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Research Project

Decision Tree Models for Audio Feature Classification in Depression Prediction

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Abstract

This study explores the utility of vocal biomarkers for depression diagnosis through binary classification methods. Using audio features, specifically Mel-Frequency Cepstral Coefficients (MFCC) and Mel Cepstral Coefficients (MCC), extracted from speech samples from the DAIC-WOZ and EATD-Corpus datasets, I employ decision tree (DT) algorithms and convolutional neural network (CNN) models to evaluate their predictive accuracy. Results suggest that traditional PHQ-8 questionnaires remain more reliable for depression screening compared to audio-based detection methods. The study highlights significant challenges in using audio data for depression detection, particularly the difficulty in generalizing to new patients and the impact of feature selection on model performance. These findings emphasize the need for careful consideration of the practical utility of audio-based depression detection systems in clinical applications.

Keywords: depression detection • audio analysis • machine learning • CNN • MFCC

1 Introduction

Depression affects millions globally and represents a significant public health issue[15]. Early detection and intervention are critical for effective management and treatment. Traditionally, depression assessment has relied heavily on clinical interviews and self-reported measures, such as the PHQ-8[7] and PHQ-9 questionnaire[5].

This research aims to advance the field of psychiatric diagnostics by exploring the potential of audio analysis to detect depression. Utilizing machine learning algorithms, specifically Decision Tree and Convolutional Neural Network (CNN) models, this study analyzes vocal biomarkers within audio recordings from two distinct datasets: the Distress Analysis Interview Corpus - Wizard of Oz (DAIC)[11] and the Emotional Audio-Textual Depression (EATD) Corpus [9]. These datasets offer source of vocal expressions aligned with validated depression assessments, providing a foundation for developing predictive models.

The challenge of accurately detecting depression from audio features encompasses several critical issues. These include addressing the class imbalance across different depression severity categories, managing the variability in audio quality, and ensuring the generalizability of models beyond the training data. This study aims to analyze these relationships between audio characteristics and depression and explore the viability of audio-based depression detection as a supplementary tool to traditional methods.

Despite the initial aim of utilizing machine learning to enhance the diagnosis of depression through audio analysis, this study reveals significant limitations. Key lessons include recognizing the efficiency of existing tools like the PHQ-8 and PHQ-9 questionnaires in predicting depression, which often outperform more complex machine learning approaches. Furthermore, this research underscores a critical flaw in many studies: using the same patients' audio samples for both training and testing, which, while improving model accuracy, fails to ensure generalizability to new individuals. These insights highlight the importance of methodological rigor and the need to prioritize practical generalization in future machine learning research. Additionally, the choice and processing of audio features play a crucial role, proving essential for the effective performance and reliability of machine learning models in clinical applications.

2 Datasets Description

2.1 DAIC

The DAIC dataset is an essential resource in computational psychiatry, pivotal for developing algorithms to diagnose psychological distress conditions such as depression and anxiety. This publicly available English depression dataset features multimodal data including audio, video, and text transcripts of interviews conducted by an animated virtual agent named Ellie in a simulated clinical setting. The dataset includes 142 participants evaluated with the PHQ-8 score, a popular depression screening tool. A PHQ-8 score of 10 or higher is indicative of depression.

The dataset is divided into three subsets: the training set includes data from 30 depressed and 77 non-depressed participants, the development set consists of 12 depressed and 23 non-depressed participants, and an unlabeled test set. This structure provides a rich, controlled environment for testing and comparing different diagnostic approaches, enhancing the reliability and accuracy of mental health diagnostics.

Interviews are designed to elicit emotional responses through predefined prompts, making the dataset highly suitable for studying vocal characteristics, speech patterns, non-verbal cues, and facial expressions associated with mental health states. The extensive annotations related to behavioral markers allow researchers to explore multimodal integration techniques, further supporting the development of sophisticated diagnostic models. This comprehensive data and detailed annotations are invaluable for advancing methodologies in mental health assessments within artificial intelligence frameworks.

2.2 EATD

The EATD Corpus, created at Tongji University is a dataset that caters to the need for multimodal data in depression research. This dataset includes audio recordings and their corresponding textual transcripts from interviews conducted with both depressed and non-depressed volunteers, making it a vital resource for the development of automated depression detection systems.

