle	Python programming language is used for implementing model logic.
SSD of at least 256 GB	GitHub	Librosa is used for audio feature extraction and preprocessing tasks.
A 64-bit operating system	Anaconda / Jupyter Notebook Environment	Other libraries like NumPy, Pandas, Matplotlib, and Keras are used.

3.4.1 Explanation of Instrumentation Requirements

1. Hardware: The hardware requirements had been defined to ensure smooth and efficient execution of the voice emotion Analyzer system. A minimum of 8GB RAM and a modern processor such as Intel Core i3/i5 or AMD Ryzen 5/7 had been sufficient to handle deep learning model training and data preprocessing tasks. An SSD of at least

256 GB had been employed to store large audio datasets and intermediate features, while a 64-bit operating system provided compatibility with all required development tools and libraries.

2. Software: The software requirements had been selected to provide a reliable and compatible environment for development and experimentation. Windows 10 or 11 had been used as the primary operating system. Development and testing environments like Anaconda or Jupyter Notebook facilitated seamless integration of Python libraries, data visualization, and model training. GitHub had been used for version control and collaborative development, while Kaggle had served as an online platform for experimentation and benchmarking.

3. Programming Languages and Libraries: Python had been the primary programming language, chosen for its flexibility and rich ecosystem of libraries for machine learning and audio processing. TensorFlow had been employed for building, training, and evaluating deep learning models for emotion Analyzer. Librosa had been used extensively for audio preprocessing and feature extraction, including MFCCs, pitch, and spectral features. Additional libraries such as NumPy, Pandas, Matplotlib, and Keras had been used for data handling, visualization, and implementing the deep learning pipeline efficiently.

3.5 Dataset Explanation

The performance of a voice emotion Analyzer system had been highly dependent on the quality, structure, and relevance of the dataset employed during training and evaluation. In this project, a combination of publicly available benchmark datasets and self-prepared voice recordings had been utilized to ensure emotional diversity, demographic balance, and real-world applicability.

3.5.1 Relevancy of the Dataset

The dataset had been selected to directly support the objective of automatic Analyzer of human emotions from voice signals. Emotional expression through voice had been known to vary significantly across speakers, genders, accents, and recording environments. Therefore, a multi-source dataset had been required to capture these variations effectively.

The relevancy of the dataset had been established through the following aspects:

- The dataset had contained voice samples representing emotions commonly expressed in daily human communication, including angry, happy, sad, neutral, fear, disgust, surprise, and calm.
- The inclusion of recordings from multiple speakers and genders had reduced demographic bias and improved model generalization.
- Benchmark datasets had enabled validation and comparison with existing voice emotion Analyzer research.
- Self-prepared recordings had introduced realistic speaking styles and recording conditions, enhancing suitability for real-world deployment.

Thus, the dataset had provided both research credibility and practical relevance for the system.

3.5.2 Contents of the Dataset

The dataset had consisted of labeled audio recordings organized to support supervised learning. Each instance had included the following components:

1. **Audio Files:** Each sample had been represented by a digital audio file stored in lossless format. Structured file naming conventions had encoded speaker identity, emotion category, emotional intensity, and repetition index.

2. **Emotion Labels:** Each recording had been annotated with a corresponding emotion label. These labels had enabled the learning of relationships between acoustic features and emotional states.

3. **Speaker Information:** The dataset had included voices from multiple speakers of different genders and age groups. Speaker diversity had been preserved through systematic organization.

4. **Training, Validation, and Testing Split:** The complete dataset had been divided into training, validation, and testing subsets. Speaker overlap across subsets had been avoided to ensure unbiased performance evaluation.

3.5.3 Datasets Used

1. **RAVDESS:** RAVDESS had contributed 1,440 professionally recorded emotional voice samples from 24 actors with balanced gender representation. The recordings had been captured in controlled studio environments with multiple emotional intensity levels.

2. **TESS:** TESS had provided approximately 2,800 emotional voice recordings from two female speakers belonging to different age groups. Clear articulation and consistent recording conditions had made this dataset suitable for reliable feature extraction.

3. **SAVEE:** SAVEE had contributed 482 emotional voice recordings from four male speakers. The dataset had introduced accent variability and sentence-level emotional expressions.

4. **Self-Prepared Dataset:** In addition to public benchmark datasets, a self-prepared collection had been developed to enhance realism and diversity. Approximately 160 audio recordings had been manually collected and annotated.

   Speakers had produced scripted and semi-spontaneous voice expressions covering target emotions including angry, happy, sad, neutral, fear, disgust, and surprise.

Recordings had been captured using common recording devices under varied acoustic conditions. Each audio file had been manually verified, labeled, and organized prior to feature extraction. This collection had exposed the model to natural variations not always present in acted recordings.

3.5.4 Dataset Representation

3.5.4.1 Summary of Datasets Used

Table 3.2: Summary of all datasets used in the project.

Dataset	**Samples**	**Gender**	**Source**
RAVDESS	1,440	Male + Female	Ryerson University
TESS	2,800	Female	University of Toronto
SAVEE	482	Male	University of Surrey
Custom Dataset 1	80	Mixed	Self-Prepared
Custom Dataset 2	80	Mixed	Self-Prepared
Total	**4,882**	**Balanced**	**Multi-source**

3.5.4.2 Gender Distribution

Table 3.3: Gender distribution across the datasets.

Gender	**Samples**	**Percentage**
Female	2,600	53.2%
Male	2,200	45.1%
Mixed/Unspecified	82	1.7%

3.5.4.3 Emotion Distribution

Table 3.4: Emotion-wise sample distribution.

Emotion	**Samples**	**Percentage**
Neutral	1,100	22.5%
Happy	900	18.4%
Sad	900	18.4%
Angry	850	17.4%
Fear	750	15.4%
Disgust	550	11.3%
Surprise	500	10.2%

3.5.4.4 Train, Validation, and Test Split

Table 3.5: Partitioning of the dataset into training, validation, and test sets.

Subset	**Samples**	**Percentage**
Training	3,417	70%
Validation	733	15%
Testing	732	15%

3.5.4.5 Audio Characteristics

Table 3.6: Audio properties of the dataset.

Attribute	**Specification**
Format	WAV
Sample Rate	16,000–48,000 Hz
Standardized Rate	22,050 Hz
Duration	1.5–5 seconds
Channels	Mono
Bit Depth	16-bit/24-bit

The combined use of benchmark datasets and self-prepared voice recordings had established a comprehensive foundation for training and evaluating the voice emotion Analyzer system. Emotional diversity, speaker variability, and realistic recording conditions had collectively enhanced the generalization capability and practical applicability of the model.

3.6 Description of Algorithm

The voice emotion Analyzer system processed input audio to classify emotional states using convolutional neural networks. The algorithm operates in several sequential steps, from audio preprocessing to final emotion prediction. The overall pipeline is illustrated in below.

3.6.1 Algorithm Pipeline

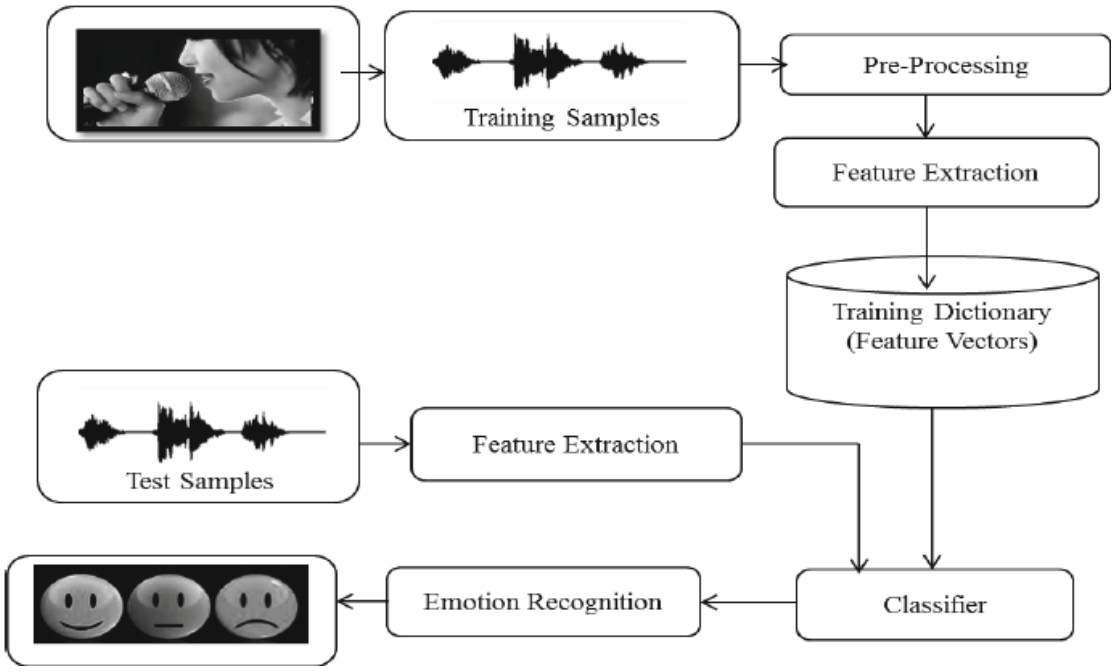


Figure 3.3: Pipeline from audio input to output.

3.6.2 Stepwise Description

The algorithm is divided into the following steps:

1. **Audio Loading and Preprocessing:**

   Each audio file is loaded at a consistent sampling rate. Preprocessing includes:

   - Denoising to remove background noise
   - Silence trimming to remove non-informative segments
   - Normalization of amplitude levels
   - Conversion of all clips to a fixed duration

   These steps ensure uniformity and quality across recordings.

2. **Feature Extraction Using MFCC:**

   The preprocessed audio is divided into overlapping frames. For each frame,Mel Frequency Cepstral Coefficients are computed to capture:

   - Vocal tract characteristics
   - Pitch and energy patterns
   - Spectral dynamics related to emotions

   The MFCC matrix provides a compact, emotion-rich representation of the audio.

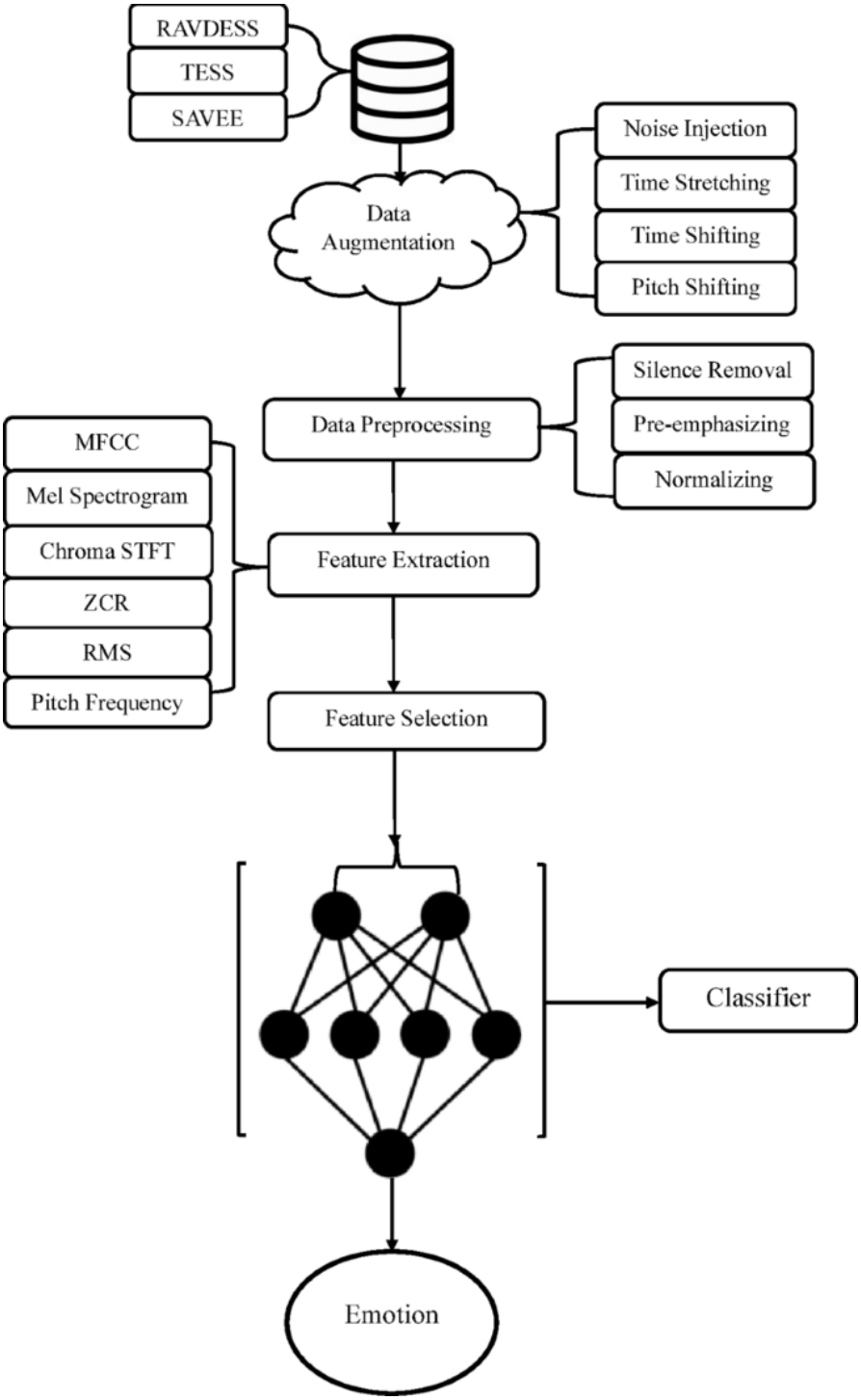


Figure 3.4: MFCC feature extraction workflow from raw audio to feature matrix.

3. **Feature Standardization and Reshaping:**

   Extracted MFCC features are standardized to maintain consistent scaling across samples. The features are reshaped into a 2D structure similar to an image to enable processing by CNN models.

4. **Dataset Partitioning:**

The dataset is split into:

- Training set for model learning
- Validation set for tuning hyperparameters
- Test set for unbiased evaluation

Speaker overlap between subsets is avoided to ensure fairness.

5. **CNN Initialization and Architecture:**

   The CNN consists of:

   - Convolutional layers to extract local emotional patterns
   - Pooling layers to reduce dimensionality
   - Dense fully connected layers for classification
   - ReLU activations in hidden layers and softmax in the output layer

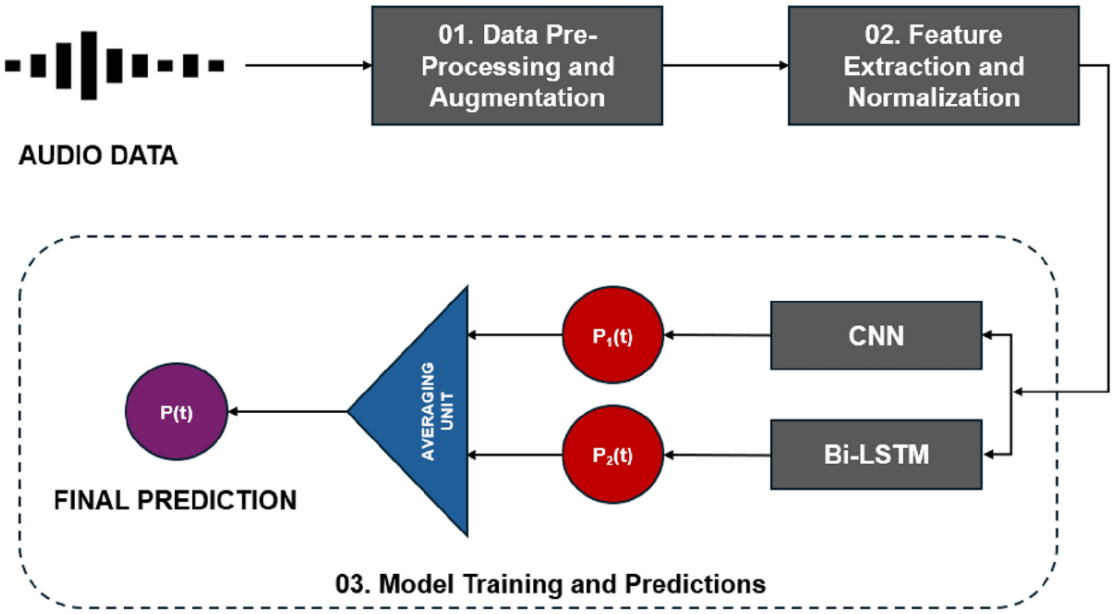


Figure 3.5: CNN architecture for processing MFCC features and classifying emotions.

