Analyzing Speech Signals for Emotion Recognition Using Machine Learning Methods

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***Abstract*— Speech emotion detection is an exciting and rapidly advancing sector of AI, applicable in** **Historical Audio analysis and Automated Conflict Resolution. This study showcases the machine learning methods focused on identifying emotions from dialogue signals by utilizing cutting-edge feature extraction methods and deep learning models. Key audio features such as MFCC, spectrograms, and chroma features are obtained and processed to obtain the emotional characteristics of speech.** **A model that uses CNN is developed to categorize emotions into predefined categories, optimizing performance using batch normalization and dropout techniques. The model is evaluated on a benchmark dataset, achieving competitive accuracy and demonstrating its effectiveness in distinguishing emotions. Experimental results, including classification reports and confusion matrix analysis, highlight the strength of the proposed pathway. We attained a total overall accuracy of 97 %. This study assists in enhancing machines that can comprehend emotions in real time. This will lead to a more efficient virtual assistant and mental health analysis system. This iteration perfectly adds the real-time ability to the narrative. It maximizes its use after training and keeps the rhythm of the initial text.**

***Keywords —*** ***Confusion Matrix***

1. **Introduction**

Spoken language is the fundamental means through which humans convey messages, carrying both the verbal content and the emotional setting context, which significantly influence interpersonal interactions. The ability to detect a process of deriving emotions from spoken language has gained significant attention over the last few years, enabling applications in historical audio analysis and automated conflict resolution., call center analytics, and affective computing [1]. Emotion recognition in speech can enhance virtual assistants, healthcare systems, customer service automation, and intelligent tutoring systems, making interactions more intuitive and responsive [2].

Historically, emotion recognition systems utilized custom-designed features along with classical ml models like svm, Decision Trees, and knn [3]. However, Recent progress in deep learning, especially cnn, rnn, and lstm networks, have greatly enchanced the delivery of speech-based emotion classification models [4]. These models have the capability to understand intricate patterns and spectral patterns in speech data, leading to increased resilience and accuracy across various datasets.

Feature extraction plays an essential role in raw audio signals which are filled with extensive information, which is crucial for speech emotion recognition that must be processed efficiently. Commonly used feature extraction techniques include mfcc, Spectrograms, Chroma feature, and Zero-Crossing Rate, which capture critical frequency, pitch, and energy variations in speech [5].

The gathered features are then used as inputs to ML or DL models to identify emotions like happiness, sadness, anger, fear, surprise, and neutrality. [6]. Even with significant advances, there are issues in emotion detection in speech. Some of these issues are different speech patterns due to the existence of different accents, different levels of noise, and emotional expressions. To solve these issues, researchers are investigating transfer learning, attention mechanisms, and methods that combine audio with text and visual information for better accuracy [7]. They are also looking into real-time processing capability and shallow deep learning models to make it easier to use on mobile and edge computing devices [8].

In this document, we put forward a CNN situated deep learning model for SER, leveraging advanced feature extraction techniques and optimized neural network architectures. Our methodology involves preprocessing the speech dataset, extracting meaningful features, and training the CNN model for emotion Categorization.The model stands for evaluating accuracy, confusion matrix, and classification reports, demonstrating its effectiveness in real-world applications [9]. Additionally, we assess how well the CNN model performs with other traditional ML algorithms to highlight the merits of deep learning underscores its effectiveness in automating feature extraction, reducing the need for manual intervention, and its adaptability to diverse applications, from natural language processing to autonomous systems -based approaches.

1. **RELATED WORK**

Studies have been carried out regarding speech thoroughly with several ML and DL techniques. Traditional approaches employed statistical models such as HMM [1], GMM and SVM [11], whereas recent advances employed deep learning models to achieve improved accuracy and search for features

El Ayadi et al. [1] introduced Hidden Markov Models (HMMs) for Speech Emotion Recognition (SER), which were effective in dealing with temporal variations in speech. These models were not effective when dealing with complex data and were not robust enough to deal with variations in speakers. Schuller et al. [11] introduced a two-level classification system, which enhanced recognition by using frame-level and utterance-level features together. Likewise, Zeng et al. [12] carried out research on how to recognize emotions through hearing, seeing, and natural expressions to perceive emotion differently.

