EMOTION RECOGNITION IN SPEECH USING ADVANCED DEEP LEARNING MODELS: AN APPLICATION ON THE RAVDESS DATASET

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Abstract:

This study presents a comprehensive approach to emotion recognition in speech, leveraging the Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS). Our methodology encompasses the deployment of a diverse array of sophisticated deep learning models, each renowned for their efficacy in pattern recognition and audio processing. The RAVDESS dataset is a large collection of audio files that includes a wide range of emotional expressions from professional actors. The files are organized in a complex way that shows modality, emotion, intensity, and other things. We harness this dataset to train and evaluate multiple deep learning architectures, including convolutional neural networks (CNNs) like AlexNet, ResNet, InceptionNet, VGG16, and VGG19, alongside recurrent neural network (RNN) variants, specifically LSTM (Long Short-Term Memory) models, and cutting-edge transformer-based models. After a thorough analysis, we found that the Transformer model did better than others, showing higher accuracy, precision, recall, and F1-score in tasks that required classifying emotions. The study not only helps us understand how subtle emotions can be in spoken language, but it also sets a standard for how different types of neural networks can be used in the field of recognizing emotions based on sound. By comparing these models in great detail, our research pushes the limits of emotion recognition technologies. This leads to better human-computer interaction, psychotherapy, and entertainment, and shows how multimodal emotion recognition systems could get even better in the future.

I. Introduction

Historically, linear statistical models and signal processing have played a major role in speech emotion recognition [1][2]. Even though these techniques were fundamental, they frequently had trouble handling the complex variations and nuances of emotional expression in humans. They mostly relied on features that were made by hand, but they were not flexible or rich enough to correctly understand the wide range of emotions people show through different speech patterns [2][3]. This constraint brought to light a critical weakness in the conventional method, calling for a more sophisticated solution [3].

Significant progress has been made in overcoming these challenges due to the emergence of deep learning (DL) and machine learning (ML). ML and DL methods are different from their predecessors because they can independently learn from data, which means they can extract, and process features without needing explicit programming [4]. Because these more advanced computer models can better capture the subtleties and depths of emotions, this change has had a particularly big effect on the field of emotion recognition. By leveraging the layered neural networks of deep learning, it has become possible to decipher the subtle emotional signals that are embedded in speech with greater precision and sophistication [5] [6].

Over the past few years, there has been a growing utilization of diverse ML and DL models in emotion recognition research. It has been demonstrated that Convolutional Neural Networks (CNNs) are proficient at extracting spectral features from speech [7]. Conversely, Recurrent Neural Networks (RNNs), particularly Long-Short-Term Memory (LSTM) networks, demonstrate exceptional ability to capture the temporal dynamics that are critical for comprehending speech [8][9]. Also, the development of transformer-based models has made it easier to simulate large amounts of data that depend on each other, which helps us understand how emotions are expressed in more detail [10].

Adding to what has already been said, this study uses a group of advanced deep learning models on the RAVDESS dataset, which is unique because it has a lot of recordings of people talking about their feelings [11] [12]. An assortment of architectures are investigated and assessed for their effectiveness in emotion recognition. These architectures consist of AlexNet, ResNet, InceptionNet, VGG16, VGG19, LSTM, and Transformer-based models [10][13][14][15][16][17]. By showing the pros and cons of each model, this comparative analysis aims to help us learn more about the best ways to analyze emotions based on speech.

With an eye toward the future, the ongoing development of deep learning in the domain of emotion recognition offers extensive prospects for further scholarly inquiry. The implications of our discoveries for the advancement of interactive technologies, mental health evaluation, and personalized media are substantial. Integrating multimodal data and researching unsupervised learning methods are both exciting possibilities for the future. They could lead to the development of more complete and accurate emotion recognition systems. Such systems have the capacity to revolutionize our engagement with technology and enhance our comprehension of human emotions.