The EATD is distinctive as it is the first publicly available Chinese dataset that integrates both audio and text modalities specifically for depression analysis. It comprises contributions from 162 student volunteers who provided informed consent, ensuring the data's authenticity and ethical integrity. Each session in the dataset is annotated according to the Self-Rating Depression Scale (SDS)[18], providing researchers with valuable clinical metrics to correlate with linguistic and acoustic features.

The nature of this dataset allows for research opportunities, including the enhancement of feature extraction methods for depression detection and the development of ML-driven models that utilize multimodal data to assess mental health states more accurately. Moreover, it supports the exploration of computational techniques in identifying depressive symptoms, thereby advancing the field of mental health technology.

3 Literature Review

During the literature review, I primarily focused on the DAIC dataset for several reasons. Firstly, while the EATD dataset is relevant, it is considerably smaller in scale, containing only three single sentences (negative, positive, neutral) from 162 participants. In contrast, the DAIC dataset provides a more comprehensive array of audio and textual data from 189 participants, enhancing the potential to train more robust machine learning models. This choice allows for a deeper exploration of methodologies and outcomes pertinent to the use of vocal biomarkers in depression detection within a larger and more varied participant base, thereby improving the generalization and statistical power of the findings.

For finding the best accuracy, this paper[8] was used, and three three papers were checked which reached the best accuracy. Among these Homsiang et al[2] achieved 95% accuracy using a 1D CNN architecture with data augmentation. Their approach involved converting audio to Mel Cepstral Coefficients (MCC)[13] and implementing various augmentation techniques including noise reduction, pitch shifting, and speed adjustment. Their comparative study of different architectures (1D CNN, 2D CNN, LSTM, and GRU) demonstrated that 1D CNN with augmented data significantly outperformed other approaches, showing strong performance in both depression detection (precision: 0.91, recall: 1.00) and non-depression classification (precision: 1.00, recall: 0.90). This work particularly highlights the importance of data augmentation in improving model performance, as their non-augmented experiments only achieved 71% accuracy with 2D CNN.

Ishmaru et al. [3] achieved 97% accuracy using a Graph Convolutional Neural Network (GCNN) approach that analyzes correlations between audio features. Their model represented the relationships between 65 different audio features (including 24 MCC) as graph structures, allowing it to capture complex interactions between voice characteristics. They conducted two types of experiments: one with overlapping subjects in training and test sets (Setting 1, Speaker-dependent test) and another with completely separated subjects (Setting 2, Speaker-independent test). While Setting 1 achieved 95% accuracy, Setting 2's performance dropped significantly, highlighting a critical challenge in generalizing to new patients. This finding raises important questions about the practical applicability of current depression detection models when applied to previously unseen patients. This research suggests that while high accuracies are achievable in controlled settings, real-world application requires addressing the gap between training and new patient performance.

Yin et al. [16] introduced a novel approach to depression detection from speech by combining transformers with parallel Convolutional Neural Networks (TCC), achieving an accuracy of 94% using 40 band Mel-Frequency Cepstral Coefficients (MFCC)[13]. This method of feature extraction was critical in maintaining the fidelity of audio signals, thereby enhancing model accuracy. Importantly, the high accuracy was obtained under experimental conditions similar to "Setting 1" from prior research, where the model was trained and tested on audio samples from the same set of participants. This setup often leads to inflated performance metrics due to the model's limited generalization to new subjects. Their model, which incorporates two CNN streams for local feature extraction alongside a transformer using linear attention mechanisms with kernel functions, reduces computational demands while enhancing the ability to capture temporal dynamics in speech. The results, derived from the DAIC dataset, indicated that their hybrid model outperforms traditional CNN-LSTM architectures. This showcases the effectiveness of parallel processing and advanced attention mechanisms in recognizing depression from long speech sequences, highlighting the importance of robust feature extraction techniques like the 40 band MFCC in achieving high model performance.

In the literature on audio processing for depression detection, various audio preprocessing techniques have been utilized to enhance the quality of the data before analysis. Notably, Homsiang's approach involved some form of audio preprocessing, though specific details are not provided. Other studies have explicitly detailed their methods: for example, Ishmaru et al. described techniques for speech enhancement that include noise estimation and filtration using deep learning models, aiming to improve the clarity and quality of the audio data for better model performance[4]

Conversely, Yin et al. opted not to apply any preprocessing to their audio data. This approach can offer insights into the raw data's effectiveness but may require more sophisticated modeling techniques to deal with potential noise and variability in the audio signals.

