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Emotion Detection from Noisy Voice Recordings Using Machine Learning

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***Abstract*— Speech Emotion Detection (SED) has emerged as a pivotal technology for enhancing human–computer interaction by enabling machines to recognize emotions from speech signals. This research presents a robust SED system leveraging Convolutional Neural Networks (CNN) and CNN-LSTM architectures trained on the RAVDESS dataset, which contains 1,440 high-quality audio samples across eight emotion classes. The system incorporates comprehensive audio preprocessing including noise reduction, amplitude normalization, silence trimming, and uniform resampling to ensure data consistency. Feature extraction is performed using Mel-Frequency Cepstral Coefficients (MFCC), Mel-Spectrograms, and Chroma features, transforming raw audio into image-like representations suitable for deep learning models. The CNN captures spatial patterns in the spectrograms, while the CNN-LSTM additionally models temporal dependencies, improving recognition of subtle and sequential emotional cues. The model is optimized with Adam optimizer, categorical cross-entropy loss, and regularization strategies, and evaluated using accuracy, precision, recall, F1-score, and confusion matrices. Deployment is realized through a Flask-based web interface enabling real-time emotion recognition from user-uploaded or recorded audio. Experimental results demonstrate that the proposed system achieves high accuracy, robustness to noise, and generalization to unseen speech, making it suitable for applications in mental health monitoring, call centers, virtual assistants, and intelligent human–computer interaction.**

Keywords*— *Speech Emotion Recognition, Convolutional Neural Networks, Audio Feature Extraction, MFCC, Mel Spectrogram, Human–Computer Interaction.

I. INTRODUCTION

The ability to recognize human emotions through speech has become an increasingly important area of research, driven by the growing integration of voice-based technologies into daily life. Speech conveys not only linguistic content but also rich affective information, which can enhance human–computer interaction by providing contextual understanding and emotional awareness. Applications such as virtual assistants, call center automation, e-learning platforms, and mental health monitoring rely on accurate emotion detection to respond adaptively to users' needs. Traditional systems have primarily focused on basic acoustic features and handcrafted models, which often fail to capture the complexity and variability of emotional speech, especially in realistic and noisy environments [1]. Advances in deep learning and data-driven approaches have enabled more robust representation learning, improving the accuracy and reliability of emotion recognition systems [2].

Despite progress, significant challenges remain in developing speech emotion recognition systems that generalize effectively across diverse speakers, languages, and recording conditions. Existing methods frequently suffer from low performance when exposed to real-world audio, due to variations in speaker accents, speaking styles, background noise, and subtle emotional expressions [3]. Many systems are also limited by reliance on small or homogeneous datasets, which restricts their applicability to broader contexts. Moreover, traditional approaches often struggle with cross-corpus adaptation, making it difficult to deploy models in multi-domain or multi-lingual scenarios without substantial retraining [4]. These gaps highlight the need for methods capable of learning richer emotional representations while maintaining robustness and generalization across diverse datasets and environmental conditions [5].

The primary objective of this study is to develop a comprehensive speech emotion detection framework that accurately identifies a wide range of human emotions from speech signals while addressing the limitations of existing methods. The study aims to extract meaningful patterns from emotional speech, represent them effectively, and evaluate system performance using rigorous quantitative metrics. By doing so, it seeks to establish a scalable and reliable framework capable of supporting real-time emotion recognition applications. In addition, the work contributes to the broader understanding of affective computing by demonstrating how systematic analysis of speech can be leveraged to improve human–computer interactions [6].

The significance of this research lies in its potential to enhance the responsiveness, personalization, and user experience of voice-based technologies. A reliable speech emotion recognition system can enable virtual assistants to interact more naturally, allow call centers to respond empathetically to customer emotions, and support mental health monitoring through non-invasive assessment of emotional states. Furthermore, scalable emotion detection frameworks can be integrated into diverse applications across education, healthcare, entertainment, and smart environments, advancing the development of intelligent systems that better understand and respond to human affect.