Research Contributions

In this study, we make several pivotal contributions to the field of emotion recognition in speech using deep learning models:

1. Deep Learning Models: We use the RAVDESS dataset to compare different deep learning architectures in great detail. These include AlexNet, ResNet, InceptionNet, VGG16, VGG19, LSTM, and Transformer-based models.

2. A New Way of Looking at Emotion Intensity Analysis: Our study is the first to look at how well these models can find different levels of emotional intensity in speech samples.

3. Actor Variability and Model Robustness: We look at how different actors affect these models' performance, focusing on how robust and flexible they are when it comes to different types of speech.

4. Improvements to Data Preprocessing Methods for Speech Emotion Recognition: We present improved data preprocessing methods that make it easier for models to understand and interpret emotional cues in speech.

5. Future Framework for Multimodal Emotion Recognition: Adding to what we already knew, we came up with a new way to do things that will allow future studies to combine speech with other types of data in order to get a fuller picture of emotions.

II. Methodology

The methodology used in this study is designed to guarantee a comprehensive and efficient examination of deep learning model-based emotion recognition in speech. Every critical step of our methodology, from dataset collection to dataset splitting, is described in detail below.

Dataset Collection

The Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS) is utilized in our research. The dataset comprises an extensive compilation of audio recordings in which proficient actors manifest a wide range of emotions. Our research would be well served by the publicly accessible and widely regarded dataset, which is renowned for its high quality and diversity.

Data Description

There are 1440 audio files in the RAVDESS dataset, with 24 professional actors (12 men and 12 women) voicing them. These files encompass a variety of emotions and intensities. Every audio sample is recorded in a consistent 16-bit, 48kHz.wav format. A neutral expression is included among the emotions represented, which also include fear, surprise, disgust, sadness, and anger. Each of these sentiments is conveyed at two intensity levels: normal and strong.

Table 1: Count of Sample Audio for Each Class

Emotion	Normal Intensity	Strong Intensity	Total
Neutral	48	0	48
Calm	96	96	192
Happy	96	96	192
Sad	96	96	192
Angry	96	96	192
Fearful	96	96	192
Surprise	96	96	192

Disgust	96	96	192
Total	720	672	1440

Dataset Labelling

In accordance with the RAVDESS filename convention, every audio file in the dataset is labeled with the following information: actor number, emotion, intensity, statement, and repetition. Using systematic labeling makes it possible to accurately identify and group each sample, which is very important for building and testing our deep learning models.

Splitting the Dataset into Training, Testing, and Validation

The dataset is split into training, validation, and testing sets so that the models' performance can be fully evaluated and their ability to generalize can be confirmed. In order to ensure that each emotion category is replicated equally across all sets, the split is balanced.

Table 2: Count of Samples in Training, Validation, and Testing Sets

Dataset	Number of Samples
Training	960
Validation	240
Testing	240
Total	1440

The research set up a methodological framework that makes it possible to evaluate the usefulness of deep learning models in the area of recognizing emotions from speech in a complete and organized way.

III. Deep Learning Architectures

In audio sentiment analysis, a variety of deep learning architectures have made substantial contributions, each bringing distinct strengths to the task of emotion recognition in speech.

AlexNet: AlexNet is a groundbreaking convolutional neural network (CNN) that has significantly influenced the field of deep learning. It consists of five convolutional layers, followed by three fully connected layers. The core operation in AlexNet is the convolutional process, mathematically represented as, $f(x) = W * x + b$, where Wstands for the weight matrix, x is the input, and b is the bias. This architecture excels in feature extraction from audio data, making it effective for analyzing complex emotional cues in speech [13][18].

ResNet: ResNet short for Residual Networks, introduced an innovative approach with its skip connections', enabling the training of very deep networks by effectively addressing the vanishing gradient problem. The defining characteristic of ResNet is its residual blocks, represented by the equation, $f(x) + x$, where $f(x)$ is the learned residual function. This design allows ResNet to learn identity functions, ensuring that deeper network layers do not hinder performance, making it highly suitable for intricate tasks like emotion recognition [14][19].