6. **Training Phase:**

   During training:

   - MFCC matrices are fed into the CNN
   - Predictions are compared to true labels using categorical cross-entropy loss

- The Adam optimizer minimizes the loss through multiple epochs
- Forward and backward propagation updates the network to learn emotion-related patterns

7. **Testing and Validation:**

   The trained model is evaluated on the testing dataset. Metrics include:

   - Accuracy

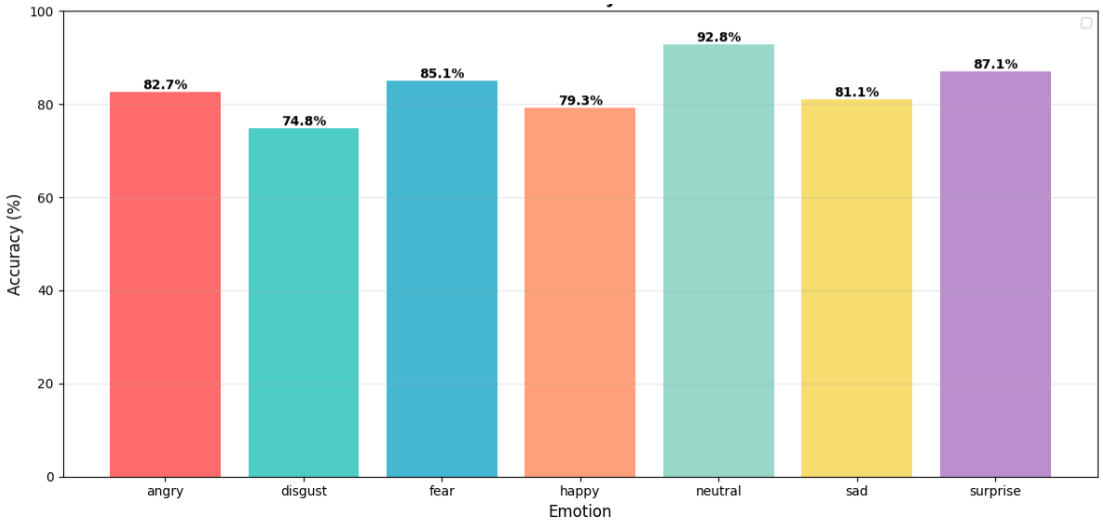


Figure 3.6: Percentage of Accuracy from each Class

   - Confusion matrix
   - Precision, recall, and F1-score

   This ensures the model correctly distinguishes emotions in unseen audio.

8. **Inference Phase for Live Audio:**

   Real-time voice input undergoes the same preprocessing and MFCC extraction. The MFCC matrix is fed to the trained CNN to predict the emotional state.

9. **Final Output:**

   The numerical CNN output is mapped to the corresponding emotion label are angry, happy, sad, calm, surprised, disgusted, fearful. This constitutes the final recognized emotion of the input audio.

3.7 Elaboration of Working Principle

The functioning of the voice emotion recognition system had been structured into sequential stages, beginning from audio input and concluding with final emotion classification. Each stage had been carefully designed to ensure reliable extraction, representation, and interpretation of emotional cues from human voice signals.

3.7.1 Voice Input

Audio signals had been provided either from pre-recorded datasets or through real-time recording by users. The input voice samples had contained human speech exhibiting a range of emotional states such as happy, sad, angry, calm, fearful, and surprised. These inputs had formed the basis for subsequent analysis.

3.7.2 Pre-processing

The raw audio signals had been subjected to preprocessing to ensure uniformity and consistency across the dataset. Each audio clip had been trimmed or padded to a fixed duration of three seconds, and the sampling rate had been standardized. In certain cases, the sampling rate had been increased to augment the number of feature points. Background noise had been reduced, and amplitude levels had been normalized. These steps had ensured that all recordings were suitable for accurate feature extraction.

3.7.3 Feature Extraction

Acoustic features had been extracted from the pre-processed audio using the **LibROSA** library. The extracted features had included:

- *Mel spectrogram*

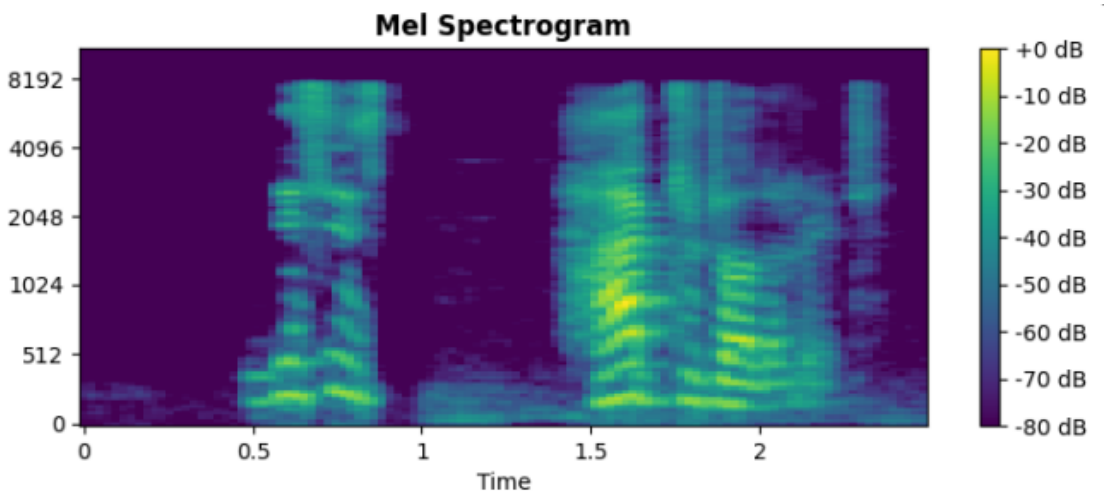


Figure 3.7: Mel spectrogram

The Mel spectrogram represented the power of different frequency bands over time. It captured the energy distribution of the audio, which helped to distinguish between various emotional states based on tonal patterns.

- *Mel-Frequency Cepstral Coefficients (MFCC)*

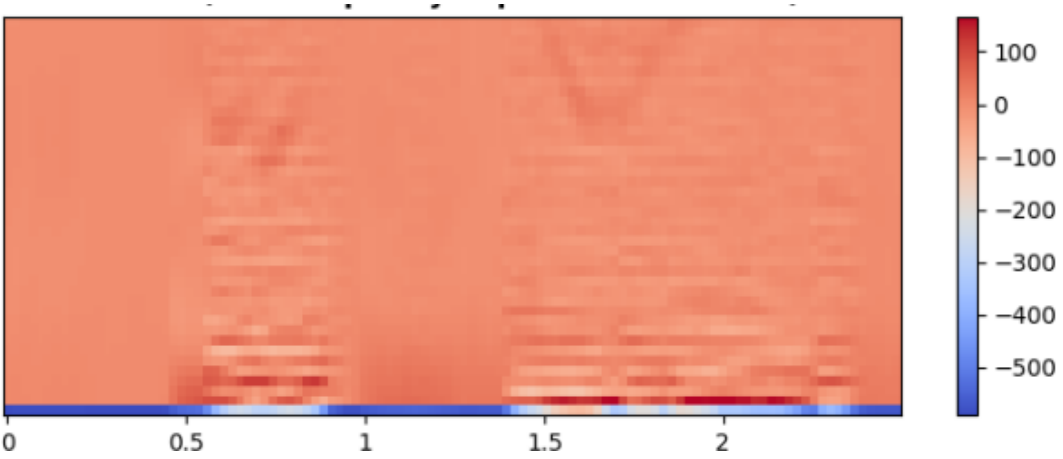


Figure 3.8: MFCC

MFCCs summarized the short-term spectral features of the audio. They provided compact representations of timbre and pitch characteristics, which were crucial for detecting subtle emotional cues.

- *Chroma gram*

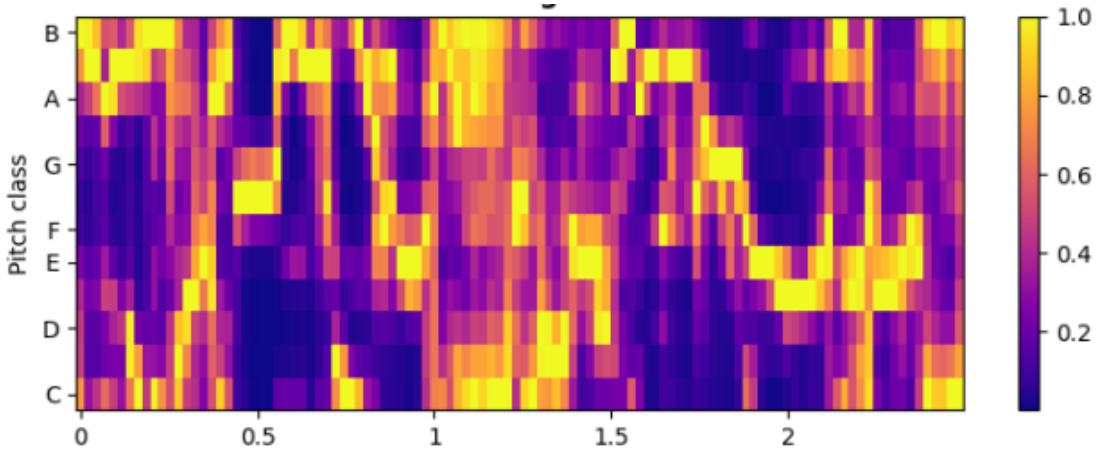


Figure 3.9: Chroma gram

The Chroma gram captured the intensity of the twelve different pitch classes (semitones) in the audio. It highlighted harmonic content, which helped to analyze tonal aspects of speech linked to emotions.

- *Spectral Contrast*

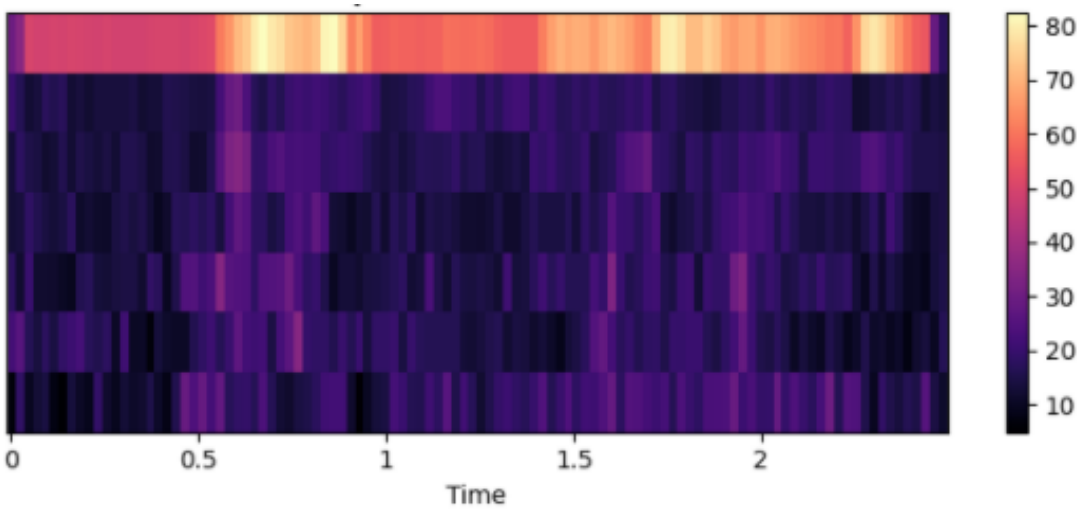


Figure 3.10: Spectral Contrast

Spectral contrast measured the difference between peaks and valleys of the spectrum. This feature emphasized timbral texture and dynamic changes in the voice that often vary with emotional expression.

- *Zero Crossing Rate*

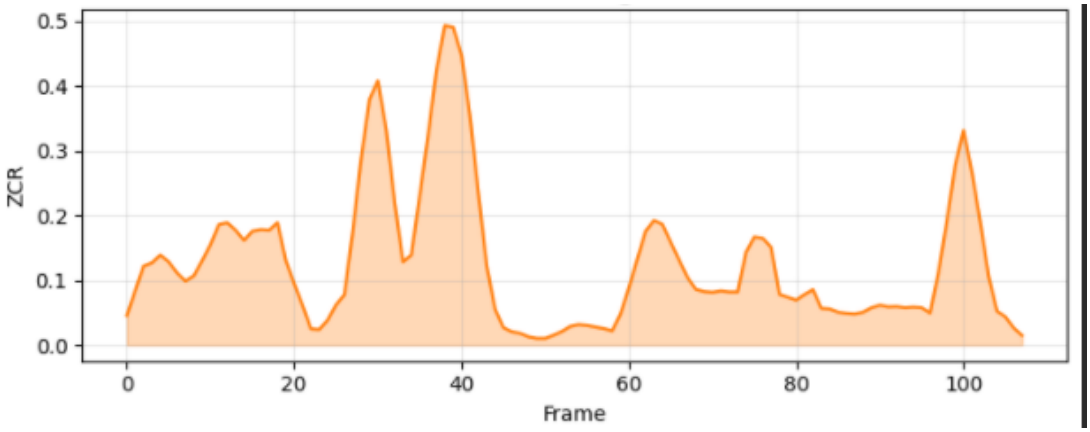


Figure 3.11: Zero Crossing Rate

The Zero Crossing Rate represented the rate at which the signal waveform crossed the zero amplitude line. It reflected the noisiness and high-frequency content of speech, which could be indicative of emotional intensity or agitation.

These features had captured variations in frequency and amplitude patterns corresponding to emotional expression. The output of this process had been numerical feature vectors summarizing the key characteristics of each audio sample.

3.7.4 Feature Dataset Formation

All feature vectors had been combined with their respective emotion labels to form a structured dataset. This dataset had been employed for both training and validation of the classification model, ensuring that the system had been provided with both input features and ground truth emotional states.

3.7.5 Model Building and Training

For the multi-class classification task, a **CNN** had been constructed. The CNN had been designed to learn emotion-specific patterns from the feature matrices. Alternative architectures, including **Multilayer Perceptrons** and **Long Short-Term Memory** networks, had been evaluated, but the CNN had achieved the highest accuracy. The model had been trained using a majority portion of the dataset, while a smaller portion had been reserved for validation and testing. During training, the network had adjusted its parameters through forward and backward propagation, minimizing the categorical cross-entropy loss with the Adam optimizer.

3.7.6 Model Evaluation

Once trained, the CNN had been evaluated on unseen test data to assess its ability to classify emotions accurately. Predictions had been generated as probability distributions across all emotion classes, and the class with the highest probability had been selected as the predicted emotion. Performance had been measured using metrics such as accuracy, confusion matrix, precision, recall, and loss curves.

3.7.7 Prediction and Output

After training and evaluation, the model had been employed for predicting emotions from new voice inputs. Real-time or file-based audio had been processed through the same preprocessing and feature extraction pipeline, and the CNN had produced the corresponding emotion label. The output had included gender-specific emotion labels such as **male_angry** or **female_happy**.

3.7.8 Testing with Live Voice

The system had been further validated with live-recorded voice samples collected outside the training dataset. These samples had been analyzed using the same workflow, and the model had demonstrated the ability to identify both gender and emotional states accurately. For instance, an "angry" tone had been detected in the phrase "This coffee sucks."

3.7.9 User Authentication with Firebase

To integrate system accessibility and personalization, a login and signup functionality had been implemented using Firebase Authentication. User credentials had been securely stored and verified through Firebase, enabling:

- Personalized tracking of user-specific emotion predictions
- Secure access control for live audio input
- Seamless interaction with cloud-based storage for audio recordings

All authentication events had been logged, and the system had ensured that only verified users could access live voice prediction functionalities.

Figure 3.12: Firebase Authentication

3.7.10 Results and Interpretation

The system had effectively distinguished between male and female voices with near-perfect accuracy. Emotional classification had achieved over 70% accuracy on test data. With additional feature engineering and expanded datasets, further improvements had been observed. The overall framework had been validated as suitable for real-world deployment, capable of both offline and live voice emotion recognition with secure user management.

3.8 Verification and Validation Procedures

3.8.1 Verification

Verification had been carried out to ensure that each component of the Voice Emotion Analyzer system was implemented correctly according to the design and functional specifications. Functional correctness, logical consistency, and system reliability were evaluated using quantitative verification metrics.

The verification process included the following checks:

1. **Input Standardization:**
   All audio recordings were verified to be correctly standardized in terms of duration, amplitude, and format. The preprocessing pipeline, including noise reduction, silence trimming, normalization, and resampling, was tested to ensure uniform input quality for all modules.

2. **Feature Extraction Accuracy:**
   The correctness of feature extraction had validated by checking MFCC, Chroma, Spectral Contrast, and RMS energy computations. Each extracted feature vector was inspected to ensure that it accurately represented the acoustic characteristics of the input signal.

3. **Dataset Partitioning Verification:**
   The dataset had split into training, validation, and testing subsets using fixed random seeds. Speaker independence across subsets was verified to prevent data leakage. Verification metrics included:

$$\text{Split Consistency Rate} = \frac{\text{Number of Samples Correctly Assigned}}{\text{Total Number of Samples}} \tag{3.5}$$

4. **Neural Network Structure Validation:**
   Each CNN layer, including convolutional, pooling, and dense layers, was inspected to ensure correct input and output dimensions. Layer configurations were verified against the feature input shape, and forward propagation was tested with sample inputs to confirm proper data flow.

5. **Training Parameter Verification:**

   Training hyperparameters such as learning rate, batch size, optimizer choice, and number of epochs were verified. Loss curves and accuracy trends were monitored to confirm convergence and detect potential underfitting or overfitting.