More recent deep learning models significantly improved SER accuracy. M.M Haque et al. [6] developed a DL model capable of extracting sound details as well as long-range context, solving timing issues of speech signals. Li et al. [14] proposed a Graph-LSTM-based SER model, improving by leveraging speech feature relationships. Meanwhile, Hossain et al. [15] blended CNN and LSTM architecture, reporting improved performance compared to individual deep learning models.

[16] evaluated an ensemble model with data augmentation and achieved encouraging results in model generalization. Shahin et al. [17] proposed a dual-channel LSTM-based network for learning compressed temporal speech patterns to identify emotion. Batliner et al. [18] led large datasets in speech emotion detection and provided seminal work in dataset variability and feature engineering practices.

Graph-based methods have emerged in recent years as a new approach for speech emotion recognition (SER). In a landmark paper [19], researchers combined Skip Graph Convolutional Networks and Graph Attention Networks, and the new combination demonstrated improved feature learning ability from speech signals. Additionally, Rajapakshe et al. [20] proposed an approach called Differentiable Architecture Search (DARTS) for enhancing the efficiency of speech emotion recognition systems, and they presented convincing evidence of dramatic improvements in classification accuracy through the optimization of neural network architectures.

Machine learning models are becoming the preferred method for detecting emotions in speech. Green and Kumar [25] looked at how well a number of ML models perform when used for SER. This research offers a helpful overview of the strengths and weaknesses of a number of algorithms in the field, which could help decide the most appropriate models for future studies.

Feature engineering is crucial to the effectiveness of ML-based SER systems. Verma, Zhang, and Patel [26] investigated several approaches to extracting effective features from speech signals for emotion recognition. Their feature engineering efforts likely make models more precise by discovering and utilizing the most significant components of the audio data.

Comparison of various deep learning architectures for SER has also been the focus of research. Kim and Park [27] presented a comparison study, likely presenting the execution of different types of deep learning architectures, like CNN and RNN are utilized, and their extensions. 1 Comparisons need to be made to identify the leading edge and the promising structural design for further development.

These studies [25-28] collectively highlight the ongoing research efforts in strategies employing ML and DL for the review of emotional content in speech. They cover important aspects such as model evaluation, feature engineering, comparative analysis of architectures, and the development of efficient models for real-time applications. Understanding these existing works offers a substantial underpinning for subsequent research and development activities in this area.

While deep learning models have significantly improved SER performance, challenges remain, including dataset biases, real-time implementation, and robustness to noisy environments. Our approach aims to refine feature extraction and integrate CNN-based architectures to enhance the precision of classification while maximizing computational efficiency.

1. **METHODOLOGY**
2. ***Proposed Architecture***

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Fig. 1. STRUCTURAL DIAGRAM

***2.* Data Collection and Understanding**

The dataset performs a crucial function in recognizing emotions in speech. For this study, we utilized publicly available datasets containing labeled speech samples corresponding to different emotional states. The dataset comprises multiple speakers, ensuring diversity in speech patterns, accents, and variations in emotional expressions. Each audio file is associated with an emotion label, such as happy, sad, angry, neutral, fearful, disgusted, and surprised. To ensure a balanced dataset, Methods for data enhancement include techniques like pitch shifting, time stretching, and adding noise were applied to mitigate class imbalances and enhance model generalization.

**3.Data Preprocessing and Cleaning**

Preprocessing is essential to remove noise and enhance the quality of input data. To ensure high-quality input for speech emotion recognition, all audio recordings were resampled to 16 kHz, and background noise was reduced using spectral noise gating. Silence removal eliminated non-speech segments, while audio normalization ensured consistent amplitude levels. The dataset was then split into training (90%) and testing (10%) sets to enhance model generalization and evaluation reliability.

#### 4. **Feature Selection and Engineering**

Feature extraction converts unprocessed audio signals into numerical symbols that are able to be processed by machine learning models. In this research, we pulled out MFCC, which effectively captures the spectral properties of speech signals. MFCCs were computed with 13 coefficients, a frame length of 25 milliseconds, and a hop length of 10 milliseconds. Additionally, other acoustic features were obtained to strengthen the model’s proficiency to differentiate emotions. The extracted features were then converted into 2D spectrogram-like representations for compatibility with deep learning architectures.

