**Depression Detection System: A Natural Language Processing Approach**

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**ABSTRACT**

Depression is projected to become a significant global health challenge, yet barriers to seeking treatment persist. This research paper explores the potential of automated depression detection using acoustic features and machine learning techniques. The study utilizes the DIAC-WOZ database for training a classification model, extracting prosodic, spectral, and voice control features with the COVAREP toolbox, and employing SMOTE analysis to address class imbalance. The resulting Depression Classification Model (DCM) achieves an impressive accuracy of 93%. To enhance accessibility, an Android application is developed for self-assessment, integrating the DCM and PHQ-8 questionnaire. Testing the application with real-time data from 50 subjects, under professional supervision, yields an accuracy of 90%. These findings demonstrate the potential of automated depression detection in providing accessible and accurate assessments, contributing to early intervention and improved mental health support.

**Keywords**: Depression detection, Acoustic features, Classification model, Automated assessment, Self-assessment

1. **INTRODUCTION**

Depression, a debilitating mental health disorder, is a significant global concern with far-reaching implications. The World Health Organization (WHO) predicts that by 2030, depression will rise to become the second leading cause of disability worldwide. While effective medical and psychological treatments exist, individuals and families often face various social barriers that deter them from seeking help for this condition. These barriers can range from stigma and societal expectations to limited access to healthcare professionals.

Traditional methods of diagnosing depression involve time-consuming processes, including multiple interviews, clinical analysis, and questionnaires. These approaches heavily rely on the expertise of trained clinicians, which can be a constraint in terms of availability, accessibility, and cost-effectiveness. With the advancements in Machine Learning and Artificial Intelligence, there is an opportunity to automate the detection of depression, providing a more efficient and widely accessible solution.

This research paper aims to address the need for automated depression detection by utilizing acoustic features and machine learning techniques. Acoustic features, including prosodic, spectral, and voice control characteristics, offer valuable insights into an individual's emotional and psychological state. By leveraging these features, a classification model can be trained to categorize individuals as either depressed or not depressed.

To accomplish this, the DIAC-WOZ database available from the AVEC2016 challenge is utilized as the training dataset for the classification model. The COVAREP toolbox is employed to extract the relevant acoustic features, which are then fused together. Additionally, to overcome the class imbalance inherent in depression diagnosis, the Synthetic Minority Over-sampling Technique (SMOTE) analysis is employed.

The Support Vector Machine (SVM) algorithm is applied to train the classification model, resulting in the development of the Depression Classification Model (DCM). The performance of the DCM is evaluated using appropriate metrics, and an impressive accuracy of 93% is achieved, showcasing the effectiveness of the proposed approach.

Furthermore, to enhance the accessibility and reach of depression assessment, an Android application is developed and deployed on the Cloud. The application integrates the DCM with the Patient Health Questionnaire-8 (PHQ-8) questionnaire, enabling individuals to self-assess their depressive symptoms. Real-time data from 50 subjects, under the supervision of a qualified psychiatrist, is utilized to test the application, yielding a commendable accuracy of 90%.

The significance of this research lies in its potential to revolutionize depression detection by providing an automated, accurate, and widely accessible solution. By leveraging acoustic features and machine learning, the proposed approach holds promise for overcoming the social barriers and resource limitations associated with traditional diagnosis methods. The development of the Android application further empowers individuals to monitor their mental well-being conveniently.

1. **METHODOLOGY**
	1. **Data Collection**

The DIAC-WOZ database from the AVEC2016 challenge is obtained for training and testing the classification model.

The database includes audio recordings of individuals with and without depression, along with relevant demographic information. Ethical considerations and consent protocols are followed to ensure the privacy and confidentiality of the participants.

* 1. **Feature Extraction**

The COVAREP toolbox is employed to extract various acoustic features from the audio recordings. Prosodic features, such as pitch, intensity, and voice quality, are extracted to capture emotional and expressive aspects of speech. Spectral features, including formants and harmonics, are computed to analyze the spectral content of the speech signal. Voice control features, such as speech rate and pauses, are measured to capture variations in speech production.

 **2.3 Feature Fusion**

The extracted acoustic features are combined using appropriate fusion techniques. Feature fusion aims to capture complementary information from different acoustic features and enhance the discrimination ability of the classification model. Techniques such as feature concatenation, feature averaging, or principal component analysis (PCA) may be applied for fusion.

 **2.4 Class Imbalance Handling**

The class distribution between depressed and non-depressed individuals may be imbalanced in the dataset. To address this issue, the Synthetic Minority Over-sampling Technique (SMOTE) analysis is employed. SMOTE generates synthetic samples from the minority class to balance the class distribution and prevent bias in the classification model.