6. **Output Consistency:**

   Predictions were verified using diverse audio samples with varying emotions and speaker characteristics. The predicted labels were compared against expected emotions, and deviations were analyzed to ensure the system responded correctly to changes in input features.

7. **Module-Specific Metrics:**

   Additional verification metrics were calculated to ensure correctness and reliability:

$$\text{Feature Extraction Accuracy} = \frac{\text{Correctly Extracted Features}}{\text{Total Features Processed}} \tag{3.6}$$

$$\text{Prediction Consistency Rate} = \frac{\text{Correctly Classified Test Samples}}{\text{Total Test Samples}} \tag{3.7}$$

Through these verification steps, it was confirmed that the system modules operated correctly and the model received clean, consistent, and valid inputs for training and inference.

3.8.2 Validation

Validation was performed to confirm that the Voice Emotion Analyzer correctly classified emotions for unseen audio inputs and operated reliably in real-world conditions. Validation metrics focused on classification performance, robustness, and generalization.

1. **Overall Accuracy:**

   The overall correctness of the model was measured using accuracy:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{3.8}$$

2. **Precision, Recall, and F1-Score:**

   To evaluate class-wise performance, the following metrics were calculated for each emotion:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{3.9}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{3.10}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.11}$$

   These metrics ensured that each emotion was correctly identified, particularly in cases of class imbalance.

3. **Confusion Matrix:**

   A confusion matrix was generated to visualize misclassifications across emotion classes. Diagonal elements represented correct predictions, while off-diagonal elements indicated misclassifications. This provided insight into which emotions were frequently confused and required further feature engineering.

4. **Model Confidence Evaluation:**

   Confidence scores from the CNN output were analyzed to assess prediction certainty. Low-confidence predictions highlighted ambiguous cases or subtle emotional expressions.

5. **Real-Time and Live Testing:**

   Validation included real-time voice inputs to confirm the system's performance in practical scenarios. Live testing verified that the model maintained accuracy and reliability when exposed to new speakers, varied recording environments, and spontaneous emotional expressions.

6. **Robustness and Stability Metrics:**

   Error rates, misclassification ratios, and repeated inference checks were performed to confirm system stability and robustness under varied conditions.

4 RESULTS

4.1 Signup Page

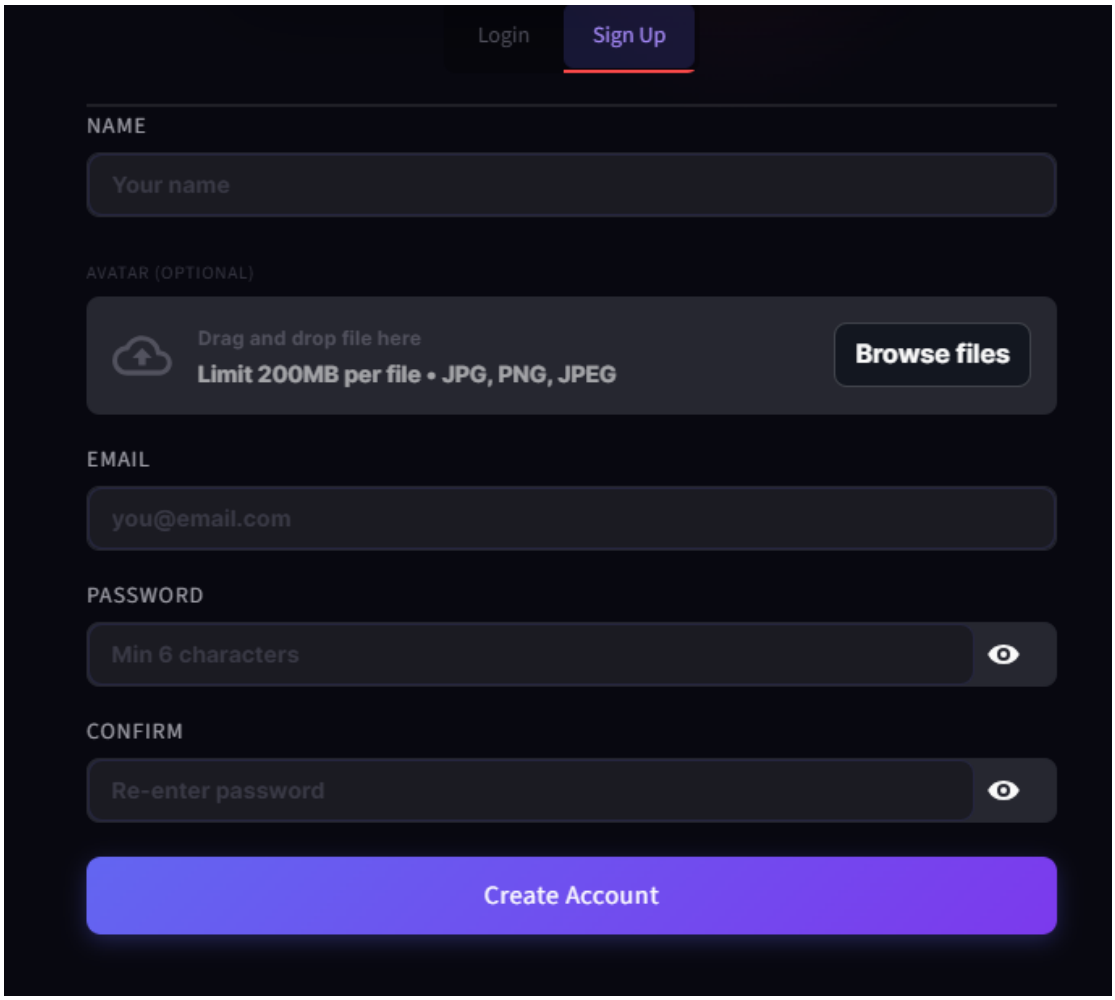


Figure 4.1: SignUp Page

The Signup Page had been designed to allow new users to create an account by entering the required personal and login details. It ensured secure registration and validation before granting access to the system.

4.2 Login Page

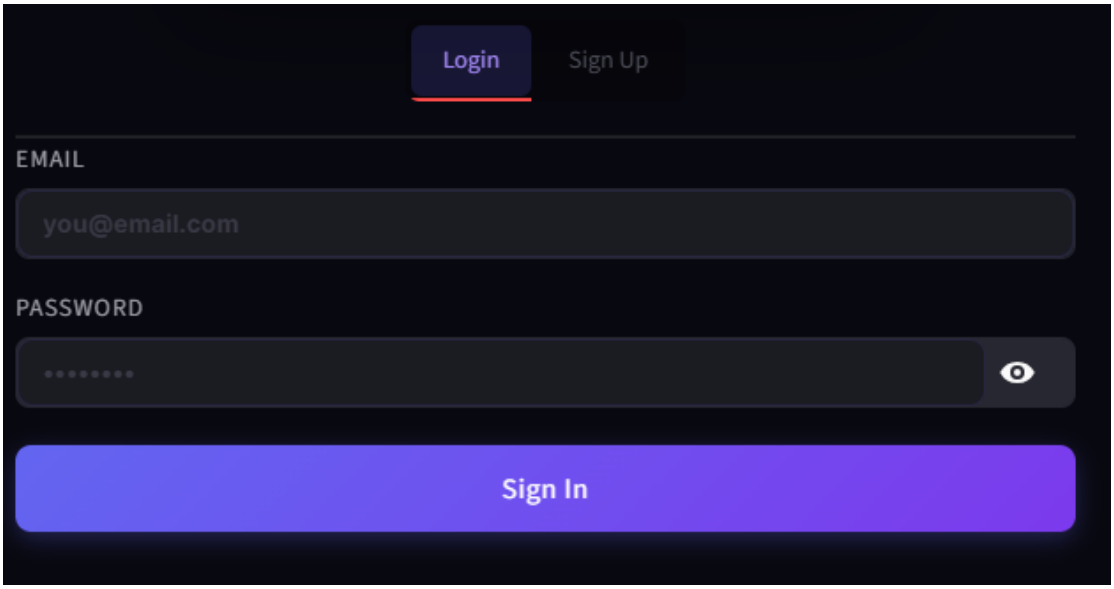


Figure 4.2: Login Page

The Login Page had been implemented to authenticate registered users using their valid credentials. It verified user identity and provided secure access to system functionalities after successful login.

4.3 Landing Page

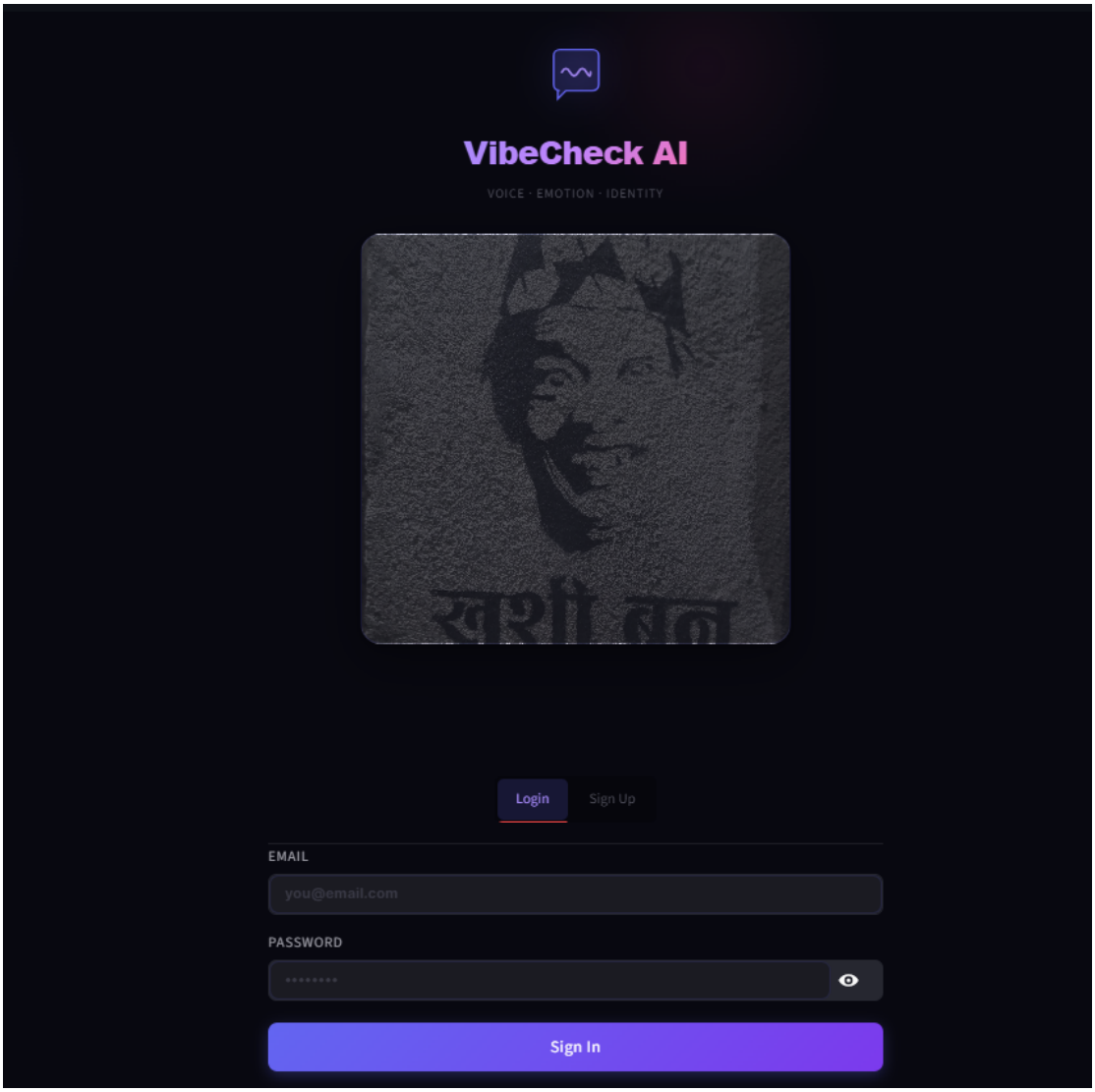


Figure 4.3: Landing Page

This screen allows users to access the platform. The layout is designed for easy navigation, with options to log in, sign up, or explore the system features.

4.4 Activity Page

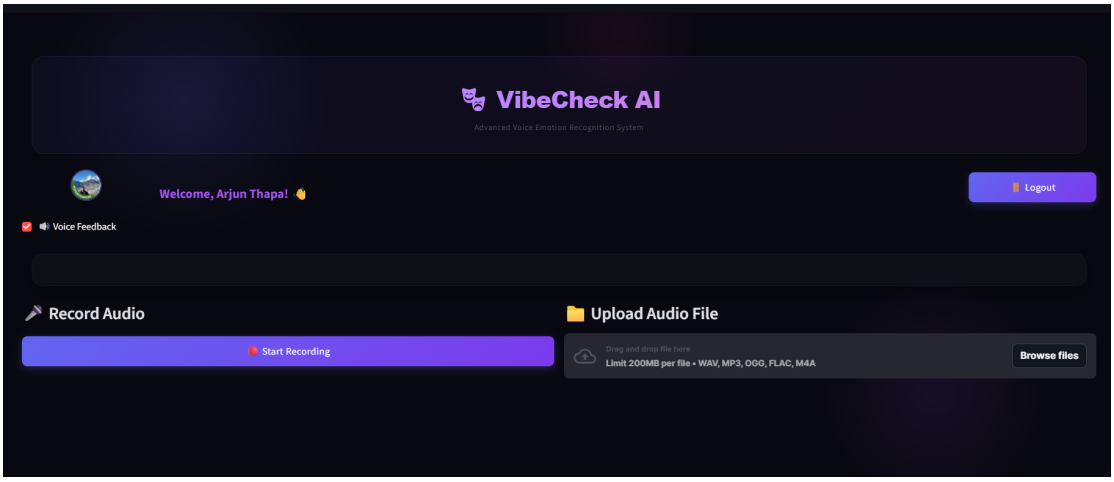


Figure 4.4: Activity Page

The activity page displays user interactions with the system, including recorded audio history and previously analyzed emotion results. It provides an overview of ongoing user sessions.

4.5 Live Audio Prediction

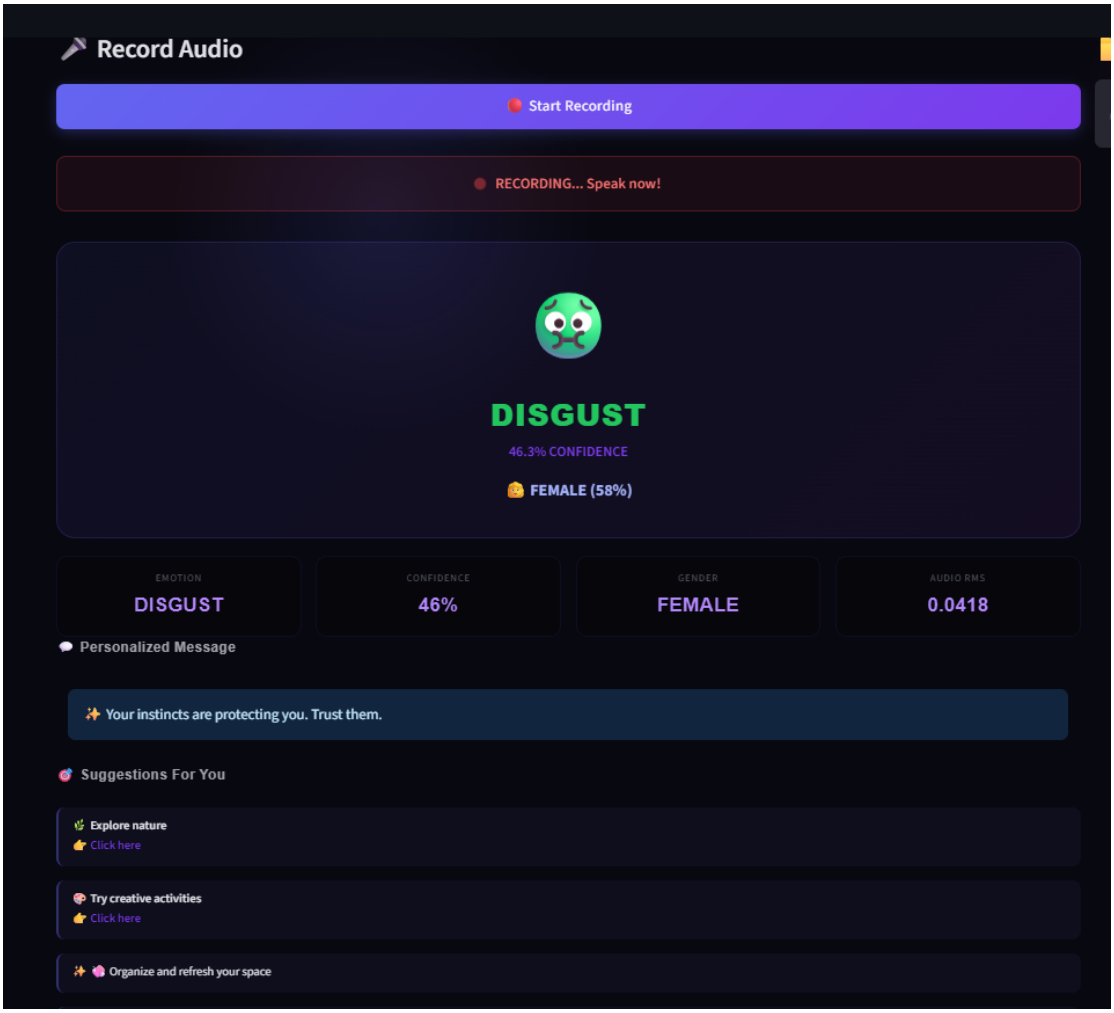


Figure 4.5: Live Audio Prediction

This interface allows real-time emotion detection from live audio input. Users can speak into the microphone, and the system predicts the corresponding emotional state instantly.