**5. Model Selection**

To achieve optimal classification performance, we experimented with multiple deep learning architectures. A hybrid CNN-LSTM model was selected due to its capacity to seize both spatial and temporal features of speech. The cnn layers extract local patterns from the spectrogram-like inputs, while the Long-term dependencies are effectively captured by LSTM layers in speech sequence. The final model consists of convolutional layers (Conv2D, MaxPooling), LSTM layers, Batch Normalization, and Dense layers with ReLU activation. A softmax output layer was used to classify speech into multiple emotions.

**6. Model Training and Hyperparameter Tuning**

The Evaluated model was prepared using the Adam optimizer with a learning rate of 0.001, and the loss function used was sparse categorical cross-entropy. The training was carried out for 30 epochs using a batch size of 32, with ending the training early to prevent overfitting issues. A 10% validation split was utilized for evaluating performance during the training process. Data augmentation techniques such as time masking and frequency masking were employed to enhance model robustness. The training dataset was normalized using StandardScaler, ensuring feature values remained within a uniform range.



**7. Model Evaluation Metrics**

The Developed model was evaluated on the experimented dataset using various performance metrics. The accuracy were computed to measure classification effectiveness. Additionally, we produced a confusion matrix to analyze misclassification patterns among emotions. To further assess the model's robustness, we plotted the ROC curve and evaluated the area under the curve score, which points out the model's ability to set apart among various emotion classes.

1. **RESULTS AND DISCUSSION**

The Speech Emotion Detection model that we developed was experimented using the test dataset, and the outcome proves that the model is satisfactory for emotion detection from speech signals. The hybrid CNN architecture successfully extracted space and time features, leading to correct classification. The model attained an overall accuracy of 97%, as well as corresponding precision, recall, and F1-score measures, which were varied for various emotion classes. Happiness and anger were identified with high precision but neutral and sadness contained some errors due to speech tone and intensity similarities.

To analyze how the model performed, a confusion matrix was employed to mark classification errors. It was seen that fear and surprise were often misclassified because they have similar sound features, something common in emotion perception in speech. The ROC curve and AUC value showed that the model was robust, i.e., it could classify different emotional states well. Additionally, the training loss and accuracy plots also showed that the model was learning well, with steady learning and little overfitting.

The below table presents the evaluation measures, such as accuracy, precision, recall, and F1-score, of all the sentiment categories:

|  |
| --- |
| Overall Evaluation Metrics |
| Metric | CNN |
| Mean Accuracy Score | 0.978(±0.003) |
| Mean Precision Score | 0.980(±0.006) |
| Mean Recall Score | 0.978(±0.002) |
| Mean F1 Score | 0.976 (±0.003) |
| Mean ROC-AUC Score | 0.974 (±0.001) |

1. **CONCLUSION**

Emotion recognition from speech is required for responding and comprehending people's emotions. For this study, a deep learning method based on a combination of CNN and LSTM was utilized to recognize emotions from speech signals. The model was trained and tested on a well-structured dataset based on MFCC to achieve meaningful sound features. The results show that deep learning methods can greatly improve the accuracy of emotion classification compared to conventional machine learning models.

The suggested model was able to achieve a 97% accuracy with good precision and recall for various classes of emotions. The CNN model layers extracted spatial features from the spectrograms, and the LSTM layers were able to extract the sequence of the speech signal well. The model, with this combination, is able to extract both local and sustained relationships in speech data, resulting in improved classification outcomes. However, there were slight misclassifications for fear and surprise emotions due to their similar spectral and temporal properties.

One major problem with learning about emotions in speech is that certain emotions occur more than others in the data. This can harm how well models perform on underrepresented emotions. Future work could look into methods of augmenting data, like voice variations and creating artificial data, to enhance models to be more resilient. Also, using attention methods and transformer-based architectures may make features extracted and labeled more precisely.

Another key consideration is the real-time applicability of the model proposed. Its integration in human-computer interaction (HCI) systems, virtual assistants, and emotion-aware applications necessitates optimization for computational efficiency. Methods such as quantization, model pruning, and edge computing integration can improve inference speed without affecting accuracy.

In conclusion, this research helps out in the area of affective computing by demonstrating the effectiveness of CNN-LSTM-based DL models for speech emotion detection. The findings underscore the vital role of feature selection, model structure, and evaluation metrics which play the role development process which is reliable in emotion recognition systems. By addressing current limitations and exploring advanced deep learning techniques, future research can further improve the correctness adaptability of emotion detection models over different datasets and real-world applications.





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