This variety in approaches highlights a crucial aspect of audio-based depression detection research: the balance between enhancing data quality through preprocessing and developing models robust enough to handle raw, unfiltered data.

4 Methodology

4.1 Data Preparation

PHQ8 values are organized to multiclass[5] and binary values (non depression, depression)[6]. Table1 shows how these values are organized. In case of EATD the the SDS index is categorized by and it is mapped to binary categories as it shown in Table2.

PHQ-8 Scores	Severity	Binary
0–4	Non depression	0
5–9	Mild	0
10–14	Moderate	1
15–20	Moderately severe	1
21–	Severe	1

Table 1: Severity levels according to the PHQ-8 score.

SDS Index	Severity	Binary
0–49	Normal	0
50–59	Mild	1
60–69	Moderate	1
70–100	Severe	1

Table 2: Depression severity levels based on SDS index scores with corresponding binary classification.

For feature extraction in decision trees, I used a variety of audio features including MFCC as outlined by Tiwari[10]. For CNNs experiments, I have used MCC as well. Additionally, the decision tree model incorporated fundamental frequency (F0)[12], harmonic-to-noise ratio (HNR)[17], and spectral slope[14] to capture the dynamics and tonal quality of speech.

MFCCs are pivotal for analyzing the power spectrum of audio signals, particularly in tasks like speech recognition. The extraction involves transforming the audio signal from the time domain to the frequency domain using the Fast Fourier Transform (FFT) to capture frequency components. Subsequently, these components are mapped onto the mel scale via a mel filter bank that mimics the human auditory system's response more effectively than linearly-spaced frequency bands. The outputs of the mel filter bank are logged to approximate human perception of loudness, followed by a Discrete Cosine Transform (DCT) to de-correlate the log mel spectrum, resulting in MFCCs that represent the audio signal's timbral characteristics effectively.

In the decision tree model, additional spectral features such as centroid, bandwidth, rolloff, and zero-crossing rate are computed along with the overall signal energy. These features are combined with statistical measures—mean and standard deviation—across frames to create a comprehensive feature vector for each audio sample. This approach not only captures the fundamental characteristics of sound but also the complex dynamics and tonal qualities associated with speech, making it effective for emotion recognition from speech. To manage data complexity, features like minimum, average, and maximum values are calculated for entire audio segments where the participant speaks, condensing long sequences of numbers into single values for each statistic.

Figure 1 shows the MFCC and MCC representation of the word "Depression". The MFCC representation captures the spectral features of the audio signal, while the MCC representation emphasizes the cepstral features, providing a more detailed view of the audio signal's temporal dynamics. The choice of feature representation is crucial for model performance, as it determines the information available to the model for classification.

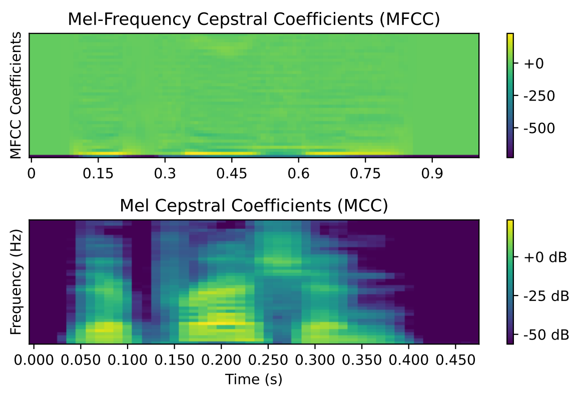

Figure 1: Visual comparison of MFCC and MCC representations for the word "Depression", highlighting their distinct audio feature emphases. Length of the audio signal is 1 seconds, sampling rate is 24Khz, it generates a 100 long MFCC and MCC.

For audio preparation, no additional cleaning processes were applied to the audio files prior to extracting MFCC and MCC. In the DAIC dataset, audio segments where the patient speaks were isolated. Each segment underwent feature extraction, and the minimum, average, and maximum values across all segments for each patient were computed. These statistics were then used as inputs for the DT models. For CNN, the raw MFCC and MCC spectra were utilized directly in 200 frame chuncks.

For the EATD dataset, audio samples included three emotional states: neutral, positive, and negative. For each state, features were extracted and the minimum, average, and maximum values were calculated and used similarly to the DAIC dataset processing.