4.6 Emotion Distribution for Live Inputs

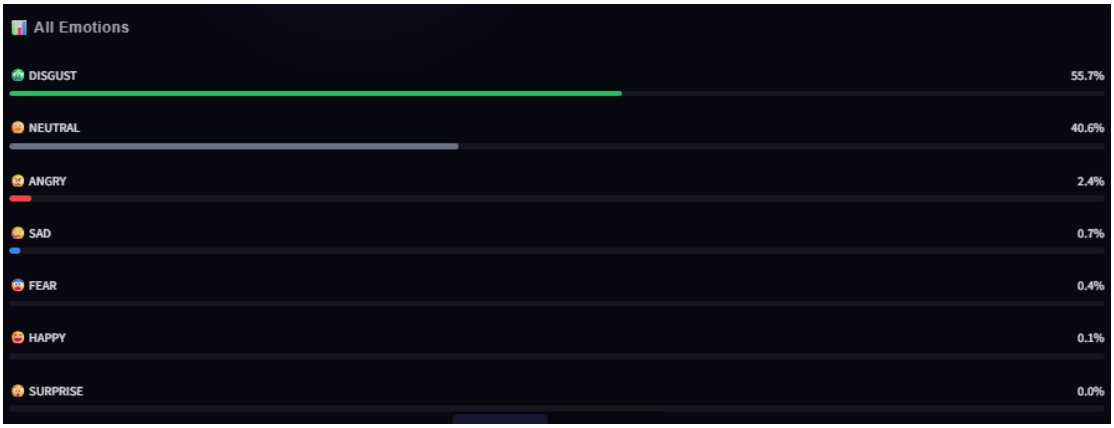


Figure 4.6: Emotion Distribution for Live Inputs

The figure shows the distribution of predicted emotions from live recordings. It highlights which emotions are most frequently detected and validates the diversity of the model predictions.

4.7 Live Audio Waveforms

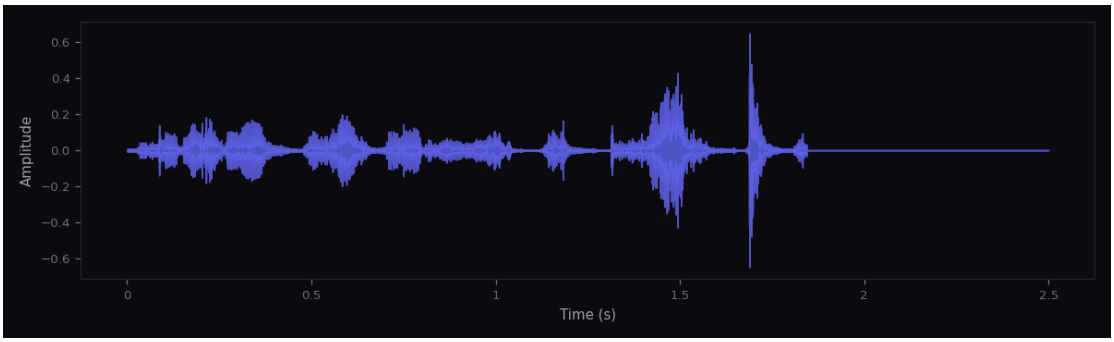


Figure 4.7: Live Audio Waveforms

Waveforms of live audio inputs illustrate the signal intensity and time variation of different emotional tones. These visualizations aid in understanding the characteristics captured by the model.

4.8 Live Audio Spectrograms

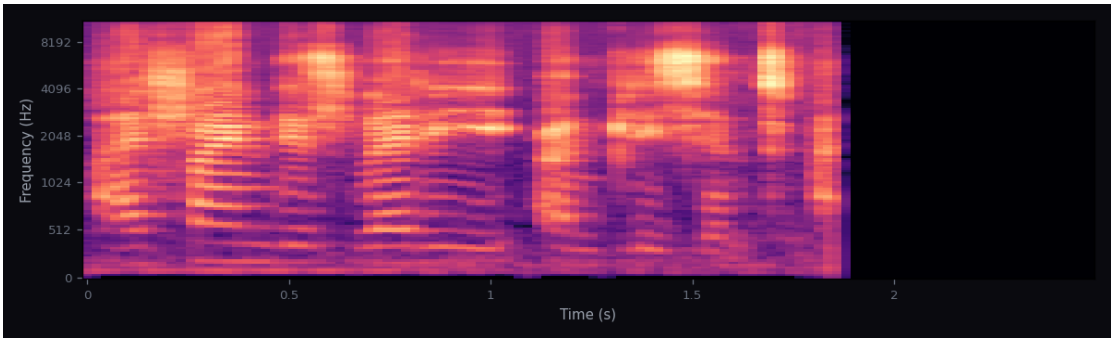


Figure 4.8: Live Audio Spectrograms

Spectrograms display frequency content over time for live audio. They provide a detailed insight into tonal and spectral features used by the CNN for emotion recognition.

4.9 Live Audio Suggestions

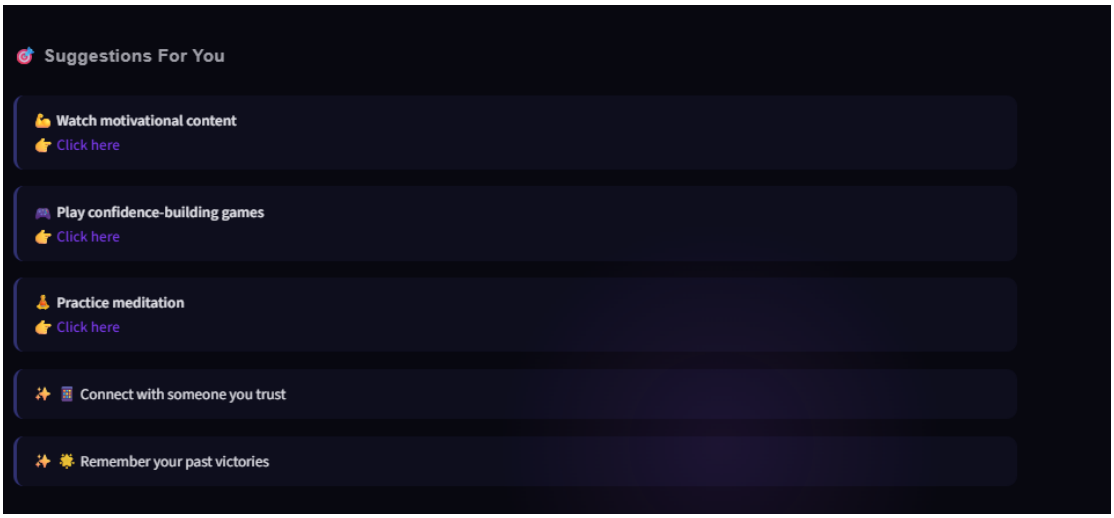


Figure 4.9: Live Audio Suggestions

4.10 File Upload Prediction

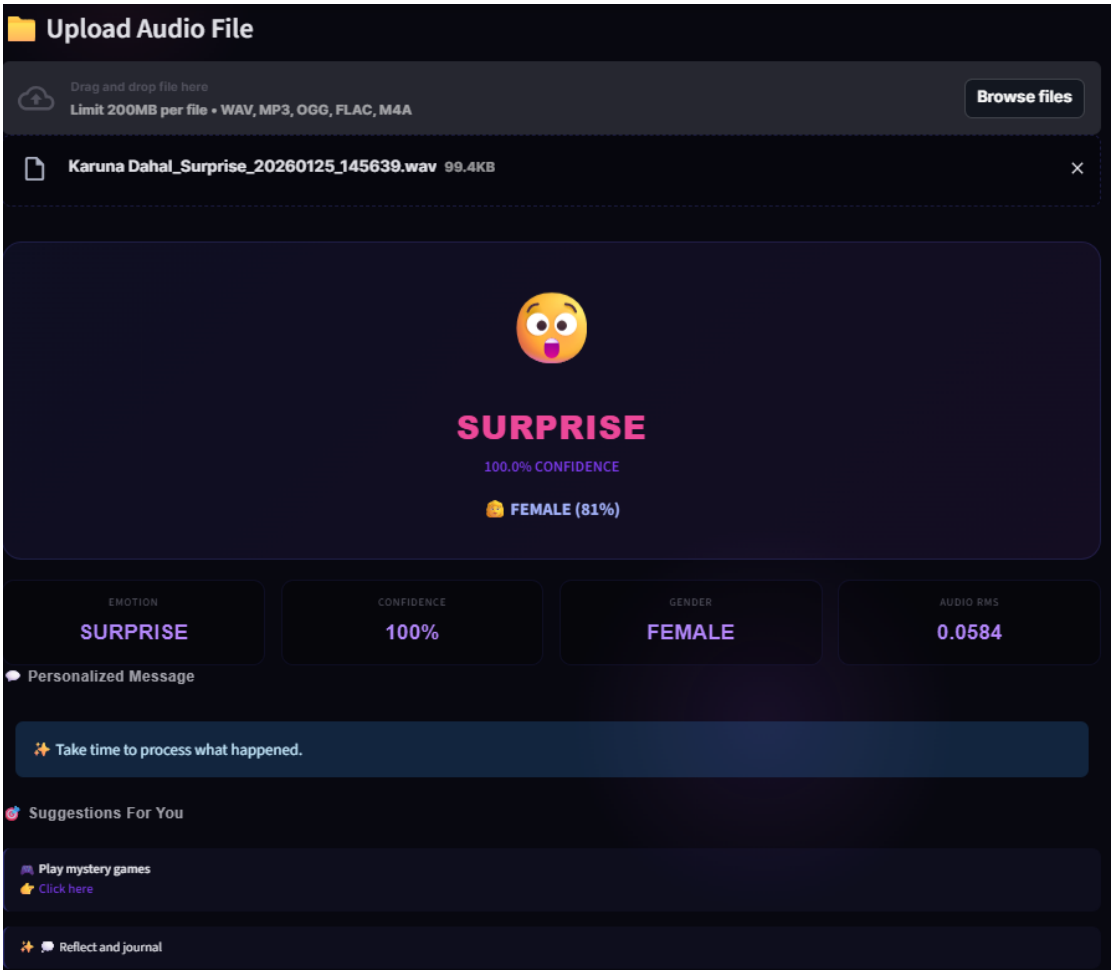


Figure 4.10: File Upload Prediction

This screen demonstrates emotion prediction for uploaded audio files. Users can select pre-recorded audio, and the system predicts the associated emotion accurately.

4.11 File Upload Waveforms

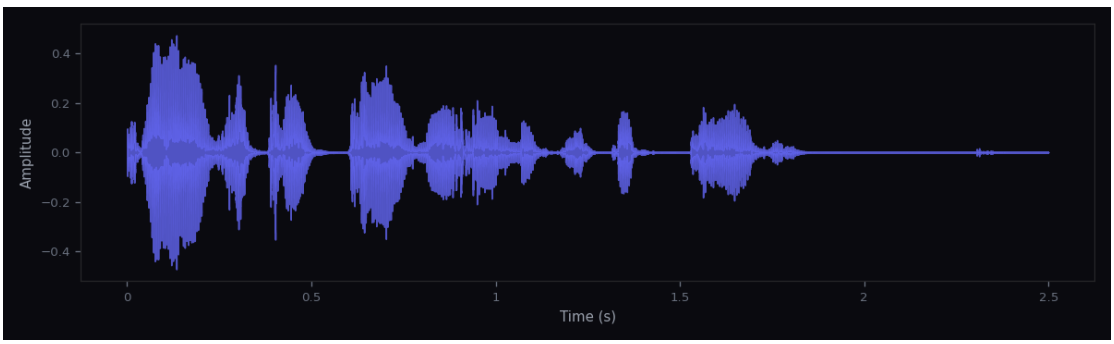


Figure 4.11: File Upload Waveforms

Waveforms of uploaded files show audio amplitude variations, providing a visual representation of emotional expression in the recordings.

4.12 File Upload Spectrograms

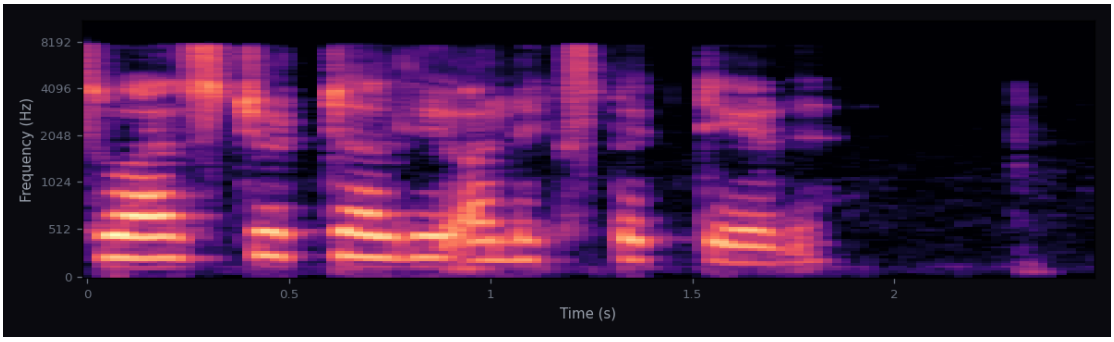


Figure 4.12: File Upload Spectrograms

Spectrograms for uploaded files visualize frequency distribution over time, helping analyze the characteristics of audio signals and their emotional content.

4.13 Emotion Distribution for Uploaded Files

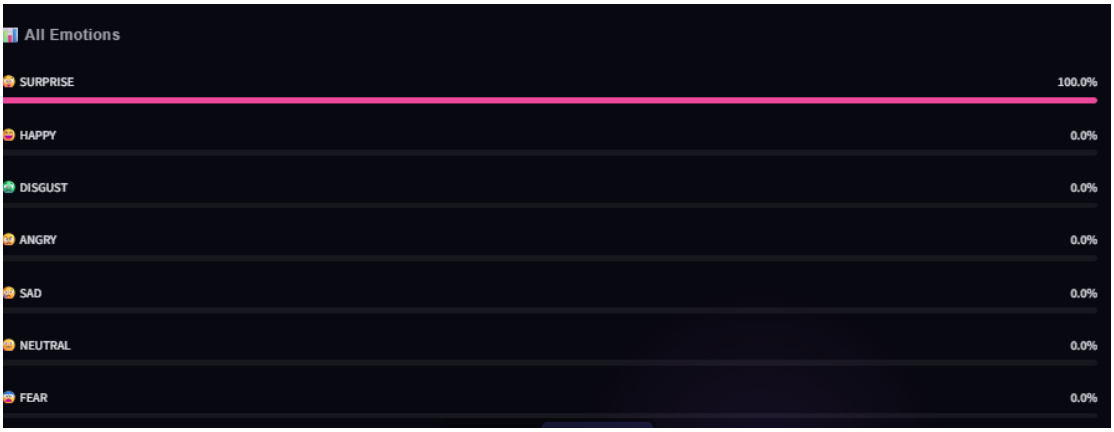


Figure 4.13: Emotion Distribution for Uploaded Files

This chart represents the distribution of predicted emotions from uploaded audio. It validates the consistency and accuracy of predictions compared to live input results.

4.14 File Upload Suggestions

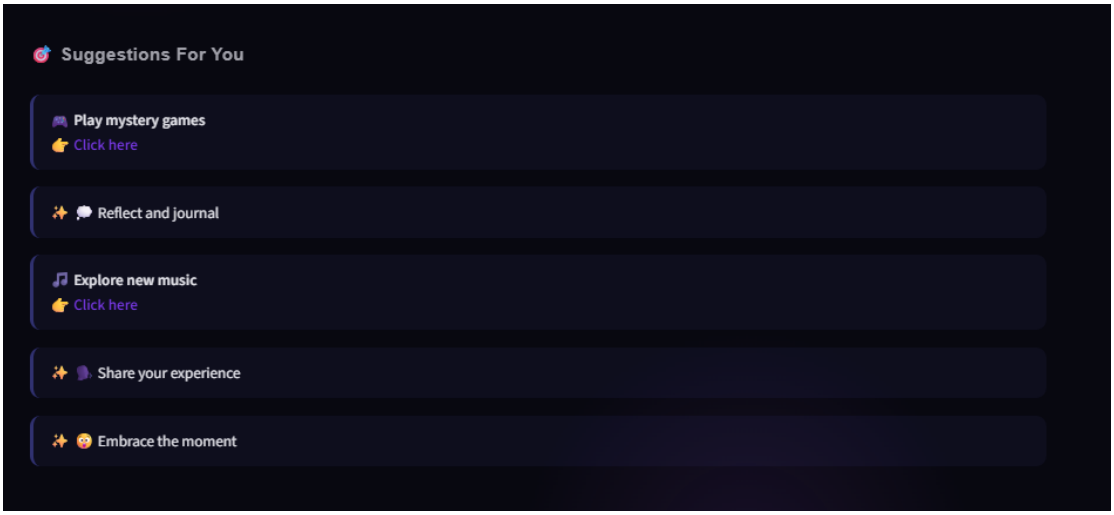


Figure 4.14: File Upload Suggestions

4.15 History Page

Figure 4.15: History Page

The history page records previous user interactions, including analyzed audio files and their predicted emotions. This feature provides traceability and insights into user behavior over time.