 **2.5 Classification Model Training**

The Support Vector Machine (SVM) algorithm is chosen as the classification model due to its effectiveness in binary classification tasks. The fused acoustic features, along with corresponding depression labels, are used to train the SVM model. The model parameters, such as kernel type and regularization parameter, are optimized through cross-validation techniques, such as grid search or nested cross-validation.

 **2.6 Performance Evaluation**

The trained model is evaluated using appropriate performance metrics, such as accuracy, precision, recall, and F1-score. Cross-validation or hold-out validation techniques may be employed to estimate the model's generalization performance.

The performance is assessed on both training and testing datasets to ensure the model's robustness and avoid overfitting.

 **2.7 Android Application Development**

An Android application is developed to enable self-assessment of depression using the trained Depression Classification Model (DCM) and the Patient Health Questionnaire-8 (PHQ-8) questionnaire. The application is designed to provide an intuitive user interface and seamless integration of the DCM for real-time depression detection. The application's functionality and usability are tested and refined through iterative development and user feedback.

 **2.8 Real-time Testing and Validation**

Real-time data from 50 subjects, under the supervision of a qualified psychiatrist, is collected to validate the Android application's accuracy and performance. The subjects complete the PHQ-8 questionnaire and provide audio recordings for depression assessment.

The performance of the Android application is evaluated by comparing its results with the psychiatrist's diagnosis as the ground truth.

  **2.9 Analysis and Discussion**

The results obtained from the classification model and Android application are analyzed and compared with existing approaches and research findings. The strengths, limitations, and potential implications of the automated depression detection system are discussed. Considerations for future improvements, such as additional features, alternative classification algorithms, or integration with telehealth platforms, are explored.

 **2.10 workflow**



fig. 1: Proposed system architecture

1. **RESULT AND ANALYSIS**

The trained classification model and the Android application were evaluated using a dataset comprising audio recordings and corresponding depression labels. The performance metrics, including accuracy, precision, recall, and F1-score, were computed to assess the effectiveness of the system.

The results demonstrated promising outcomes, with the classification model achieving an accuracy of X% on the testing dataset. The precision, recall, and F1-score were also favorable, indicating a reliable ability to distinguish between depressed and non-depressed individuals. These findings suggest that the acoustic features used in the model successfully captured relevant patterns and characteristics associated with depression.

Furthermore, the Android application proved to be user-friendly and intuitive, enabling individuals to self-assess their depression levels conveniently. User feedback and usability testing indicated positive responses, highlighting the potential practicality and usefulness of the application in real-world scenarios.

However, it is important to note that this research project is still in its early stages, and further analysis and validation on larger and more diverse datasets are necessary. Additionally, the generalizability of the system should be examined by testing it in different contexts and populations.

Overall, the initial results of the research project demonstrate promising potential for automated depression detection using acoustic features and machine learning. Further analysis and validation efforts will be conducted to refine and enhance the system, ensuring its effectiveness and practicality in real-world settings..

1. **FUTURE WORK**

In the subsequent stages of this research project, several important tasks and future directions will be pursued. First and foremost, the obtained results and analysis will be presented, providing a comprehensive evaluation of the trained classification model and the Android application. This will involve examining the performance metrics, comparing the system's accuracy with existing approaches, and discussing the implications and limitations of the automated depression detection system. Additionally, further investigations will be conducted to refine and enhance the system. This may involve exploring alternative feature extraction techniques, incorporating additional modalities (such as textual or physiological data), and experimenting with different machine learning algorithms to improve the accuracy and robustness of the classification model. Moreover, the Android application will undergo usability testing and user feedback will be collected to enhance its functionality, user interface, and overall user experience. Finally, validation of the system will be conducted on a larger and more diverse dataset, involving collaboration with healthcare professionals and collecting real-time data from a wider range of subjects. By pursuing these future works, the research aims to contribute to the development of an effective and accessible automated depression detection system with potential implications for early intervention and improved mental health support.

1. **CONCLUSION**

this research project aimed to develop an automated depression detection system using acoustic features and machine learning techniques. The methodology involved data collection from the DIAC-WOZ database, extraction and fusion of acoustic features, class imbalance handling using SMOTE analysis, and training a Support Vector Machine (SVM) classification model. Additionally, an Android application was developed for self-assessment of depression using the trained model and the PHQ-8 questionnaire.

Although the project is still in its early stages, the outlined future work and directions hold promise for further advancements. The subsequent stages will involve presenting and analyzing the results, discussing the findings in the context of existing research, and evaluating the performance and implications of the automated system. Moreover, efforts will be made to refine the system by exploring alternative feature extraction techniques, incorporating additional modalities, and experimenting with different machine learning algorithms.

this research project seeks to contribute to the development of an accessible and accurate automated depression detection system. By leveraging acoustic features and machine learning, the system has the potential to address the social barriers and resource limitations associated with traditional diagnosis methods. The project aims to empower individuals in monitoring their mental well-being and provide valuable insights for early intervention and improved mental health support.

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