PALAK DATTATRAYA KOTA
1NT22IS110
ML-TUTORIAL

Detecting stress anxiety depression from voice tone and text responses

Summary on research papers

The Voice of Depression: Speech Features as Biomarkers for Major Depressive Disorder

Authors: Felix Menne et al.

This study investigates speech features as potential biomarkers for diagnosing Major Depressive Disorder (MDD). It analyzes recordings from 96 participants—44 with MDD and 52 healthy controls—who were asked to speak about both positive and negative life events. Speech features extracted included pitch, loudness, shimmer, jitter, temporal duration, lexical richness, and sentiment. These features were analyzed in relation to clinically established measures such as the Beck Depression Inventory (BDI-II) and the Hamilton Depression Rating Scale (HAMD). Depressed participants exhibited statistically significant differences in speech patterns compared to healthy controls: reduced pitch variation, altered loudness, slower and longer utterances, more negative sentiment, and simpler language. A support vector machine (SVM) classifier trained on the top 10 acoustic features achieved an AUC of 0.93—comparable to the BDI-II (AUC = 0.99)—highlighting the predictive power of speech features. The study also found that temporal features like pause duration and utterance length significantly differentiated mild and moderate depression severity. Feature selection and classification models showed speech-based features outperforming demographic and baseline neuropsychological models. The researchers conclude that speech can provide a non-invasive, objective measure of depression severity. They recommend integrating speech-based tools into clinical workflows to complement traditional assessments, especially in remote or preliminary screenings. The study also suggests expanding datasets and refining models to account for co-morbidities and multilingual factors. Overall, it supports the growing role of digital phenotyping and computational psychiatry in mental health care.

Machine Learning-Based Classification of Mental Health State Using the DASS-21 Profile

Authors: Khanita Duangchaemkarn et al.

This paper explores the classification of depression, anxiety, and stress levels using machine learning models trained on DASS-21 questionnaire responses. The study collected anonymized responses from 2,602 university students over a one-month period. The models compared include Deep Learning (multi-layer perceptron), Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), Random Forest, Naïve Bayes, and AdaBoost. Among all, the deep learning model achieved the highest performance with F1-scores and AUC values consistently above 0.95 for all emotional states. This high accuracy is attributed to its ability to handle data imbalance and capture non-linear relationships between input features. In contrast, models like SVM and Random Forest performed well for major classes but failed to classify less frequent severe or extremely severe cases effectively due to class imbalance. The study underscores the importance of using metrics like F1-score and AUC, instead of relying solely on accuracy, especially in imbalanced datasets. It further demonstrates that emotional states captured via psychometric scales can be effectively classified using computational methods, potentially reducing clinical workload. The paper suggests integrating ML-enhanced emotional screening into university mental health services and broader public health initiatives. Moreover, it proposes using larger and more diverse datasets in future studies to improve generalizability. The findings illustrate how advanced models can assist in scalable and efficient mental health assessments and early intervention, particularly among young adults, a demographic prone to mental health challenges. The study advocates for AI's role in personalized mental healthcare through data-driven decision-making.