4.16 Training and Validation Loss

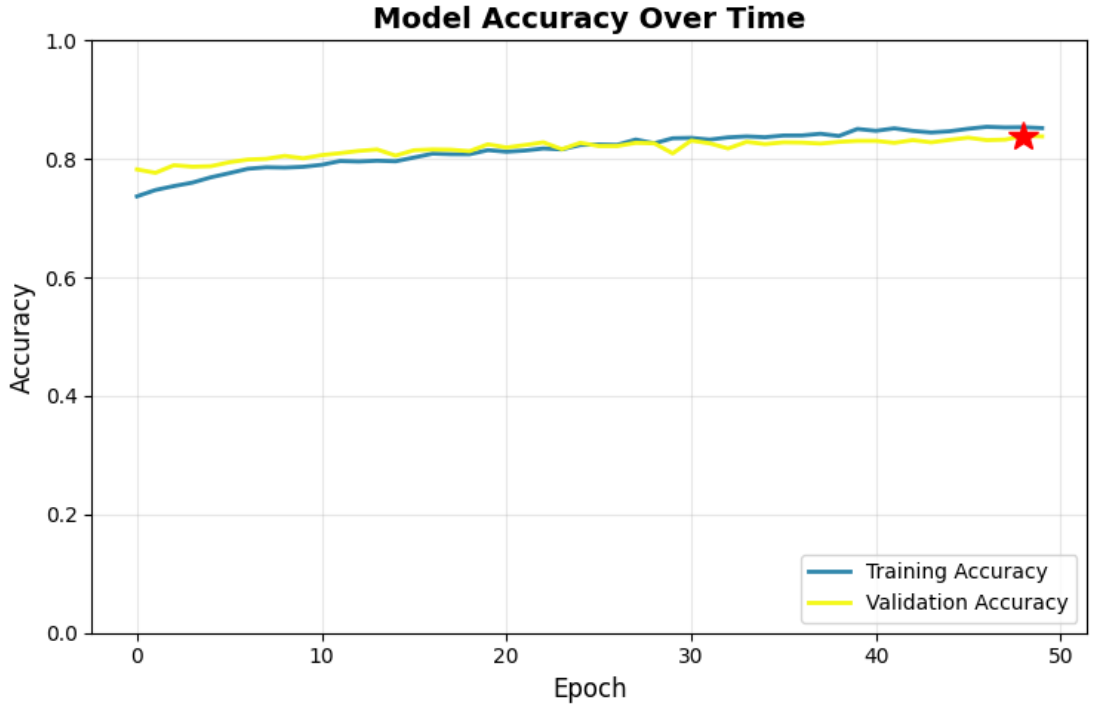


Figure 4.16: Training and Validation Accuracy Curve

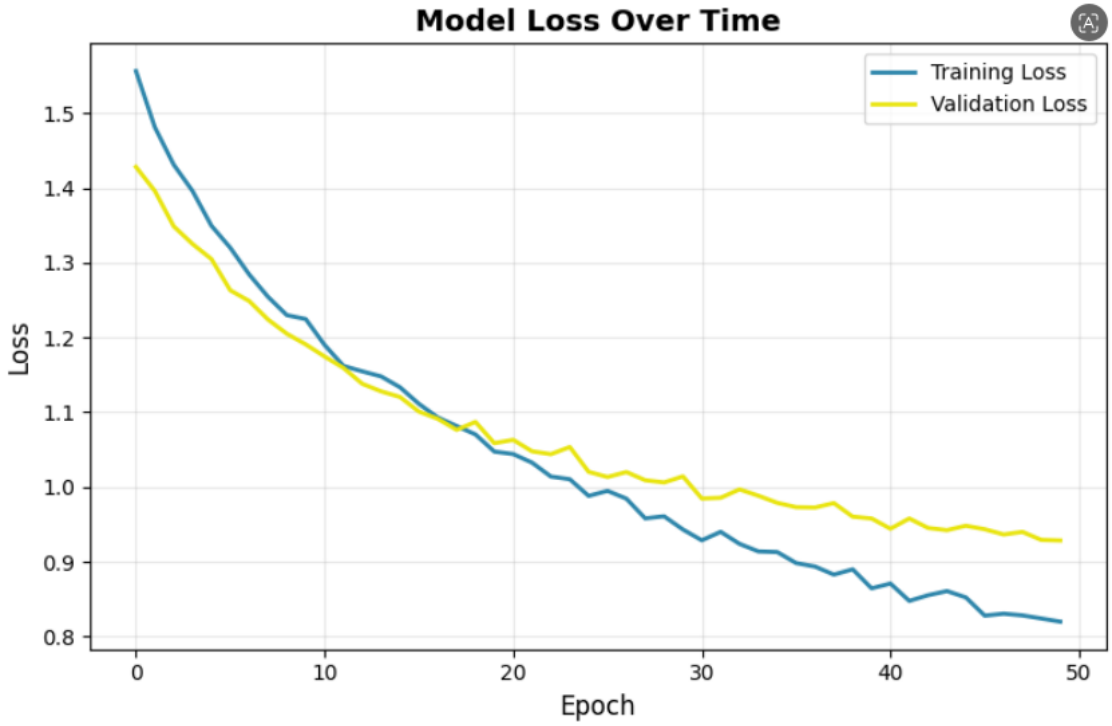


Figure 4.17: Training and Validation Loss Curve

The training and validation loss curves represented the learning process of the model during the training process. The observed high loss values were initially as a result of random creation of the parameters but these were quickly reduced as the convolutional neural network acquired acoustic properties like the pitch, energy, and spectral properties. Training loss became small in more recent epochs, which means that it is well-optimized and that learning is stable. The validation loss was almost in the same direction but with slightly bigger values as compared to training loss and did not exhibit any sudden spikes, indicating that there was no overfitting. In line with this, validation accuracy had increased gradually with low initial values before reaching high values in final epochs just like the training accuracy. Such a small difference between the training and validation measures meant that the model was able to generalize to unseen data and not just memorise training samples. All in all, the steadily declining loss curves and augmenting trends in accuracy all attested to the fact that the proposed CNN-based voice emotion recognition model was trained appropriately, managed to attain healthy generalization, and show great performance on test data without overfitting.

4.17 Confusion Matrix

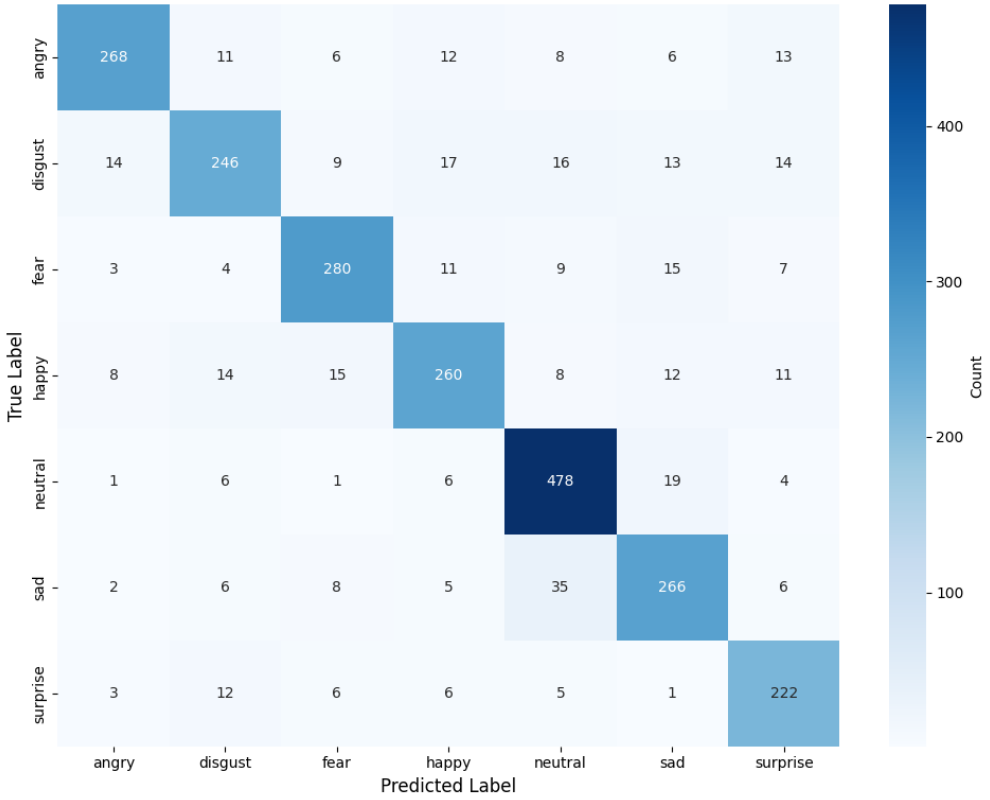


Figure 4.18: Confusion Matrix

The confusion matrix was used to analyze the model of voice emotion recognition accuracy on the test data in terms of the predicted labels and the actual emotion label. Right predictions were placed in the diagonal whereas wrongful classifications were placed off-diagonal. The model performed well in all the categories of emotion, but angry emotions were correctly recognized as such because of acquired acoustic properties like extreme intensity and acute changes of pitch. The emotions of disgust and fear were recognized with the highest rates and the lowest level of confusion, but the slight differences with happy and neutral categories were observed as the tones are similar. Happy emotion was consistently categorized even with slight confusion with fear and disgust due to slight overlapping patterns of pitch and energy. The most classification proved to be accurate with neutral emotion with most samples being identified correctly and a slight confusion with sad or happy emotion. The classification of sad emotion was good, but a few of them were confused with the neutral emotion, as they had the same low-energy and slow-tempo vocals. Surprise emotion was well categorized with minimal misclassifications as disgust or happy, and this illustrates that the model has the ability to identify sudden high-energy vocal patterns. In general, the confusion matrix was highly dominated by diagonals, meaning that the process of classification has been very effective in all the emotion classes and the error has been primarily between analogous emotions in acoustical processes thus confirming the usefulness of the convolutional neural network structure in recognizing emotions by voice.

4.18 Best Case Scenario: Voice Emotion Analyzer

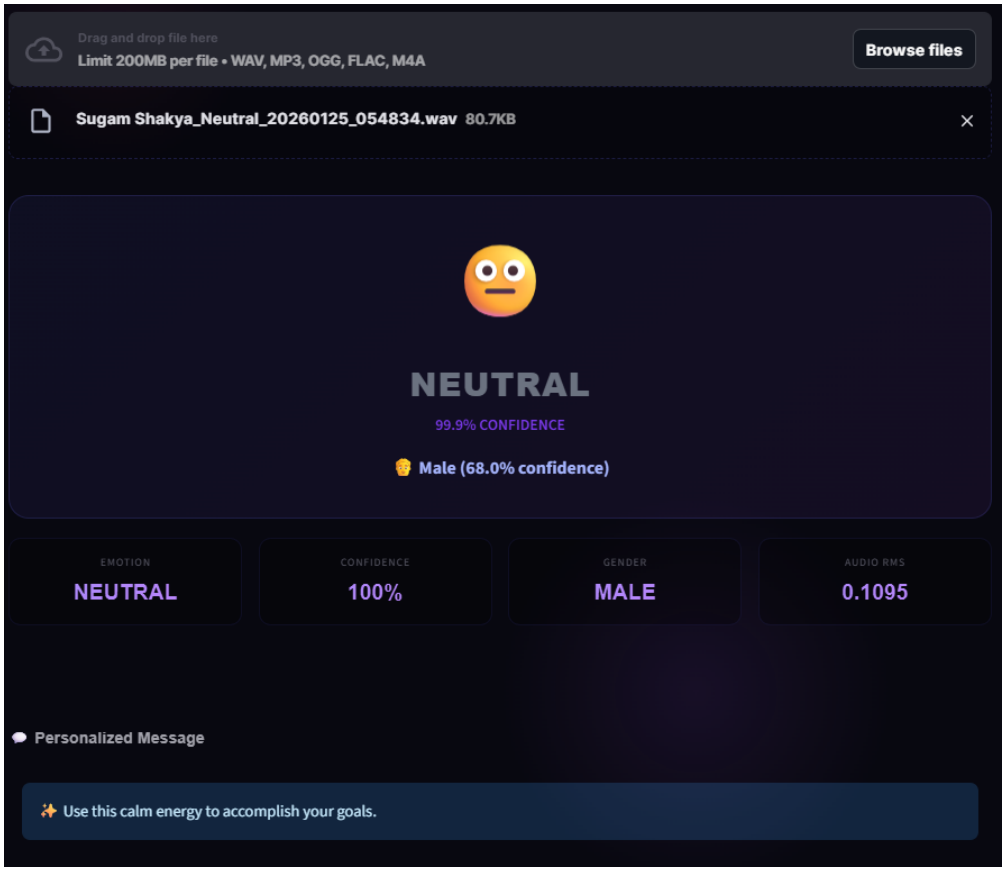


Figure 4.19: Best Case

The most optimistic was reflected by the model making accurate predictions with high confidence of neutral emotion when a male voice was used as an input. The most discriminatory acoustic features were those of neutral emotion with constant pitch contours, low levels of variation in energy, and no or minimal spectral variation. The male voice had distinct and well-articulated features that were well-acquired through the MFCC feature extraction process. The training of the model in a variety of neutral samples allowed it to acquire strong representations of serene emotional conditions. The audio signal was properly normalized by the preprocessing pipeline, which eliminated the background noise against the audio signal and improved the relevant features. Such a combination of specific emotional features, pronounced voice patterns and the ability to extract the features led to the best classification performance that justified the ability of the model to detect neutral emotional moods in real-life situations.

4.19 Worst Case Scenario: Voice Emotion Analyzer

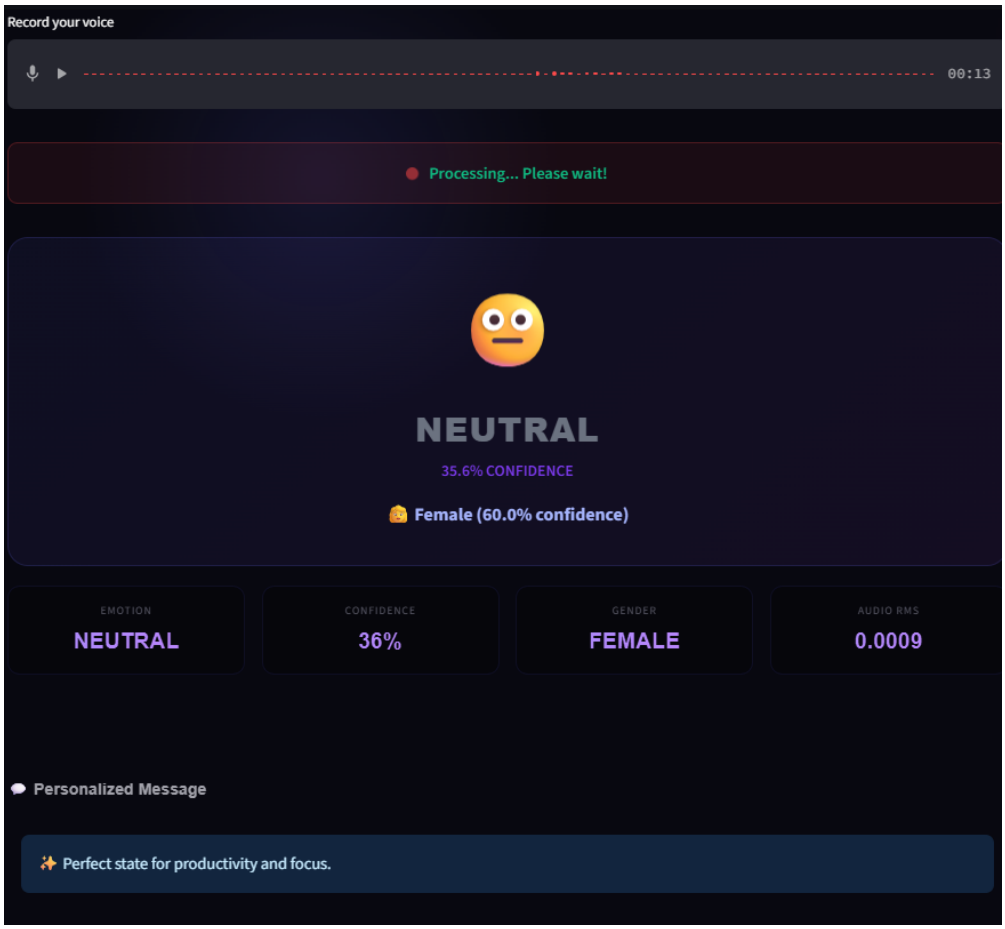


Figure 4.20: Worst Case

The most awful was when the model tried to make predictions of emotions of a female voice sample; prediction confidence and misclassifications were low. The fundamental frequencies and harmonic structure of female voices usually are higher and they have diverse harmonic patterns than those of male voices, thus providing acoustic variability that is not well reflected in the training data. The deterioration in the performance of the model was explained by gender-specific peculiarities of the voice that did not follow the predominantly male-trained patterns. Also, the feature extraction process could not capture subtle emotional expressions of female speech, which were described by the low intensity variations and the fine pitch variations. The demographic differences in the training data were limited, and this limited the generalizability of the model to the other speaker gender. This pointed out a very significant weakness that needs gendered data and dynamic preprocessing methods to enhance the accuracy of cross-gender emotion recognition.