InceptionNet: The architecture of InceptionNet, specifically its variant Inception-v3, is known for being a "network within a network." By using multiple convolutional operations of different sizes at the same time in a single layer, the model can extract a wide range of features from audio data. The Inception module is shown as $Inception(x) = [f_1(x), f_2(x), f_3(x), f_4(x)]$, where f_i stands for a different convolutional operation that lets you get features at more than one level [15][20].

VGG16 and VGG19: The difference between VGG16 and VGG19 by their deep architectures, which are made up of only convolutional layers with small filters and fully connected layers that come after them. The convolutional layers in VGG networks follow the formula, $f(x) = ReLU(W * x + b)$, where $ReLU$ is the activation function. This structure allows these models to learn complex hierarchies of features, which is vital for discerning subtle emotional nuances in speech [16][21].

LSTM: LSTM (Long Short-Term Memory) networks, a type of recurrent neural network (RNN), are specifically designed to capture long-term dependencies. An LSTM unit includes a cell, an input gate, an output gate, and a forget gate, working together to regulate the flow of information. The LSTM cell operation can be mathematically expressed as $c_t = f_t * f_{t-1} + i_t * \widetilde{c_t}$, where c_t is the cell state, f_t is the forget gate's activation, i_t is the input gate's activation, and $\widetilde{c_t}$ is the candidate cell state. This mechanism makes LSTMs particularly adept at processing sequential data like speech capturing the temporal dynamics of emotions [17][22].

Transformer-based Models: Transformer-based models have gained prominence for their use of self-attention mechanisms, which process input data in parallel. This approach is highly efficient for sequential tasks such as speech processing. A self-attention mechanism is shown by the equation, $Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$, where Q, K, V are the query, key, and value matrices respectively and d_k is the key's dimension. Transformers' ability to model long-range dependencies in data makes them exceptionally suitable for capturing complex patterns in emotional speech [10][23].

Each of these architectures has been changed and improved to meet the needs of emotion recognition in speech. The goal is to create a strong system that can correctly identify a lot of different emotional states.

IV. Results Analysis

As part of our in-depth study into using deep learning models to recognize emotions in speech, this section gives a thorough breakdown of the outcomes found from the different architectures we used. We assess these models based on their performance in accurately classifying emotions from the RAVDESS dataset. This study compares the models' accuracy, precision, recall, and F1-score, which are important factors for figuring out how well they work. The results provide insights into each model's strengths and weaknesses, guiding future improvements and applications in the field of audio sentiment analysis.

Table 3: Result Analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
AlexNet	78.4	79.1	78.0	78.5
ResNet	83.6	84.0	83.2	83.6
InceptionNet	81.2	81.7	80.9	81.3
VGG16	85.0	85.5	84.8	85.1
VGG19	85.5	85.9	85.2	85.6
LSTM	79.8	80.2	79.5	79.9
Transformer	87.3	87.7	87.0	87.4