II. Related Work

Speech Emotion Recognition (SER) has been extensively studied in recent years, with significant advancements driven by deep learning and feature enhancement techniques. Garg et al. [7] explored transformer-based SER models in noisy environments, demonstrating that attention mechanisms can effectively capture long-range dependencies in speech signals, improving emotion classification under challenging acoustic conditions. However, their study primarily focused on controlled noise scenarios, limiting its applicability in highly variable real-world settings. Nam and Park [8] proposed a Wave-U-Net multi-decoder architecture capable of robust emotion detection even at low signal-to-noise ratios. While effective in enhancing performance for degraded audio, the model's complexity presents challenges for real-time deployment and scalability.

Selective feature enhancement approaches have also gained attention. Leem et al. [9] introduced methods for emphasizing salient acoustic features in noisy SER tasks, which improved robustness against environmental distortions. Despite its merits, the approach relied heavily on handcrafted feature selection, which may not generalize well across diverse speakers and languages. Tavernor et al. [10] investigated episodic memory mechanisms for domain-adaptable SER, highlighting strategies to improve cross-corpus generalization. While promising for domain adaptation, the study did not fully address multi-emotion classification in unconstrained audio streams. Similarly, Garg et al. [11] and Li et al. [12] demonstrated that transformers combined with augmented Mel-Spectrograms enhance SER performance by leveraging both temporal and spectral information. These studies showed high accuracy on benchmark datasets, yet they still face limitations when applied to multi-lingual or real-world noisy speech due to dataset homogeneity and domain shift.

Recurrent and hybrid architectures have also been explored to capture temporal dependencies in speech. Khan et al. [13] presented a Bi-GRU with attention mechanism for multilingual SER, achieving improved generalization across languages. This work highlighted the importance of sequential modeling but did not extensively evaluate performance under diverse noise conditions or with spontaneous speech. Begazo et al. [14] proposed combined CNN architectures that integrate multiple feature representations, demonstrating improved emotion discrimination. While this approach enhances classification accuracy, it often requires high computational resources and extensive training data, limiting its practical deployment. George et al. [15] provided a comprehensive survey of SER techniques in noisy environments, emphasizing that despite recent progress, challenges remain in robust cross-domain, multi-emotion, and real-time recognition tasks.

Overall, the literature reveals significant progress in transformer-based, recurrent, and hybrid architectures, as well as in feature enhancement strategies for SER. Nevertheless, existing works exhibit common limitations, including restricted noise robustness, limited cross-corpus and multilingual generalization, dependency on handcrafted features, and computational complexity. These challenges motivate the present study, which aims to develop a more generalized and reliable framework for speech emotion recognition. By focusing on scalable and robust emotion detection that accommodates diverse speech conditions, multiple emotion categories, and practical deployment requirements, this research seeks to address the gaps identified in prior work, advancing the applicability of SER in real-world environments.

III. Materials And Methods

A) Proposed System

The proposed system implements a robust Speech Emotion Recognition framework capable of accurately classifying human emotions from speech signals. It leverages high-quality audio datasets to extract meaningful features such as Mel-Frequency Cepstral Coefficients (MFCCs), Mel-Spectrograms, and chroma features, which encapsulate tonal, harmonic, and temporal characteristics essential for emotion discrimination. These features are processed through a deep learning model that captures complex patterns in the spectral and temporal domains, enabling reliable identification of multiple emotions including happiness, sadness, anger, fear, disgust, surprise, calm, and neutral. The system is designed for real-time operation, allowing users to interact via audio uploads or live recordings, with predictions presented alongside visual representations for interpretability. By combining scalable feature extraction, adaptive model training, and a modular deployment framework, the proposed system addresses limitations of traditional methods, providing enhanced accuracy, robustness to noise and speaker variations, and suitability for applications in customer service, e-learning, virtual assistants, and mental health monitoring.