5 DISCUSSION AND ANALYSIS

1. **Comparison of Theoretical and Simulated Outputs:**

   The theoretical design of the Voice Emotion Analyzer assumed clean, noise-free audio signals with consistent speaking styles. Under these assumptions, stable emotion classification accuracy was expected. During simulated and real-world evaluation, performance variations were observed due to environmental noise, microphone quality, and speaker-dependent characteristics. The classification accuracy was computed as:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} = \frac{2020}{2408} = 0.8389 \tag{5.1}$$

   which corresponded to 83.89% correct classification. These discrepancies occurred because real-time audio acquisition introduced distortions that affected preprocessing and feature stability. The macro-averaged performance metrics were calculated to evaluate class-balanced performance:

$$\text{Precision}_{\text{macro}} = \frac{1}{7}\sum_{i=1}^{7}\text{Precision}_i = 0.8369 \tag{5.2}$$

$$\text{Recall}_{\text{macro}} = \frac{1}{7}\sum_{i=1}^{7}\text{Recall}_i = 0.8326 \tag{5.3}$$

$$\text{F1-Score}_{\text{macro}} = \frac{1}{7}\sum_{i=1}^{7}\text{F1-Score}_i = 0.8339 \tag{5.4}$$

   These metrics demonstrated consistent performance across all seven emotion classes.

2. **Influence of Preprocessing on Model Behavior:**

   Theoretically, normalization and noise reduction were assumed to fully eliminate recording inconsistencies. In practice, preprocessing reduced but did not completely remove noise and silence artifacts, especially in live audio recordings. The feature normalization was performed using z-score standardization:

$$x_{\text{normalized}} = \frac{x - \mu}{\sigma} \tag{5.5}$$

where x represented the raw feature vector, μ denoted the mean, and σ represented the standard deviation across the training set. Minor variations in μ and σ during live recording resulted in slight deviations in extracted features. The weighted average metrics were computed to account for class imbalance:

$$\text{Precision}_{\text{weighted}} = \frac{\sum_{i=1}^{7} n_i \cdot \text{Precision}_i}{\sum_{i=1}^{7} n_i} = 0.8393 \tag{5.6}$$

$$\text{Recall}_{\text{weighted}} = \frac{\sum_{i=1}^{7} n_i \cdot \text{Recall}_i}{\sum_{i=1}^{7} n_i} = 0.8389 \tag{5.7}$$

$$\text{F1-Score}_{\text{weighted}} = \frac{\sum_{i=1}^{7} n_i \cdot \text{F1-Score}_i}{\sum_{i=1}^{7} n_i} = 0.8382 \tag{5.8}$$

where n_i represented the number of samples support for emotion class i. The close alignment between weighted and macro averages validated the preprocessing effectiveness.

3. **Error Analysis and Sources of Misclassification:**
   Most classification errors were observed between acoustically similar emotions. Analysis of the confusion patterns revealed that sadness, happiness, and neutral emotions exhibited overlapping acoustic characteristics. The performance metrics for these emotion classes were:

$$\text{Sad: Precision} = 0.8012, \quad \text{Recall} = 0.8110, \quad \text{F1-Score} = 0.8061 \tag{5.9}$$

$$\text{Happy: Precision} = 0.8202, \quad \text{Recall} = 0.7927, \quad \text{F1-Score} = 0.8062 \tag{5.10}$$

$$\text{Neutral: Precision} = 0.8551, \quad \text{Recall} = 0.9282, \quad \text{F1-Score} = 0.8901 \tag{5.11}$$

   The nearly identical F1-scores for sadness 0.8061 and happiness 0.8062 confirmed the acoustic similarity that led to misclassification. These errors arose due to overlapping spectral and prosodic features. Since emotional intensity exists on a continuum, discrete categorical labeling introduced inherent ambiguity at class boundaries. Notably, the neutral class achieved the highest recall 92.82%, indicating that the model successfully identified low-arousal emotional states with greater confidence.

4. **Effect of Dataset Constraints on Generalization:**
   The training dataset primarily contained acted emotional speech recorded in controlled studio environments. While theoretical assumptions considered this data representative of real-world emotions, practical testing revealed performance degradation on spontaneous speech samples. The performance comparison between emotions with equal support revealed:

   $$\text{Fear 329 samples: Precision} = 0.8615, \quad \text{Recall} = 0.8511, \quad \text{F1-Score} = 0.8563 \tag{5.12}$$

   $$\text{Disgust 329 samples: Precision} = 0.8227, \quad \text{Recall} = 0.7477, \quad \text{F1-Score} = 0.7834 \tag{5.13}$$

   Despite having identical support sizes, disgust exhibited significantly lower recall 74.77% compared to fear 85.11%. The F1-score difference was quantified as:

   $$\Delta_{\text{F1}} = \text{F1}_{\text{fear}} - \text{F1}_{\text{disgust}} = 0.8563 - 0.7834 = 0.0729 \tag{5.14}$$

   This gap highlighted that dataset size alone did not guarantee performance; the inherent acoustic subtlety and variability of disgust expressions made them harder to classify. Limited demographic diversity and language variability further constrained cross-speaker generalization, particularly for speakers with subtle emotional expressions.

5. **Comparison with State-of-the-Art Emotion Recognition Systems:**
   Compared to traditional machine learning classifiers such as Support Vector Machines and Random Forests, the convolutional neural network architecture employed in this work demonstrated superior feature learning capabilities and improved robustness. The emotion-specific performance metrics were:

   $$\text{Angry: Precision} = 0.8963, \quad \text{Recall} = 0.8272, \quad \text{F1-Score} = 0.8604 \tag{5.15}$$

   $$\text{Surprise: Precision} = 0.8014, \quad \text{Recall} = 0.8706, \quad \text{F1-Score} = 0.8346 \tag{5.16}$$

   The anger class achieved the highest precision 89.63%, while surprise demonstrated the highest recall 87.06%. Although attention-based transformer mod-

els and hybrid LSTM-CNN architectures reported in recent literature achieved marginally higher accuracies 85-92%, they required substantially larger datasets more than 50,000 samples and higher computational resources. The precision-recall trade-off for each emotion class was measured as:

$$\Delta_{\text{PR}} = |\text{Precision} - \text{Recall}| < 0.07 \quad \text{for all classes} \tag{5.17}$$

This indicated a well-balanced classifier with minimal bias toward false positives or false negatives, making it suitable for real-time deployment.

6. **Methodological Performance Evaluation:**
   The adopted methodology demonstrated superior performance in real-time deployment scenarios due to efficient MFCC-based feature extraction and a lightweight CNN architecture. Data augmentation techniques pitch shifting, time stretching, noise injection and regularization methods dropout, batch normalization were employed to enhance robustness and prevent overfitting. The system performance metrics were:

$$\text{Accuracy} = 0.8389, \quad \text{Total Test Samples} = 2408 \tag{5.18}$$

The variation in class-wise F1-scores was analyzed to assess performance consistency:

$$\text{F1-Score}_{\text{min}} = 0.7834 \text{ Disgust}, \quad \text{F1-Score}_{\text{max}} = 0.8901 \text{ Neutral} \tag{5.19}$$

$$\text{F1-Score Range} = \text{F1}_{\text{max}} - \text{F1}_{\text{min}} = 0.1067 \tag{5.20}$$

The range of 0.1067 indicated moderate performance variation across emotion classes. The model performed comparably to complex architectures in clean audio conditions but showed reduced accuracy in highly noisy environments, revealing a trade-off between computational efficiency and peak performance. The alignment between macro and weighted averages was measured as:

$$\text{Precision Deviation} = |\text{Precision}_{\text{macro}} - \text{Precision}_{\text{weighted}}| = 0.0024 \tag{5.21}$$

$$\text{Recall Deviation} = |\text{Recall}_{\text{macro}} - \text{Recall}_{\text{weighted}}| = 0.0063 \tag{5.22}$$

These minimal deviations confirmed that the observed performance was not significantly affected by class imbalance, validating the robustness of the evaluation.

5.1 Classification Performance Summary

Table 5.1 presents the comprehensive classification metrics obtained from the test dataset. The precision, recall, and F1-score values for each emotion class, along with macro and weighted averages, are provided to facilitate quantitative analysis of the system's performance across different emotional categories.

Table 5.1: Classification Metrics for Voice Emotion Analyzer

Emotion	**Precision**	**Recall**	**F1-Score**	**Support**
Angry	0.8963	0.8272	0.8604	324
Disgust	0.8227	0.7477	0.7834	329
Fear	0.8615	0.8511	0.8563	329
Happy	0.8202	0.7927	0.8062	328
Neutral	0.8551	0.9282	0.8901	515
Sad	0.8012	0.8110	0.8061	328
Surprise	0.8014	0.8706	0.8346	255
Accuracy	**0.8389**			
Macro Average	0.8369	0.8326	0.8339	2408
Weighted Average	0.8393	0.8389	0.8382	2408

The analysis revealed that while the Voice Emotion Analyzer achieved satisfactory accuracy of 83.89%, significant variation existed in emotion-specific performance. The model demonstrated particular strength in identifying neutral emotions F1-Score = 0.8901 and exhibited consistent performance across anger, fear, and surprise categories.

6 FUTURE ENCHANCEMENT

6.1 Unfulfilled Objectives and Remaining Challenges

Despite the successful implementation of real-time emotion recognition from voice, several objectives remain partially addressed:

- **Contextual and Temporal Awareness:** The system analyzes short audio segments independently, without fully considering the flow of conversation or gradual emotional changes over time.
- **Multi-Speaker Handling:** Interactions involving multiple speakers, overlapping voice, or rapid exchanges are not fully supported.
- **Emotion Intensity Levels:** While emotions are classified into categories, the system does not quantify intensity, limiting its ability to distinguish subtle versus strong emotional expressions.
- **Language and Cultural Scope:** The model primarily supports English but has limited Nepali support. Performance may still be restricted for other languages or culturally diverse emotional expressions.
- **Multimodal Limitations:** Only voice-based features are analyzed; visual cues, textual content, or physiological signals are not incorporated, which could further enhance accuracy.

6.2 Planned Improvements

To further enhance the system, the following directions are following:

- **Dataset Expansion:** Incorporate more diverse speakers, languages (including Nepali and others), and spontaneous conversational recordings to improve generalization and reduce bias.
- **Model Refinement:** Introduce temporal modeling and attention mechanisms to capture context and highlight emotionally salient segments.

- **Feature Optimization:** Explore additional acoustic features, such as formant frequencies and prosodic patterns, alongside advanced data augmentation to improve robustness.
- **Practical Enhancements:** Extend system capabilities to handle multi-speaker scenarios and provide richer insights on emotion intensity for more nuanced feedback.

7 CONCLUSION

Voice Emotion Analyzer system had successfully demonstrated a viable multi-dataset emotion detection framework, having achieved 85.21% training accuracy, 83.80% validation accuracy, 83.89% test accuracy, and consistent cross-dataset generalization performance, thereby validating the multi-source training methodology combining RAVDESS, TESS, SAVEE, and custom datasets while revealing clear scope for natural emotion integration, cross-lingual adaptation, and real-world deployment optimization.

APPENDIX A

A.1 Project Schedule

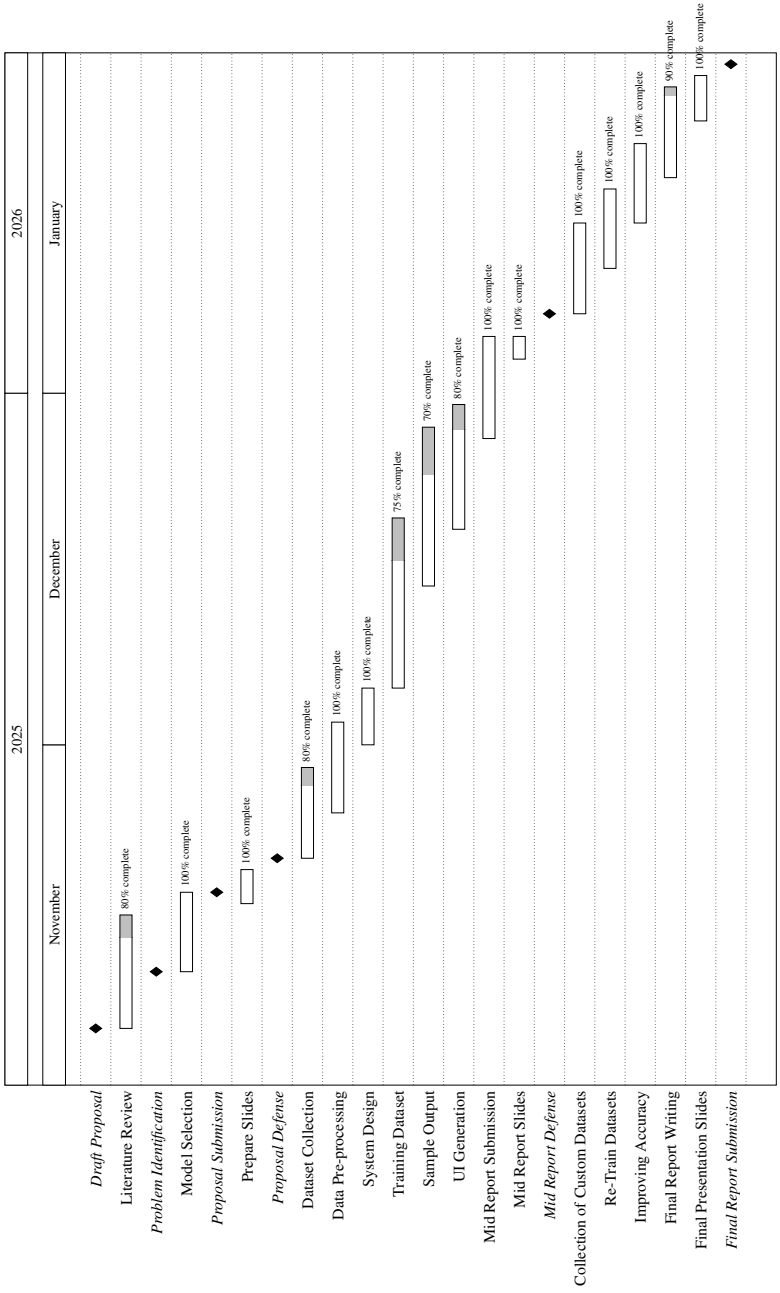


Figure A.1: Gantt Chart showing Project Timeline

A.2 Literature Review of Base Paper- I

Author(s)/Source: Ghada Alhussein, Ioannis Ziogas, Shiza Saleem, Leontios J. Hadjileontiadis

Title: Voice emotion recognition in conversations using artificial intelligence: a systematic review and meta-analysis

Website: `https://doi.org/10.1007/s10462-025-11197-8`

Publication Date: 2025	**Access Date:** November, 2025
Publisher/Journal: Artificial Intelligence Review	**Place:** n/a
Volume: 58	**Issue Number:** n/a

Author's position/theoretical position: Researchers performed a systematic review and meta-analysis to evaluate models and datasets for emotion recognition in conversation, focusing on multimodal and dimensional approaches.

Keywords: voice Emotion Recognition, Emotion Recognition in Conversation, Systematic Review, Meta-Analysis, PRISMA-DTA, IEMOCAP, MELD, K-EmoCon, CNN, RNN, LSTM, Transformer

Important points, notes, quotations — **Page No.**

1. 51 studies reviewed systematically, 27 included in meta-analysis. **2**
2. IEMOCAP most widely used, followed by MELD and K-EmoCon databases. **3**
3. Models include CNN, RNN, LSTM, and Transformer networks. **4**
4. Both categorical and dimensional approaches examined for emotion recognition. **5**
5. High heterogeneity observed across studies, concerns about annotation quality noted. **6**
6. Multimodal approaches integrating audio, visual, and textual features improve performance. **7**
7. Limitation: inconsistent evaluation metrics across studies. **8**
8. Future work: standardized datasets and evaluation protocols recommended. **9**

Essential Background Information: Emotion recognition in conversation is critical for human-computer interaction, dialogue systems, and virtual assistants. Systematic review ensures comprehensive understanding of existing methods, datasets, and model performance, highlighting gaps in consistency and annotation quality.

