### **A Machine-Learning Model for Detecting Depression, Anxiety, and Stress from Speech**

### **Authors:** Mashrura Tasnim et al.

This study introduces a machine learning pipeline for predicting depression, anxiety, and stress using only acoustic speech features extracted from longitudinal, multilingual (English and Spanish) speech recordings. Speech data from 40 participants aged 19–29 was collected over several weeks, generating over 1,000 samples. Each speech sample was paired with a DASS-21 questionnaire submission, allowing labels for all three disorders. The authors found significant comorbidity between depression, anxiety, and stress scores, and noted that individuals with higher scores showed lower adherence to the recording protocol. Each sample included guided reading and spontaneous speech, processed into spectrograms. These were passed through a pre-trained VGG-19 CNN to extract 4,096-dimensional deep feature vectors, which were then input into a custom 1D convolutional neural network (CNN). The model achieved root-mean-square errors (RMSE) of 7.09 (depression), 7.69 (anxiety), and 8.40 (stress), with competitive normalized errors against similar models in the field. The acoustic-only approach preserves user privacy and eliminates the need for transcription, making it both scalable and language-independent. Limitations include data imbalance, as most participants scored in the “normal” range. Nonetheless, the results demonstrate that speech is a rich biosignal for mental health monitoring and that CNNs trained on VGG-19 features can accurately predict emotional states. The authors suggest expanding this model using more balanced data and exploring personalized predictions using the longitudinal aspect of the dataset. This method offers a cost-effective and passive solution to mental health monitoring, especially suitable for mobile health applications and telepsychiatry.

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### **Early Detection of Anxiety, Depression and Stress Using Machine Learning and Deep Learning Models**

**Authors**: Alphonsa Sini P.J & Dr. Sherly K.K

This study presents a machine learning and deep learning-based framework to detect mental health disorders—specifically depression, anxiety, and stress—using responses from a DASS-based questionnaire. The researchers implemented three predictive models: Support Vector Machine (SVM), Artificial Neural Network (ANN), and XGBoost, with additional use of Random Forest for feature selection. Given the class imbalance in the dataset, the Synthetic Minority Oversampling Technique (SMOTE) was applied to improve model performance. Data preprocessing included cleaning, standardization, and exploratory data analysis. Performance evaluations revealed that SVM outperformed other models, achieving detection accuracies of 99.32% (depression), 99.80% (anxiety), and 98.44% (stress). The ANN model came close with over 99% in some cases, while XGBoost achieved high but relatively lower accuracy. The study emphasized the value of early mental health diagnosis, proposing that traditional methods often miss early symptoms. Unlike manual assessments, ML and DL models can learn patterns from behavioral data, enabling real-time predictions. The methodology section explains in detail the training process, use of grid search for hyperparameter tuning, and how SMOTE improved minority class representation. Key features were selected using Random Forest with feature importance above a threshold. This system could serve clinicians by acting as a decision-support tool and enabling proactive care. The research concludes that AI-powered detection systems can significantly improve mental health screening and intervention strategies. Future work includes incorporating real-time data, voice or text inputs, and testing in clinical environments for broader applicability.

1. ***Speaker-Independent Depression Detection based on Adversarial Training Method***

The paperaddresses the challenge of personalization bias in speech-based depression detection models. Traditional deep learning models often conflate speaker-specific features with depression-related characteristics,

reducing their ability to generalize across different individuals. To mitigate this issue, the authors propose an adversarial training framework using a Gradient Reversal Layer (GRL) to minimize the influence of speaker characteristics during training. The model architecture consists of three modules: Feature Embedding (FE), Depression Classification (DC), and Speaker Recognition (SR). By applying GRL between FE and SR, the network is trained to extract depression-relevant features while suppressing speaker identity cues.

The study uses the DAIC-WoZ dataset, a well-established benchmark for depression detection, and compares two baseline models—DepAudioNet and ECAPA-TDNN—with their adversarially trained counterparts (DepAudioNet-Adv and ECAPA-TDNN-Adv). Experimental

results show that adversarial training improves depression detection performance significantly. For instance, ECAPA-TDNN-Adv achieved an F1-score improvement of 7.6% using mel spectrogram input and 8.3% with raw audio compared to its baseline. Visualization of feature embeddings further confirmed that the adversarial models were more effective in separating depression-related features from speaker-specific traits.

In conclusion, the paper demonstrates that adversarial training enhances the generalization ability of depression detection models by reducing speaker-related bias. This approach offers a promising direction for developing more robust, speaker-independent systems suitable for real-world deployment. Future

work will explore alternative adversarial strategies and test the method on broader datasets to validate scalability and performance.

1. **Exploring Depression Through Social Media: A Textual Analysis**

The paper investigates how social media, specifically Twitter, can be used to identify signs of depression using natural language processing (NLP) and machine learning (ML) techniques. The researchers

collected a dataset of 20,000 English tweets and applied various preprocessing steps like punctuation removal, lemmatization, and tokenization. Sentiment analysis was conducted using the TextBlob library, which assigned scores to tweets to classify them as depressed or non-depressed.

To enhance prediction accuracy, several classification algorithms were employed, including Decision Tree, Random Forest, K-Nearest Neighbors (KNN), Naïve Bayes, and Logistic Regression. Among them, the Decision Tree algorithm achieved the highest accuracy at 93.97%, followed closely by Random Forest at 92.95%. The performance of these models was evaluated using standard metrics such as accuracy, precision, recall, and F1-score, along with a confusion matrix to assess the classification results.

The paper also addresses the ethical implications of using AI for mental health diagnoses, such as data bias and privacy concerns. It emphasizes the importance of including diverse data sources and expert oversight to ensure fairness, reliability, and responsible use of AI. The study concludes that while ML-based sentiment analysis of social media data holds significant promise for identifying depressive symptoms, further research is needed to improve generalizability, reduce bias, and integrate such systems meaningfully into mental health care practices. The work contributes to the growing field of AI-assisted mental health diagnostics and highlights avenues for future development.