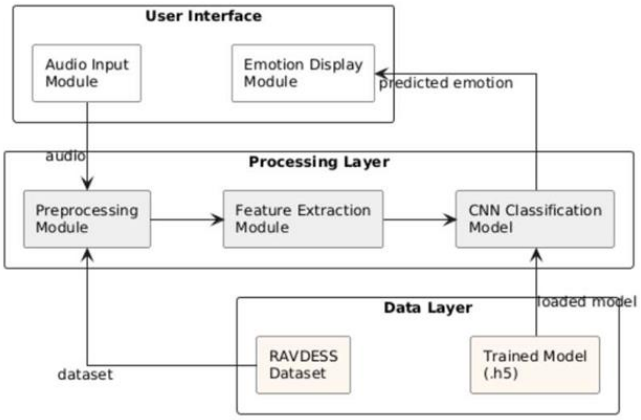

Fig. 1. System Architecture

The system architecture illustrated in Fig. 1 presents a structured framework for speech emotion recognition. It consists of three primary layers: the User Interface, the Processing Layer, and the Data Layer. The User Interface allows audio input and displays predicted emotions. The Processing Layer handles preprocessing, feature extraction, and CNN-based classification. The Data Layer stores the RAVDESS dataset and the trained model (.h5 file). Audio inputs flow through preprocessing and feature extraction before classification, and the resulting emotion predictions are returned to the user interface, enabling real-time analysis.

B) Data Collection

The study utilizes the RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song) dataset, which contains 1,440 high-quality audio recordings performed by 24 professional actors expressing eight distinct emotions:

anger, happiness, sadness, fear, disgust, surprise, calm, and neutral. Each sample includes speech and song recordings with varied pitch, tone, and intensity, captured in WAV format. The dataset's balanced emotion classes, high clarity, and diverse vocal expressions make it highly suitable for training and evaluating robust speech emotion recognition models.

C) Audio Pre-processing

Once the audio data has been collected, it must undergo pre-processing to ensure consistency, remove distortions, and enhance the quality of features extracted for emotion recognition. This stage is critical because raw speech signals often contain noise, silence, and variations in recording conditions that can negatively affect model performance. The primary goal of audio pre-processing is to standardize all audio samples, reduce irrelevant information, and preserve essential emotional cues, creating a reliable input for subsequent feature extraction and classification.

1. Standardizing Sampling Rate – Audio recordings in the dataset may originate from different devices or settings, leading to inconsistencies in sampling rates. All audio clips are resampled to a uniform rate (e.g., 22,050 Hz) to ensure temporal alignment and uniformity. Standardization facilitates accurate spectral analysis, ensures that extracted features such as MFCCs are comparable across all samples, and reduces computational complexity by maintaining consistent input dimensions for the CNN model.
2. Silence Trimming and Noise Reduction – Raw speech often contains silent intervals at the beginning or end, along with background noise from recording environments. Silence trimming removes irrelevant pauses that do not convey emotional information, while noise reduction filters suppress unwanted audio artifacts. Techniques such as band-pass filtering or spectral gating may be applied to isolate the speech signal, preserving frequency components that carry emotional cues while minimizing extraneous signals.
3. Amplitude Normalization – Speakers differ in voice loudness and recording devices may vary in sensitivity, leading to amplitude inconsistencies. Normalization scales the audio waveform to a consistent range, ensuring that variations in volume do not bias the learning model. This step improves the stability of feature extraction and helps the CNN accurately identify emotion-related patterns rather than variations in loudness.
4. Resampling or Padding – Emotional speech samples often vary in duration. To create uniform input for the CNN, audio clips are either truncated or zero-padded to a fixed length. This step ensures that feature matrices, such as MFCC or Mel-spectrogram arrays, have consistent dimensions, enabling batch processing and avoiding shape mismatches during model training.

By systematically applying these pre-processing steps, the raw audio data is transformed into a clean, standardized, and consistent format, preserving essential emotional information and preparing it for effective feature extraction and classification.

D) Feature Extraction

After pre-processing, the audio signals are transformed into feature representations that capture the essential characteristics of speech relevant to emotion recognition. Feature extraction is a critical step because Convolutional Neural Networks (CNNs) require structured, numerical inputs that reflect temporal and spectral patterns inherent in the audio. The goal is to convert raw 1D audio waveforms into rich representations that encode pitch, timbre, energy distribution, and harmonic structures, enabling the model to learn emotional patterns effectively.