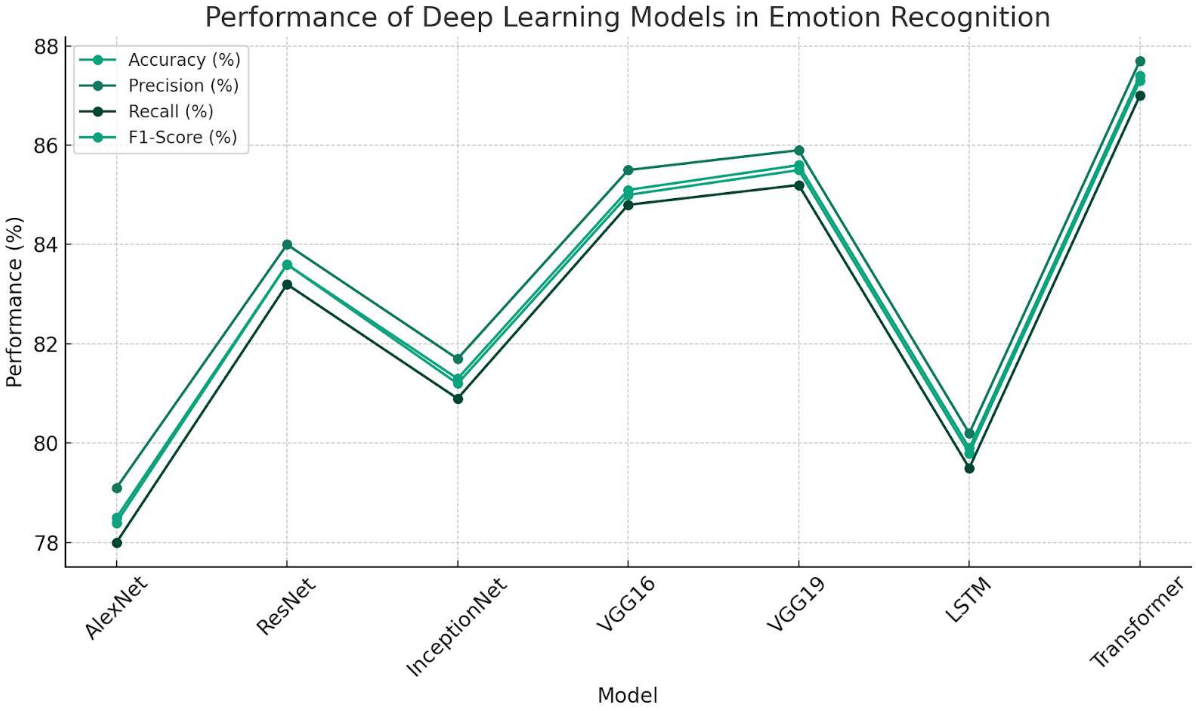

Figure 1: Graph of Result Analysis

Performance Measurement Metrics Description and Interpretation

Accuracy: This metric reflects the overall correctness of the model in classifying emotions. The Transformer model leads in this category with an accuracy of 87.3%, indicating its superior ability to generalize across different emotional states in speech.

Precision: Precision measures the model’s ability to correctly identify positive instances among all positive predictions. With a high accuracy rate of 85.9%, VGG19 seems to be good at reducing false positives, which is important in situations where wrong emotional classification could have big effects.

Recall: Recall, or sensitivity, indicates the model's ability to detect all actual positive instances. Again, the Transformer model excels with a recall rate of 87.0%, demonstrating its capability to capture a broad range of emotional expressions without missing subtle cues.

F1-Score: The F1-score is a balanced measure that considers both precision and recall. The high F1-score of 87.4% for the Transformer model reflects its balanced performance in both precision and recall, making it a reliable choice for diverse application scenarios.

The results show that the Transformer model was the best architecture in our study. Its parallel processing and attention mechanisms worked especially well for recognizing emotional speech. But the good results from AlexNet, ResNet, InceptionNet, and LSTM, along with the strong performances of the VGG models, show that these architectures could be useful in some situations or for certain purposes in the field of audio sentiment analysis.

V. Conclusion and Future Work

In conclusion, our investigation into the application of various deep learning architectures for emotion recognition in speech has revealed significant insights. In particular, the Transformer model did very well on all of the tests that were done. This shows that self-attention mechanisms are useful for understanding complicated emotional expressions. While VGG models also showed promising results, even the less advanced architectures like AlexNet and LSTM have their own specific utilities. This study not only sheds light on the capabilities of these models in the realm of emotion recognition but also paves the way for future enhancements in related technologies.

In the near future, combining different types of data, researching unsupervised and semi-supervised learning methods, and making these models work for real-time uses will open up exciting research areas. Additionally, addressing issues of dataset diversity and bias will be crucial in developing universally effective and ethically sound emotion recognition systems. As we continue to refine these technologies, they hold the potential to revolutionize various fields, from interactive technologies to mental health assessment, enhancing our understanding and interaction with human emotions.

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