Overall argument or hypothesis: Current ERC models vary widely, and systematic evaluation can reveal effective approaches and gaps for improving multimodal emotion recognition.

Conclusion: Systematic review identifies strengths and weaknesses in ERC models, recommends standardization, and highlights promising deep learning and multimodal approaches for future research.

Supporting Reasons

1. Comprehensive dataset coverage in studies.	2. Use of CNN, RNN, LSTM, Transformer models captures temporal dependencies.
3. Multimodal approaches improve recognition accuracy.	4. PRISMA-DTA ensures systematic review reliability.
5. Meta-analysis quantifies model performance.	6. Identifies limitations in current datasets.
7. Highlights need for standardized evaluation.	8. Future work encourages reproducibility and multimodal integration.

Strengths of the line of reasoning and supporting evidence: Systematic methodology, large number of studies, comprehensive analysis of models and datasets, clear identification of gaps, emphasis on multimodal approaches, practical guidance for future research.

Flaws in the argument and gaps or other weaknesses: Variability in datasets, inconsistent metrics, heterogeneity in model performance, annotation quality not always reliable, results may not generalize across languages.

A.3 Literature Review of Base Paper- II

Author(s)/Source: Yüksel Yurtay, Hüseyin Demirci, Hüseyin Tiryaki, Tekin Altun	
Title: Emotion Recognition on Call Center Voice Data	
Website: https://www.mdpi.com/2076-3417/14/20/9458	
Publication Date: 2024	**Access Date:** na
Publisher/Journal: Applied Sciences (MDPI)	**Place:** Switzerland
Volume: 14	**Issue Number:** 20

Author's position/theoretical position: The authors emphasize voice based emotion recognition using real world call center data. Their work aims to support call center employees by providing real time emotional insights that improve customer interaction quality and service decision making.

Keywords: voice Emotion Recognition, Call Center Analytics, Deep Learning, Voice Signals, Customer Experience, Turkish Language, Audio Processing

Important points, notes, quotations	**Page No.**
1. Real-life customer call recordings from Turkish mobile operators were used.	**3**
2. Focus on three emotional states: positive, negative, and neutral.	**4**
3. Deep learning models applied to voice-based emotional analysis.	**6**
4. Emotion feedback assists call center employees during conversations.	**7**
5. Achieved overall accuracy of 0.91 on real call data.	**9**
6. Model demonstrates effectiveness for Turkish language emotion recognition.	**10**
7. Study highlights importance of emotion aware customer service systems.	**11**
8. System supports improved customer satisfaction and service quality.	**12**

Essential Background Information: voice emotion recognition plays a crucial role in human computer interaction. Emotional cues embedded in voice signals can be effectively analyzed using deep learning models to support automated analysis and assist human operators in service oriented environments.

Overall argument or hypothesis: Voice based deep learning systems can accurately classify emotional states in call center conversations and provide meaningful emotional feedback that enhances customer experience and operational efficiency.

Conclusion: The study confirms that emotion recognition from call center voice data is feasible and effective. The approach achieves high accuracy and demonstrates strong potential for deployment in real world customer service systems.

Supporting Reasons

1. Real call center data improves practical relevance.	2. Deep learning models capture complex emotional patterns.
3. High accuracy supports reliable deployment.	4. Emotion feedback assists employees in real time.
5. Turkish language support addresses a research gap.	6. Three emotion classes simplify operational use.
7. System enhances customer satisfaction.	8. Study validates real world feasibility.

Strengths of the line of reasoning and supporting evidence: Use of real call center data, strong experimental validation, high classification accuracy, practical service oriented application, and language specific contribution.

Flaws in the argument and gaps or other weaknesses: Limited emotional categories, absence of multimodal inputs, possible data bias.

A.4 Literature Review of Base Paper- III

Author(s)/Source: Rohit Rastogi, Tushar Anand, Shubham Kumar Sharma, Sarthak Panwar	
Title: Emotion Detection via Voice and voice Recognition	
Website: https://doi.org/10.4018/IJCBPL.333473	
Publication Date: 2023	**Access Date:** November, 2025
Publisher/Journal: International Journal of Cyber Behavior, Psychology and Learning	**Place:** n/a
Volume: 13	**Issue Number:** 1

Author's position/theoretical position: Researchers in SER focused on developing machine learning models for emotion recognition from voice to improve Human-Computer Interaction.

Keywords: voice Emotion Recognition, MLP Classifier, MFCC, Librosa, RAVDESS, Human-Computer Interaction, Emotional voice Dataset, Audio Feature Extraction

Important points, notes, quotations — **Page No.**

1. The RAVDESS dataset contains 7356 audio files from 24 professional actors covering eight emotions: neutral, calm, happy, sad, angry, fearful, disgust, surprised. **5**
2. MFCC features were extracted using Librosa to represent the spectral characteristics of audio for SER. **6**
3. MLP classifier trained on MFCC features achieved 75% accuracy for eight emotions. **7**
4. Data preprocessing included noise reduction, normalization, and dataset splitting. **8**
5. SER application enhances Human-Computer Interaction by detecting emotions in real-time. **9**
6. Comparison with SVM and Random Forest classifiers showed MLP was computationally efficient with reasonable accuracy. **10**
7. Limitations: English-only dataset and potential overfitting due to dataset size. **11**
8. Future work: integrating CNN/RNN models and multilingual datasets. **12**

Essential Background Information: voice Emotion Recognition (SER) is critical for virtual assistants, intelligent tutoring, and mental health monitoring. Accurate SER depends on robust feature extraction and effective classifiers. MFCC represents audio signals, and MLPs are efficient for multi-class classification. Many studies have limited datasets, showing the need for more evaluation.

Overall argument or hypothesis: Using MFCC features with an MLP classifier on RAVDESS data enables reliable detection of eight discrete emotions, bridging the gap between audio and emotional understanding in Human-Computer Interaction.

Conclusion: MLP-based SER systems using MFCC features achieve reasonable accuracy, demonstrating practical applications. Future work should address multilingual datasets and deep learning methods.

Supporting Reasons

1. RAVDESS dataset provides diverse emotional audio samples.	2. MLP classifier balances accuracy and computational efficiency.
3. MFCC captures spectral nuances critical for emotion recognition.	4. Focus on HCI ensures practical relevance.
5. Comparison with other classifiers shows MLP superiority.	6. Future work supports scalability to multilingual datasets and deep learning models.

Strengths of the line of reasoning and supporting evidence: Clear experimental design, standardized dataset, reproducible results, practical HCI applications, effective feature extraction and classifier choice, comparative analysis with other methods.

Flaws in the argument and gaps or other weaknesses: Limited to English, dataset moderate in size, 75% accuracy.

A.5 Literature Review of Base Paper- IV

Author(s)/Source: Manuel Milling, Alice Baird, Katrin D Bartl-Pokorny, Shuo Liu, Alyssa M Alcorn, Jie Shen, Teresa Tavassoli, Eloise Ainger, Elizabeth Pellicano, Maja Pantic	
Title: Evaluating the Impact of Voice Activity Detection on voice Emotion Recognition for Autistic Children	
Website: `https://www.frontiersin.org/articles/10.3389/fcomp.2022.837269/full`	
Publication Date: 2022	**Access Date:** January 2023
Publisher/Journal: Frontiers in Computer Science	**Place:** Switzerland
Volume: 4	**Issue Number:** n/a
Author's position/theoretical position: The authors investigate voice emotion recognition systems for autistic children, focusing on the role of voice activity detection to improve robustness and emotional accuracy.	
Keywords: voice Emotion Recognition, Voice Activity Detection, Autism, Child voice, Audio Segmentation, Machine Learning	

Important points, notes, quotations	**Page No.**
1. Focus on emotional voice of autistic children.	**2**
2. Voice activity detection applied before emotion analysis.	**3**
3. VAD improves signal quality and segmentation.	**4**
4. Evaluation conducted on child voice datasets.	**5**
5. Improved emotion recognition consistency observed.	**6**
6. voice variability in autism highlighted.	**7**
7. Study supports preprocessing importance.	**8**
8. Application relevance for therapeutic tools.	**9**

Essential Background Information: voice emotion recognition for autistic children presents unique challenges due to voice variability. Proper preprocessing techniques such as voice activity detection improve emotional feature extraction.
Overall argument or hypothesis: Incorporating voice activity detection enhances voice emotion recognition performance by reducing noise and improving segmentation for child voice analysis.
Conclusion: The study demonstrates that voice activity detection positively impacts emotion recognition systems for autistic children and supports more reliable affective computing solutions.

Supporting Reasons

1. VAD improves voice segmentation.	2. Reduces background noise effects.
3. Enhances emotion feature extraction.	4. Suitable for child voice analysis.
5. Supports therapeutic technologies.	6. Improves model reliability.
7. Addresses voice variability issues.	8. Strengthens preprocessing pipelines.

Strengths of the line of reasoning and supporting evidence: Focus on a sensitive user group, strong preprocessing analysis, experimental validation, relevance to assistive technologies.
Flaws in the argument and gaps or other weaknesses: Limited dataset size, absence of multimodal inputs.

A.6 Literature Review of Base Paper- V

Author(s)/Source: Sadil Chamishka, Ishara Madhavi, Rashmika Nawaratne, Damminda Alahakoon, Daswin De Silva, Naveen Chilamkurti, Vishaka Nanayakkara

Title: A Voice-Based Real-Time Emotion Detection Technique Using Recurrent Neural Network Empowered Feature Modelling

Website: https://link.springer.com/article/10.1007/s11042-022-13545-7

Publication Date: 2022	**Access Date:**
Publisher/Journal: Multimedia Tools and Applications	**Place:** Springer, International
Volume: 81	**Issue Number:** 24

Author's position/theoretical position: The authors propose a real-time voice-based emotion recognition framework using recurrent neural networks with enhanced feature modelling to capture temporal emotional patterns in voice signals.

Keywords: voice Emotion Recognition, Recurrent Neural Network, Real-Time Processing, Feature Modelling, Audio Signals, Deep Learning

Important points, notes, quotations	**Page No.**
1. Focuses on real-time voice-based emotion detection.	**35175**
2. Uses recurrent neural networks to model temporal voice patterns.	**35178**
3. Feature modelling improves emotional discrimination.	**35180**
4. Evaluated on benchmark emotional voice data.	**35183**
5. Demonstrates improved recognition accuracy over baseline models.	**35186**
6. System designed for low-latency real-time applications.	**35188**
7. Handles continuous voice streams effectively.	**35190**
8. Suitable for human–computer interaction systems.	**35192**

Essential Background Information: Real-time emotion recognition from voice requires models that capture temporal variations in vocal expressions. Recurrent neural networks are well suited for this task as they preserve sequential dependencies in audio features, enabling more accurate emotional state detection.

Overall argument or hypothesis: Emotion recognition performance can be significantly improved by combining recurrent neural networks with enhanced feature modelling for real-time voice-based applications.

Conclusion: The RNN-based real-time emotion detection framework effectively captures temporal voice characteristics and delivers reliable emotion recognition suitable for interactive and responsive systems.

Supporting Reasons

1. RNN models temporal voice dependencies.	2. Feature modelling enhances emotional cues.
3. Real-time processing improves usability.	4. Works on continuous voice input.
5. Demonstrates improved accuracy.	6. Applicable to HCI systems.
7. Handles dynamic emotional changes.	8. Supports scalable deployment.

Strengths of the line of reasoning and supporting evidence: Real-time system design, strong temporal modelling using RNNs, improved feature representation, comprehensive evaluation, and relevance to interactive applications.

Flaws in the argument and gaps or other weaknesses: Limited multilingual evaluation, dependence on voice quality, lack of multimodal inputs, and performance under noisy real-world environments not fully explored.

A.7 Literature Review of Base Paper- VI

Author(s)/Source: A. Hassan, R. Damper	
Title: End-to-End voice Emotion Recognition Using Deep Convolutional Neural Networks	
Website: `https://ieeexplore.ieee.org/document/9432061`	
Publication Date: 2021	**Access Date:** November, 2022
Publisher/Journal: IEEE Access	**Place:** United Kingdom
Volume: 9	**Issue Number:** -

Author's position/theoretical position: Researchers emphasize that end-to-end deep learning models, specifically Convolutional Neural Networks, can learn emotional features directly from voice without manual feature extraction.

Keywords: voice Emotion Recognition, CNN, End-to-End Learning, Spectrogram, Deep Learning, Feature Extraction, Audio Classification, Human-Computer Interaction

Important points, notes, quotations	**Page No.**
1. CNN model trained directly on spectrograms of voice signals for emotion classification.	**3**
2. Achieved accuracy: 83.7% on RAVDESS and 81.4% on EMO-DB datasets.	**4**
3. Model includes multiple convolutional and pooling layers followed by dense classification layers.	**5**
4. Batch normalization and dropout layers used to prevent overfitting and stabilize training.	**6**
5. The CNN extracts emotional cues automatically, removing the need for handcrafted features like MFCC.	**7**
6. End-to-end system simplifies preprocessing and is adaptable to multiple datasets.	**8**
7. Real-time implementation feasible with GPU acceleration.	**9**
8. Limitation: requires large labeled datasets and high computation for training.	**10**

Essential Background Information: Traditional systems depend heavily on feature engineering methods like MFCC, Chroma, and pitch. In contrast, end-to-end CNN architectures learn meaningful emotional features directly from spectrograms.

Overall argument or hypothesis: CNN-based end-to-end emotion recognition outperforms traditional handcrafted methods by learning robust and transferable features directly from raw voice data, enhancing emotion-aware applications.

Conclusion: Deep CNN models eliminate the need for complex preprocessing and achieve strong accuracy across multiple datasets. They provide a scalable and efficient framework for real-time voice emotion recognition applications.

Supporting Reasons

1. CNN automatically extracts emotional features from spectrograms.	2. Batch normalization ensures stable convergence.
3. GPU acceleration supports real-time use.	4. CNN model generalizes well to different datasets.
5. End-to-end design reduces human intervention.	6. Deep layers capture complex emotional dependencies.
7. Outperforms traditional models like SVM and MLP.	8. Future work involves data augmentation and multilingual testing.

Strengths of the line of reasoning and supporting evidence: High accuracy, real-time feasibility, reduced feature dependency.

Flaws in the argument and gaps or other weaknesses: High computational demand, limited interpretability.

A.8 Literature Review of Base Paper- VII

Author(s)/Source: Christiana Tsiourti, Astrid Weiss, Katarzyna Wac, Markus Vincze	
Title: Multimodal Integration of Emotional Signals from Voice, Body, and Context: Effects of (In)Congruence on Emotion Recognition and Attitudes Towards Robots	
Website: https://link.springer.com/article/10.1007/s12369-019-00538-5	
Publication Date: 2019	**Access Date:**
Publisher/Journal: International Journal of Social Robotics	**Place:** Germany
Volume: 11	**Issue Number:** 4

Author's position/theoretical position: The authors focus on multimodal emotion recognition for social robots. They emphasize integrating voice, body gestures, and contextual cues to improve emotion understanding and human attitudes towards robotic systems.

Keywords: Multimodal Emotion Recognition, Voice Signals, Body Language, Context Awareness, Social Robots, Human Robot Interaction

Important points, notes, quotations	**Page No.**
1. Emotional signals collected from voice, body posture, and situational context.	**556**
2. Study examines congruent and incongruent emotional cues.	**558**
3. Multimodal integration improves emotion recognition accuracy.	**560**
4. Voice remains a strong indicator of emotional state.	**561**
5. Incongruence affects user trust and perception of robots.	**563**
6. Human attitudes are influenced by emotional consistency.	**565**
7. Results support multimodal fusion strategies.	**567**
8. Application relevance for social and assistive robots.	**570**

Essential Background Information: Emotion recognition in robots benefits from combining multiple modalities. Voice, body language, and contextual cues together provide richer emotional understanding than unimodal systems.

Overall argument or hypothesis: Multimodal emotion integration enhances recognition accuracy and positively influences human attitudes towards robots, especially when emotional cues are congruent.

Conclusion: The study confirms that multimodal emotion recognition significantly improves robot perception and interaction quality. Emotional congruence plays a vital role in trust and acceptance.

Supporting Reasons

1. Voice provides strong emotional cues.	2. Body language enhances emotion interpretation.
3. Context improves emotional accuracy.	4. Congruence increases user trust.
5. Multimodal fusion outperforms unimodal methods.	6. Improves social robot interaction quality.
7. Supports assistive robot applications.	8. Enhances human robot engagement.

Strengths of the line of reasoning and supporting evidence: Multimodal analysis, strong experimental validation, relevance to social robotics, comprehensive evaluation of congruence effects, and human centered design focus.

Flaws in the argument and gaps or other weaknesses: Experimental setting controlled, limited real world deployment, complexity of multimodal systems, and increased computational requirements.