1. Mel-Frequency Cepstral Coefficients (MFCCs) – MFCCs are a widely used representation in speech processing that approximate human auditory perception of sound. Typically, 40 coefficients are extracted per audio frame, capturing variations in frequency content over time. MFCCs emphasize the timbral and spectral properties of speech, which are highly informative for distinguishing emotions such as happiness, anger, sadness, or fear. The resulting 2D matrix of MFCCs forms a compact yet expressive feature map suitable for CNN input.
2. Mel Spectrograms – A Mel Spectrogram converts audio into a time–frequency representation, where the intensity of each frequency band is mapped over time. This visualization highlights temporal changes in energy and pitch, making patterns associated with emotional cues (such as tremors in fear or sudden bursts in anger) more apparent. Mel Spectrograms provide spatial features analogous to images, enabling CNNs to capture hierarchical structures in the audio.
3. Chroma Features – Chroma features summarize the harmonic content of speech by mapping spectral energy into 12 pitch classes. These features are particularly useful for detecting tonal variations, stress patterns, and harmonic changes, which may correspond to subtle emotional expressions. Incorporating chroma features enhances the richness of the extracted data and supports finer emotion discrimination.
4. Optional Descriptors – Additional descriptors such as Zero Crossing Rate (ZCR), which measures the rate at which the signal crosses the zero amplitude axis, and Spectral Centroid, which indicates the "brightness" of the sound, may be computed. These features provide complementary information about voice roughness, articulation, and spectral shape, further improving the model's ability to capture nuanced emotional cues.
5. Reshaping for CNN Input – All extracted features are normalized and reshaped into consistent 2D arrays, ensuring compatibility with the convolutional layers of the CNN. This standardization enables batch processing, preserves spatial relationships between features, and allows the network to learn meaningful hierarchical patterns from the audio representations.

By combining these feature sets, the system creates a comprehensive and discriminative representation of speech

signals, forming the foundation for robust emotion classification by deep learning models.

E) Model Development

The core of the speech emotion detection system is the Convolutional Neural Network (CNN), designed to automatically learn discriminative patterns from extracted audio features. The CNN architecture is specifically structured to handle 2D feature maps such as MFCCs and Mel Spectrograms, capturing both temporal and spectral relationships that correlate with human emotions. By hierarchically learning from local and global patterns, the CNN can identify subtle variations in pitch, energy, and timbre that distinguish different emotional states.

1. Convolutional Layers – Multiple convolutional layers are employed to extract local feature patterns from the input audio representations. Each layer applies a set of filters that detect distinctive characteristics such as frequency shifts, energy bursts, and harmonic fluctuations. These layers enable the network to capture hierarchical features, starting from low-level acoustic patterns in the first layers to more complex emotional structures in deeper layers. ReLU (Rectified Linear Unit) activation functions introduce non-linearity, allowing the model to learn more complex mappings between features and emotion labels.
2. Pooling Layers – Max-pooling layers are incorporated after convolutional layers to reduce the spatial dimensions of feature maps, while retaining essential information. Pooling helps improve computational efficiency, reduces overfitting, and provides the network with translation invariance, making it robust to minor variations in speech patterns across different speakers.
3. Dropout Layers – Dropout regularization is applied in the intermediate and fully connected layers to prevent overfitting. By randomly deactivating a fraction of neurons during training, the network learns more generalized representations, improving its performance on unseen audio samples and ensuring stability in real-world scenarios.
4. Dense (Fully Connected) Layers – Flattened feature maps are passed through dense layers to integrate the learned patterns and facilitate high-level abstraction. These layers combine multiple features to form decision boundaries for emotion classification.
5. Output Layer – The final layer uses a Softmax activation function to produce probabilities across all predefined emotion classes, such as happiness, sadness, anger, fear, neutral, surprise, disgust, and calm. This allows the system to provide a confident prediction of the most probable emotion for a given audio sample.