4.2 Models

Two model will be built for the evaluation. One is a decission tree (DT) another one is a Transformer-CNN-CNN (TCC)[16].

4.3 DT

The methodology employed for optimizing the DT classifier involves an integrated approach to feature selection and tree depth configuration. The objective is to enhance model performance while preventing overfitting. Feature selection was performed using three techniques to evaluate their effectiveness in identifying the most predictive features:

1. **ANOVA F-value:** Determines the statistical significance of each feature in differentiating between classes.

2. **Mutual Information (MI):** Measures the dependency between the features and the target variable, crucial for capturing nonlinear relationships.

3. **Random Forest Feature Importance (RF):** Utilizes the Random Forest algorithm to estimate the usefulness of each feature based on the impurity reduction it brings to the model.

These methods were chosen to provide a comprehensive analysis of feature relevance from both statistical and machine learning perspectives. The Decision Tree's depth was then tuned to find the optimal balance that yielded the highest accuracy on the validation set, using the most predictive features identified by the feature selection process.

To mitigate the risk of overfitting, I methodically investigated a range of tree depths from 1 to 19, while also varying the number of top-ranked features from 1 to 29. This approach allowed me to assess the model's performance at each depth, using different subsets of top features to determine the optimal combination that enhances model accuracy without overfitting. The evaluation metrics include F1-score and accuracy, with a particular emphasis on the weighted average F1-score due to the imbalanced nature of our dataset. This metric adjusts for label imbalance by weighting the F1-score of each class by its support (the number of true instances for each label). This approach ensures that my model's performance is robust across different class distributions and provides a more reliable indication of its generalization ability.

The final model parameters—optimal feature count and tree depth—are selected based on their performance on the development set, aiming to maximize the weighted average F1-score while maintaining generalizability across the dataset.

4.4 TCC

I have adapted the TCC model for our application. The model consists of two parallel CNN streams and a transformer stream, integrating both local and global information processing capabilities. In my adaptation, I employ the CNN streams to extract local features from the input while the transformer stream captures the temporal dynamics through linear attention mechanisms, optimized for the dataset.

Each CNN stream processes the input independently to capture diverse aspects of the data, and the transformer stream analyzes the sequence as a whole. The outputs of these streams are then fused, combining their feature spaces to enhance the model's prediction accuracy. This fusion happens in a fully connected layer that integrates learned features before the final classification layer.

Modifications include adjusting the dimensionality of the input features and streamlining the transformer's attention mechanism to reduce computational complexity.

5 Experimental Setup

5.1 Feature Selection - DT

Feature selection was critical in determining the best predictors for the binary depression score. Three different methods were evaluated:

- **ANOVA:** Used to identify features that showed significant differences between the two classes of depression scores.

- **Random Forest (RF):** Provided insight into feature importance based on ensemble learning.

- **Mutual Information:** Assessed each feature's mutual dependency with the target variable.

Despite the dataset's imbalance, the features selected through the ANOVA method demonstrated the most substantial impact on model performance. This method effectively distinguished features that are highly predictive of the binary outcome, thereby facilitating a more focused and effective model training process. The top features identified through ANOVA were then used to train the Decision Tree, leading to the best result in terms of accuracy and generalization on unseen data.

5.2 Model Parameters TCC

The implementation of the TCC model is based on the original paper [16]. some model parameters are lowered simply due to the HW limitations (to be able to fit into VRAM wiht limit of 4GB). The model is trained with a batch size of 32, a learning rate of 0.0005, and a maximum of 100 epochs.

6 Results and Analysis

This section presents the results of the experiments conducted in this study, organized into subsections focusing on specific aspects of the project. Initially, the performance of DT models is compared across the DAIC and EATD datasets. In the subsequent TCC section, only the DAIC dataset is used for evaluation. The different strategies are visualized on figure2.