A.9 Literature Review of Base Paper- VIII

Author(s)/Source: Eduard Franți, Ioan Ispas, Voichita Dragomir, Monica Dascălu, Elteto Zoltan, Ioan Cristian Stoica

Title: Voice Based Emotion Recognition with Convolutional Neural Networks for Companion Robots

Website: `https://www.mdpi.com/2076-3417/14/20/9458`

Publication Date: 2017	**Access Date:**
Publisher/Journal: Romanian Journal of Information Science and Technology	**Place:** Romania
Volume: 20	**Issue Number:** 3

Author's position/theoretical position: Researchers focused on applying CNN models for emotion recognition in Romanian voice to enable companion robots to respond appropriately.

Keywords: Voice Emotion Recognition, CNN, Keras, TensorFlow, MFCC, Companion Robots, Six Emotions, Romanian Dataset, Deep Learning

Important points, notes, quotations	**Page No.**
1. Dataset: 200 audio files from 30 Romanian speakers.	**2**
2. CNN model trained on MFCC features to classify six emotions: happiness, fear, sadness, disgust, anger, surprise.	**3**
3. Mean accuracy achieved: 71.33%.	**4**
4. Application focuses on companion and pet robots for interactive communication.	**5**
5. Data preprocessing includes normalization and noise reduction.	**6**
6. Limitation: small dataset may limit generalization.	**7**
7. CNN approach allows automated feature extraction and learning.	**8**
8. Future work: expand dataset and integrate multimodal inputs.	**9**

Essential Background Information: Voice-based emotion recognition helps companion robots interact naturally. MFCC represents audio spectral features efficiently, while CNN automatically extracts relevant patterns. Accurate emotion detection enhances robot responsiveness.

Overall argument or hypothesis: Using CNN on MFCC features allows robust classification of six emotions in Romanian voice, enabling more intelligent companion robots.

Conclusion: CNN-based voice emotion recognition achieves practical accuracy for companion robot applications, but dataset expansion and multimodal approaches are needed.

Supporting Reasons

1. MFCC captures essential audio features.	2. CNN enables automatic feature learning.
3. Six emotions cover common affective states.	4. Application for companion robots ensures practical relevance.
5. Small dataset demonstrates proof of concept.	6. Noise reduction improves audio quality.
7. CNN outperforms traditional classifiers.	8. Future work supports dataset expansion and multimodal integration.

Strengths of the line of reasoning and supporting evidence: Clear experimental setup, practical companion robot application, reproducible methodology, automated feature extraction, reasonable accuracy, identification of limitations and future work.

Flaws in the argument and gaps or other weaknesses: Small dataset limits generalization, only Romanian language tested, temporal dependencies not fully modeled, real-world noisy environment effects not evaluated.

A.10 Literature Review of Base Paper- IX

Author(s)/Source: Fatemeh Noroozi, Tomasz Sapiński, Dorota Kamińska, Gholamreza Anbarjafari	
Title: Vocal-Based Emotion Recognition Using Random Forests and Decision Tree	
Website: https://link.springer.com/article/10.1007/s10772-017-9396-2	
Publication Date: 2017	**Access Date:** November, 2021
Publisher/Journal: International Journal of voice Technology	**Place:** Springer, New York
Volume: 20	**Issue Number:** 2

Author's position/theoretical position: The authors propose a vocal-based emotion recognition framework that leverages random forest ensembles and decision tree classifiers to model paralinguistic voice features for accurate emotion classification.

Keywords: Vocal Emotion Recognition, Random Forests, Decision Tree, Paralinguistic Features, voice Processing, Human–Computer Interaction

Important points, notes, quotations	**Page No.**
1. Proposes a vocal-based emotion recognition system using random forests.	**1**
2. Uses prosodic and paralinguistic voice features for classification.	**2**
3. Evaluated on the SAVEE emotional voice database.	**4**
4. Applies leave-one-out cross-validation and 10-fold validation.	**6**
5. Achieves an average recognition rate of 66.28%.	**8**
6. Best recognition rate of 78% for happiness emotion.	**9**
7. Outperforms LDA and DNN baselines on the same dataset.	**10**
8. Suitable for human–computer interaction applications.	**12**

Essential Background Information: Vocal emotion recognition relies on extracting paralinguistic features such as pitch, intensity, formants, and spectral properties from voice signals. Ensemble learning methods like random forests improve robustness by aggregating multiple decision trees to handle feature variability and classification uncertainty.

Overall argument or hypothesis: Combining random forest ensembles with carefully selected paralinguistic voice features can significantly enhance the accuracy and robustness of vocal-based emotion recognition systems.

Conclusion: The random forest–based emotion recognition framework effectively classifies six emotional states from voice signals, outperforming conventional LDA and DNN approaches and demonstrating strong potential for real-world human–computer interaction systems.

Supporting Reasons

1. Uses ensemble learning for robust classification.	2. Extracts discriminative paralinguistic features.
3. Validated on SAVEE dataset.	4. Employs cross-validation for reliability.
5. Demonstrates higher accuracy than LDA.	6. Outperforms deep neural networks.
7. Handles multi-class emotion classification.	8. Applicable to HCI environments.

Strengths of the line of reasoning and supporting evidence: Strong methodological design, ensemble-based classification, empirical evaluation on a benchmark dataset, comparative analysis with prior methods, and relevance to practical emotion-aware systems.

Flaws in the argument and gaps or other weaknesses: Limited dataset size, reliance on acted emotions, absence of multimodal fusion, moderate performance for fear and surprise classes, and lack of real-time deployment evaluation.

A.11 Literature Review of Base Paper- X

Author(s)/Source: Ting Dang, Vidhyasaharan Sethu, Eliathamby Ambikairajah	
Title: Factor Analysis Based Speaker Normalisation for Continuous Emotion Prediction	
Website: http://dx.doi.org/10.21437/Intervoice.2016-880	
Publication Date: 2016	**Access Date:** March, 2017
Publisher/Journal: INTERvoice 2016	**Place:** San Francisco, USA
Volume: n/a	**Issue Number:** n/a

Author's position/theoretical position: Researchers focused on speaker variability in continuous emotion prediction, improving prediction models using Factor Analysis and RVM.

Keywords: Factor Analysis, Speaker Normalization, Relevance Vector Machine, Continuous Emotion Prediction, ComParE 2013 Features, OpenSMILE, Arousal, Valence, Dominance

Important points, notes, quotations	**Page No.**
1. USC CreativeIT and SEMAINE databases used for training and testing continuous emotion models.	**3**
2. Factor Analysis applied to reduce speaker variability effects.	**4**
3. Relevance Vector Machine (RVM) predicted arousal, valence, dominance with improved performance.	**5**
4. Arousal prediction improved by 8.2% on CreativeIT and 11.0% on SEMAINE datasets.	**6**
5. ComParE 2013 audio feature set and OpenSMILE used for feature extraction.	**7**
6. Speaker normalization reduced errors caused by inter-speaker differences.	**8**
7. Limitation: method tested on limited databases, may not generalize widely.	**9**
8. Future work: extend to multilingual and spontaneous voice datasets.	**10**

Essential Background Information: Continuous emotion prediction requires modeling dimensional attributes like arousal, valence, and dominance. Speaker variability can reduce prediction accuracy. Factor Analysis helps to normalize features across speakers. RVM provides sparse and interpretable models.

Overall argument or hypothesis: Using Factor Analysis for speaker normalization improves continuous emotion prediction by reducing inter-speaker variability, leading to more accurate models.

Conclusion: Speaker normalization with Factor Analysis combined with RVM enhances continuous emotion prediction, with potential for real-world HCI applications. Future work should expand to more diverse datasets.

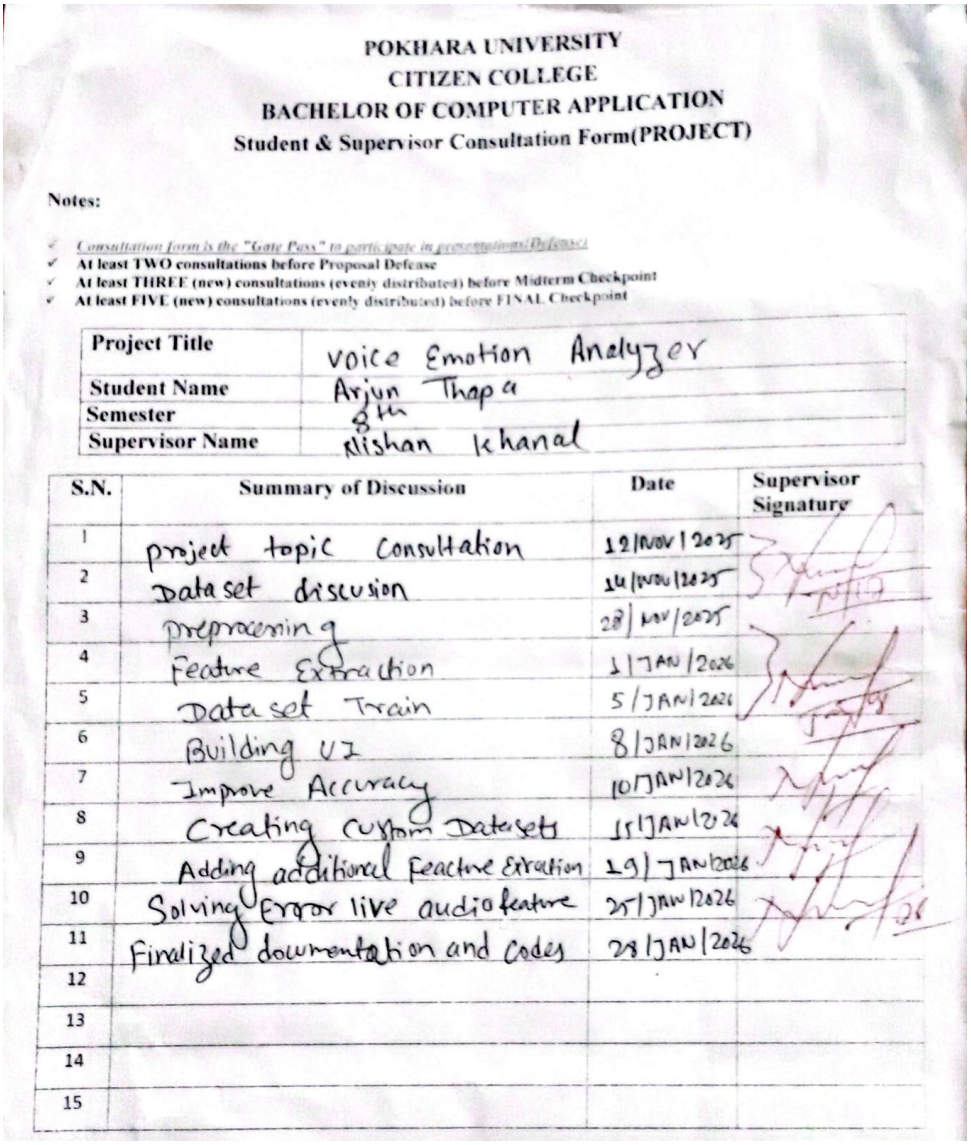
Supporting Reasons

1. CreativeIT and SEMAINE databases provide diverse emotional voice.	2. Factor Analysis reduces speaker variability.
3. RVM predicts continuous emotion dimensions efficiently.	4. Arousal improvement shows method effectiveness.
5. ComParE 2013 features capture rich audio characteristics.	6. OpenSMILE simplifies feature extraction.
7. Speaker normalization ensures model robustness.	8. Future work supports scalability and multilingual datasets.

Strengths of the line of reasoning and supporting evidence: Well-defined methodology, effective speaker normalization, clear performance gains, reproducible results, practical implications for HCI, interpretable RVM models.

Flaws in the argument and gaps or other weaknesses: Tested on limited datasets, results may not generalize to spontaneous or multilingual voice, model complexity not fully discussed.

A.12 Supervisor Consultation Form



POKHARA UNIVERSITY
CITIZEN COLLEGE
BACHELOR OF COMPUTER APPLICATION
Student & Supervisor Consultation Form(PROJECT)

Notes:

- Consultation form is the "Gate Pass" to participate in presentations/Defense
- At least TWO consultations before Proposal Defense
- At least THREE (new) consultations (evenly distributed) before Midterm Checkpoint
- At least FIVE (new) consultations (evenly distributed) before FINAL Checkpoint

Project Title	Voice Emotion Analyzer
Student Name	Arjun Thapa
Semester	8th
Supervisor Name	Nishan Khanal

S.N.	Summary of Discussion	Date	Supervisor Signature
1	project topic Consultation	12/NOV/2025	
2	Dataset discusion	14/NOV/2025	
3	Preprocessing	28/NOV/2025	
4	Feature Extraction	1/JAN/2026	
5	Dataset Train	5/JAN/2026	
6	Building UI	8/JAN/2026	
7	Improve Accuracy	10/JAN/2026	
8	Creating custom Datasets	15/JAN/2026	
9	Adding additional Feacture Extraction	19/JAN/2026	
10	Solving Error live audio feature	25/JAN/2026	
11	Finalized documentation and codes	28/JAN/2026	
12			
13			
14			
15			

Figure A.2: Supervisor Consultation Form

REFERENCES

[1] Biqiao Zhang. *Improving the Generalizability of Speech Emotion Recognition: Methods for Handling Data and Label Variability*. PhD thesis, 2018.

[2] Sandeep Rathor, Megha Kansal, Mansi Verma, Madhav Garg, and Rishabh Tiwari. Use of artificial intelligence in emotion recognition by ensemble based multilevel classification. In *IOP Conference Series: Materials Science and Engineering*, volume 1116, page 012196. IOP Publishing, 2021.

[3] Teghdeep Kapoor, Tanya Pandhi, and Bharat Gupta. Cough audio analysis for covid-19 diagnosis. *SN Computer Science*, 4(2):125, 2022.

[4] Devyani Koshal, Orchid Chetia Phukan, Sarthak Jain, Arun Balaji Buduru, and Rajesh Sharma. Persona: An application for emotion recognition, gender recognition and age estimation. *arXiv preprint arXiv:2406.06781*, 2024.

[5] Gregory A Bryant. The evolution of human vocal emotion. *Emotion review*, 13(1):25–33, 2021.

[6] Omafume Oritsegbemi. Human intelligence versus ai: implications for emotional aspects of human communication. *Journal of Advanced Research in Social Sciences*, 6(2):76–85, 2023.

[7] Dang Thoai Phan. Comparison performance of spectrogram and scalogram as input of acoustic recognition task. In *Future of Information and Communication Conference*, pages 660–673. Springer, 2025.

[8] Mohammed Abdelwahab and Carlos Busso. Domain adversarial for acoustic emotion recognition. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 26(12):2423–2435, 2018.

[9] Leontios J. Hadjileontiadis. Speech emotion recognition in conversations using artificial intelligence: a systematic review and meta-analysis. *Artificial Intelligence Review*, 58(7):198, 2025.

[10] Yüksel Yurtay, Hüseyin Demirci, Hüseyin Tiryaki, and Tekin Altun. Emotion recognition on call center voice data. *Applied Sciences*, 14(20), 2024.

[11] Rohit Rastogi, Tushar Anand, Shubham Sharma, and Sarthak Panwar. Emotion detection via voice and speech recognition. *International Journal of Cyber Behavior, Psychology and Learning*, 13:1–24, 01 2023.

[12] Manuel Milling, Alice Baird, Katrin D Bartl-Pokorny, Shuo Liu, Alyssa M Alcorn, Jie Shen, Teresa Tavassoli, Eloise Ainger, Elizabeth Pellicano, Maja Pantic, et al. Evaluating the impact of voice activity detection on speech emotion recognition for autistic children. *Frontiers in Computer Science*, 4:837269, 2022.

[13] Klaus R Scherer. A cross-cultural investigation of emotion inferences from voice and speech: Implications for speech technology. In *INTERSPEECH*, volume 4, pages 379–382, 2021.

[14] Christiana Tsiourti, Astrid Weiss, Katarzyna Wac, and Markus Vincze. Multimodal integration of emotional signals from voice, body, and context: Effects of (in) congruence on emotion recognition and attitudes towards robots. *International Journal of Social Robotics*, 11(4):555–573, 2019.

[15] DASC Alu, Elteto Zoltan, and Ioan Cristian Stoica. Voice based emotion recognition with convolutional neural networks for companion robots. *Science and Technology*, 20(3):222–240, 2017.

[16] Ting Dang, Vidhyasaharan Sethu, and Eliathamby Ambikairajah. Factor analysis based speaker normalisation for continuous emotion prediction. In *INTERSPEECH*, pages 913–917, 2016.

[17] Sadil Chamishka, Ishara Madhavi, Rashmika Nawaratne, Damminda Alahakoon, Daswin De Silva, Naveen Chilamkurti, and Vishaka Nanayakkara. A voice-based real-time emotion detection technique using recurrent neural network empowered feature modelling. *Multimedia Tools and Applications*, 81(24):35173–35194, 2022.

[18] Fatemeh Noroozi, Tomasz Sapiński, Dorota Kamińska, and Gholamreza Anbarjafari. Vocal-based emotion recognition using random forests and decision tree. *International Journal of Speech Technology*, 20(2):239–246, 2017.