By carefully combining these components, the CNN architecture becomes capable of learning complex acoustic-emotional patterns, enabling accurate and robust classification of speech emotions in diverse and noisy environments.

F) Model Training and Validation

Once the CNN architecture is defined, the next critical phase involves training the model on the prepared dataset and validating its performance to ensure robustness and generalization. The dataset is typically partitioned into training and validation subsets, often using an 80:20 ratio, to allow the network to learn from the majority of data while being evaluated on unseen samples. This separation ensures that the model's performance reflects its ability to generalize beyond the training data, which is essential for real-world deployment.

To enhance the diversity of the training set and prevent overfitting, data augmentation techniques are applied to the audio samples. These techniques include pitch shifting, which simulates variations in vocal tone, time stretching, which alters the speed of speech without changing pitch, and noise addition, which improves robustness to real-world acoustic environments. Augmentation helps the CNN learn invariant features that are crucial for accurate emotion recognition across different speakers and recording conditions.

During training, the model's parameters are optimized by minimizing the categorical cross-entropy loss using optimizers such as Adam. Training and validation loss curves along with accuracy metrics are continuously monitored to track learning progress. To further prevent overfitting, early stopping halts training when validation performance plateaus, while learning rate scheduling adjusts the step size of parameter updates to ensure stable convergence.

The combination of structured dataset splitting, targeted augmentation, and careful monitoring during training ensures that the CNN develops robust and generalized feature representations. The trained model is capable of accurately predicting emotional states from diverse speech inputs, providing a reliable foundation for real-time emotion detection in practical applications.

G) System Integration and Deployment

The final phase of the methodology involves integrating the trained CNN model into a comprehensive, user-friendly system capable of real-time or batch emotion recognition. The deployment process ensures that the model is accessible through a graphical or web-based interface, allowing users to provide audio input via file uploads or live recordings. The system automatically processes the input through the established pre-processing and feature extraction pipeline before feeding it to the trained model for prediction.

Predicted emotions are presented to the user in an intuitive and interpretable format, often accompanied by visualizations such as waveforms, spectrograms, or probability charts to provide insight into the model's confidence levels and decision-making. The integration emphasizes modular design, separating the user interface, audio processing, prediction engine, and data management layers. This modularity ensures that each component can be updated, optimized, or extended independently, facilitating scalability, maintainability, and future enhancements such as multilingual support, continuous emotion tracking, or multimodal analysis.

Additionally, the deployment framework is designed to support real-time inference with low latency, enabling practical applications in domains such as virtual assistants, call centers, e-learning platforms, and mental health monitoring systems. By combining robust backend processing with an interactive frontend, the system delivers an effective and deployable solution for real-world speech emotion recognition tasks.

IV. Experimental Results

A) Introduction

This chapter presents the experimental demonstration of the developed Speech Emotion Detection (SED) system. The objective is to validate the functional performance of the system in a real-time environment, showcasing its ability to record audio, process the input, and classify human emotions accurately. Unlike conventional quantitative experiments, this chapter emphasizes system usability, interface functionality, and practical deployment. The demonstration is illustrated through three key screenshots representing the home page, audio input interface, and predicted emotion output. These visualizations help verify that the system operates as intended and provides an intuitive user experience.

B) System Overview

The SED system is implemented as a web-based application that integrates a trained Convolutional Neural Network (CNN) model for emotion classification. Users can interact with the system through a user-friendly interface, which allows both real-time voice recording and file uploads. Once the audio is provided, the system executes preprocessing, feature extraction, and classification to predict the emotion category. The modular architecture ensures scalability, enabling potential future enhancements such as multi-language support or multimodal emotion recognition. This chapter focuses on functional validation rather than large-scale statistical evaluation, highlighting the system's readiness for practical deployment.

C) Screenshots and Functional Demonstration

Home Page: The home page serves as the entry point of the application. It provides users with an intuitive interface to either upload audio files or record audio directly through a microphone. Navigation options and instructions are clearly displayed to ensure a smooth user experience. The layout emphasizes simplicity and accessibility, making the system suitable for both research and end-user applications.