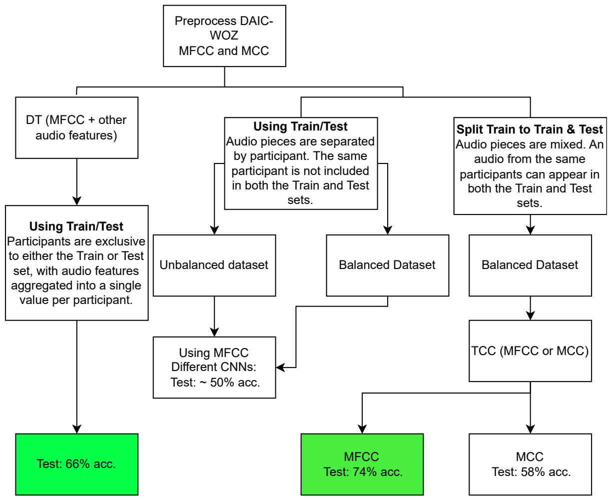

Figure 2: Train/Test split strategies and their results (DAIC)

6.1 Model Performance - DT

While the models showcased performance on the DAIC dataset with an accuracy of 98.11% on the training set (Tables 3 and Figures 3, 4), a significant drop in performance was observed on the development set.

Particularly, the development set for the DAIC dataset displayed only a 66% accuracy (Table 4), suggesting issues with the model's ability to generalize to new data.

Similarly, for the EATD dataset, while the training results were promising with an accuracy of 87% (Table 5), the development set results were considerably lower, achieving only a 68% accuracy (Table 6). This performance decrement underscores the necessity to consider alternative modeling strategies that might improve generalization across unseen datasets.

Class	Precision	Recall	F1-score	Support
0	0.97	1.00	0.99	76
1	1.00	0.93	0.97	30
Accuracy: 0.98 **of** 106				
Macro Avg: Precision 0.99, Recall 0.97, F1-score 0.98				
Weighted Avg: Precision 0.98, Recall 0.98, F1-score 0.98				

Table 3: Classification Report on Training Set - DAIC

Class	Precision	Recall	F1-score	Support
0	0.76	0.65	0.70	20
1	0.53	0.67	0.59	12
Accuracy: 0.66 **of** 32				
Macro Avg: Precision 0.65, Recall 0.66, F1-score 0.65				
Weighted Avg: Precision 0.68, Recall 0.66, F1-score 0.66				

Table 4: Classification Report on Development Set - DAIC

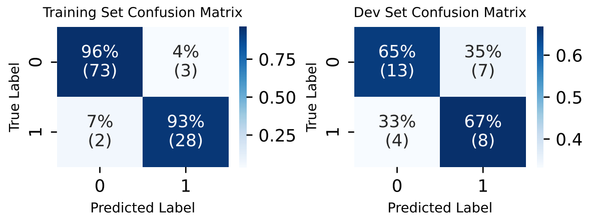

Figure 3: Confusion Matrices - DAIC

Class	Precision	Recall	F1-score	Support
0	0.96	0.84	0.90	56
1	0.74	0.93	0.82	27
Accuracy: 0.87 **of** 83				
Macro Avg: Precision 0.85, Recall 0.88, F1-score 0.86				
Weighted Avg: Precision 0.89, Recall 0.87, F1-score 0.87				

Table 5: Classification Report on Training Set - EATD

Class	Precision	Recall	F1-score	Support
0	0.71	0.88	0.79	52
1	0.54	0.27	0.36	26
Accuracy: 0.68 **of** 78				
Macro Avg: Precision 0.62, Recall 0.58, F1-score 0.57				
Weighted Avg: Precision 0.65, Recall 0.68, F1-score 0.64				

Table 6: Classification Report on Dev. Set- EATD

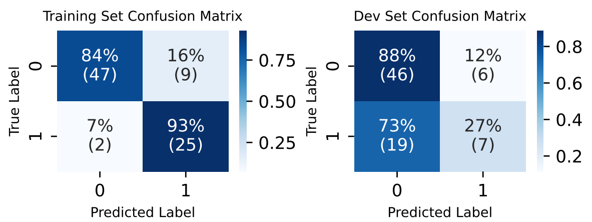

Figure 4: Confusion Matrices - EATD

Training DT on both DAIC and EATD datasets revealed that ANOVA selected different top features for each dataset, indicating potential challenges in generalizing the model across different data conditions.

6.2 Model Performance - CNN

In my experiments with various CNN models described in the literature, the models consistently underperformed, achieving only 50% accuracy on the development set. A deeper investigation into the literature revealed that the models achieving high accuracy were trained and tested on data from the same participants, merely split into different sets. This means that the same participant's audio files were divided between the train and test sets.