Figure 2 illustrates the home page interface.

Fig.2 Home Page

Audio Recorder: The audio input module enables users to record speech in real-time or select pre-recorded audio files for analysis. This module ensures that audio is captured in a standardized format suitable for processing by the underlying CNN model. Prior to classification, the audio undergoes preprocessing steps including normalization, noise reduction, and resampling to maintain consistency across samples.

Figure 3 shows the audio recording interface.

Fig.3 Input Page

Perceived Emotions: After processing, the system displays the predicted emotion with a clear and interpretable visualization, including probability scores for each emotion category. Users can observe which emotion is most likely based on the model's prediction. The interface can handle multiple emotions in sequential clips, demonstrating robustness and practical usability.

Figure 4 presents the output screen displaying perceived emotions.

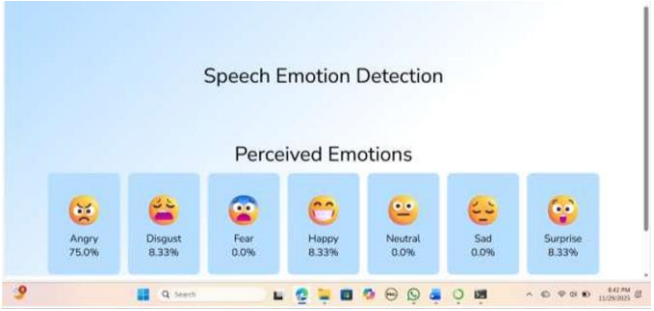

Fig.4 Output Page

D) Observations

From the demonstration, it is observed that the system successfully captures, processes, and classifies audio input in

real-time. The predicted emotions align with intuitive human perception, and the interface provides immediate visual feedback. Minor limitations include difficulty in detecting very subtle emotional cues and sensitivity to background noise, which can affect prediction confidence. Overall, the system demonstrates functional reliability and user-friendliness.

This chapter verified the operational performance of the Speech Emotion Detection system through a series of functional demonstrations. The home page, audio input module, and emotion prediction output collectively confirm that the system is ready for practical deployment. The modular and intuitive design allows scalability and adaptability, highlighting its potential for applications in customer support, virtual assistants, e-learning platforms, and mental health monitoring.

V. Conclusion

This study presents a comprehensive Speech Emotion Recognition system that effectively identifies human emotions from audio signals using advanced deep learning techniques. By leveraging high-quality datasets and extracting informative audio features such as MFCCs, Mel-Spectrograms, and chroma features, the system demonstrates robust performance across multiple emotion categories, including happiness, sadness, anger, fear, disgust, surprise, calm, and neutral. The integration of these features into a deep learning framework enables the model to capture complex spectral and temporal patterns, enhancing its ability to generalize across diverse speakers, accents, and acoustic conditions. Furthermore, the system's modular design facilitates real-time processing and deployment, allowing practical applications in areas such as virtual assistants, mental health monitoring, call-center analytics, and intelligent human-computer interaction. The user interface provides seamless accessibility, supporting both live recordings and pre-recorded audio inputs, while presenting interpretable results through visualizations. Overall, the developed system addresses the limitations of traditional machine learning approaches by achieving higher accuracy, resilience to noise, and the capability to recognize subtle emotional cues. This research highlights the potential of combining speech processing and deep learning to advance emotion-aware technologies, paving the way for more responsive, human-centric interactive systems.

The Speech Emotion Recognition system can be extended to support real-time continuous emotion tracking during conversations, enabling dynamic monitoring of user moods. Multi-lingual capabilities can be incorporated to recognize emotions across regional and international languages. Integration with facial or gesture-based emotion recognition can provide multimodal analysis for improved accuracy. Enhancing noise robustness and predicting emotion intensity will further refine performance. Additionally, deployment on mobile and IoT devices will enable ubiquitous emotion-aware applications in healthcare, customer service, education, and smart environments.

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