The CNN models struggled to generalize when tasked with predicting new, unseen participants. The variance in accuracy across different CNN architectures is not discussed in this report. Instead, we focus on the results from the TCC model, detailed in Figure 5. The training and validation accuracy and loss are depicted in Figure 6. The model underwent training for approximately 100 epochs, not to achieve the best possible accuracy but to demonstrate the model's learning capability. The model reached a 74% accuracy on the development set, using a lightweight version of the architecture proposed by Yin et al.[16]. The evaluation metrics presented are based on the model's performance at its peak accuracy.

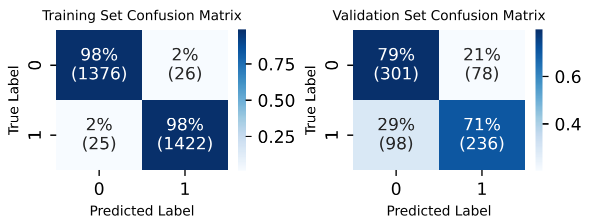

Figure 5: Confusion Matrices for Development Set (DAIC)

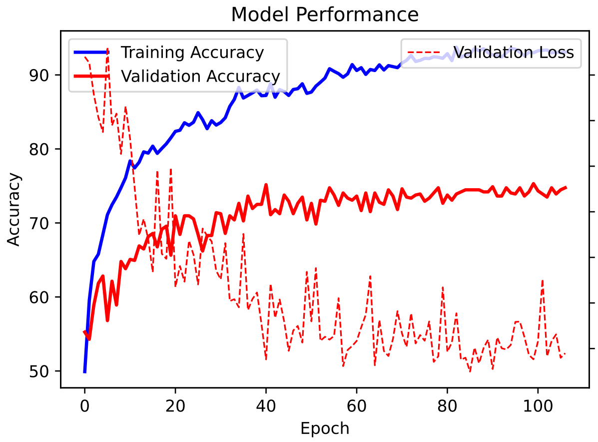

Figure 6: TCC Training (DAIC)

7 Discussion

This study's models are designed to predict PHQ-8 binary scores, which serve as a binary indicator of depression severity. Although the PHQ-8 is a reliable measure of depressive symptoms[7], this reliance raises questions about the necessity and utility of developing machine learning models based on audio data.

The technical feasibility of filling out the PHQ-8 survey, which is available online and considered trustworthy, further challenges the practicality of audio-based models. These models might seem redundant when a simpler and well-established method exists. However, audio-based applications could become relevant in scenarios where individuals are reluctant to complete the PHQ-8 survey. This might include cases where individuals, particularly those with severe or major depression, do not seek medical help.

Nevertheless, the utility of such models is constrained by the limited availability of public datasets, which impacts the robustness and generalizability of the findings. Additionally, factors such as varying audio quality and background noise—dependent on the microphone or the environment—can significantly affect the performance of models trained on audio data. Moreover, feeding the same model with different audio features, such as MFCC or MCC, yields varying results, as revealed in the case of the TCC. This underscores how the choice of audio processing techniques and feature selection can influence model performance, even when the model structure remains the same.

Furthermore, as highlighted by Bailey[1], biases such as gender discrepancies within the DAIC-WOZ dataset can lead to performance variations across machine learning models. These biases need to be addressed to enhance the fairness and accuracy of predictive modeling in clinical applications.

8 Conclusion

This study examined the effectiveness of using vocal biomarkers for depression detection through machine learning approaches, specifically comparing Decision Tree and TCC models across the DAIC-WOZ and EATD-Corpus datasets. While the Decision Tree model achieved the highest accuracy of 66% on unseen data from the DAIC dataset, the results raise important questions about the practical utility of audio-based depression detection systems. A critical finding of this research is that traditional survey methods like PHQ-8 and PHQ-9 questionnaires remain more reliable and efficient tools for depression screening compared to complex machine learning models. These surveys provide immediate, validated results without the technical complexities and potential biases inherent in audio-based systems. The study revealed significant challenges in model generalization, particularly when dealing with completely unseen participants. Notably, many high-accuracy results reported in the literature (90-95%) were achieved by mixing audio samples from the same participants in both training and test sets, which does not reflect real-world application scenarios. The substantial performance drop observed when testing on completely new participants highlights a critical limitation in current audio-based depression detection approaches. Furthermore, the varying performance of different feature extraction methods (MFCC vs. MCC) and model architectures demonstrates the inherent instability in audio-based detection systems. This variability, combined with the immediate availability and reliability of standardized questionnaires, suggests that the development of audio-based depression detection systems may be more academically interesting than practically necessary for current clinical applications.

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