A Machine Learning-Based Approach for Non-Invasive Stress Analysis Using Speech Features for Enhanced Detection and Classification

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Abstract: Stress has its impact on our physical and mental health in many forms, and thus it becomes even more important to detect it at an early stage so that we can manage it better. Standard approaches to monitoring the stress response typically involve tracking a person's physiological state or behavioural differences with the help of invasive sensors or elaborate data collection systems. As a more appealing non-intrusive option, this research paper proposes a machine learning model, to observe our speech patterns to monitor our stress levels on a real-time basis. By analysing features such as pitch, tone, frequency and the rate at which someone speaks, the system can gain a better understanding of a person's emotional state. These pieces of information are collected by techniques like Mel Frequency Cepstral Coefficient (MFCC), Fast Fourier Transform (FFT), and Spectral Analysis. These extracted features are then used to train multiple machine learning classifiers such as Decision Trees and K-Nearest (K-NN) Neighbours. This enables you to classify stress levels into three specifics categories (Neutral, Mild Stress, High Stress). This analysis allows us to make sure the model is reliable and its performance is understood using standard metrics including but not limited to accuracy, precision, recall and F1-score. The idea is to make stress detection more achievable and operable every day.

1 INTRODUCTION

Stress represents a major challenge to an individual's adaptive capacity, triggering both cerebral and physiological changes that can pave the way for severe health conditions. These include hypertension, coronary artery disease, cardiac arrest, stroke, and mental health issues such as depression and anxiety. Stress can be categorized into two distinct types: short term acute stress and long-term chronic stress. Ultimately, the body relies on the parasympathetic nervous system (PNS) to restore balance and return to homeostasis.

To evaluate the stress response, we can assess perceptual, behavioural, and physical indicators. Self-report questionnaires serve as a crucial tool in measuring an individual's subjective perception of stress levels. Many physiological markers responsive to stress have been thoroughly studied. Stress analysis via machine learning, where frequency domain features derived from audio signals are employed in classifying emotional states reflecting varying levels of stress, is the thrust of this project. The dataset consists of FFT (Fast Fourier Transform) coefficients, which represent the frequency content of speech signals. By examining these characteristics, we train and test two machine learning models- Decision Tree Classifier and K-Nearest Neighbours (KNN) Classifier. The main aim is to establish how effectively the models can classify emotions (Negative, Neutral, and Positive) and map them to possible stress levels. Model performance is tested using accuracy scores and confusion matrices to determine patterns of classification. This research has applications in mental health analyzing, workplace stress management, and healthcare, where automated stress detection can provide valuable insights for intervention and support.

The structure of this paper is divided as following, section II discusses about the various use cases of the Stress analysis, section III covers the related works of the Stress analysis, section IV

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illustrates the existing system, section V discusses the proposed system of the project, section VI discusses the result and section VII discusses the Experimental result of the project. VII discusses the conclusion of the project.

1.1 Characteristics of Stress Analysis

Below are the characteristics of Stress analysis

1.1.1 Feature Extraction from Speech Signals

Stress analysis often relies on extracting features from speech, such as FFT (Fast Fourier Transform) coefficients, Mel Frequency Cepstral Coefficients (MFCCs), and pitch variations, which help in identifying emotional states.

1.1.2 Emotion-Based Stress Classification

Stress levels are linked to emotions, commonly classified into Negative, Neutral, and Positive states. Machine learning models analyse these emotions to infer stress intensity.

1.1.3 Supervised Learning Models

Algorithms like Decision Tree Classifier and K-Nearest Neighbours (KNN) are trained on labeled to identify stress pattern from input features

1.1.4 Data Pre-processing and Label Mapping

Raw data undergoes pre-processing methods such as normalization, feature selection, and label encoding to improve model performance and interpretability.

1.2 Advantages of Stress Analysis

1. Early stress detection
2. Automated and Objective Analysis
3. Personalized Stress Management
4. Non-Intrusive and User-Friendly

This is just a fraction of the benefits of machine learning-based stress analysis that promise a new era of support for mental health, workplace well-being and healthcare. Its greatest benefit is early detection of stress, enabling interventions sooner that can have a significant impact in preventing later mental and physical health problems. In contrast to conventional techniques which tend to depend on self-reports and can be subjective and biased, machine learning provides a more objective and automated solution which results in higher accuracy. Because these models can learn from individual stress profiles, they can provide tailored advice. The cost-effective and large-scale stress measurement through smart devices minimizes the need of frequent visits to doctor. In comparison, combining speech, heart rate, EEG signals, and facial expressions from these advanced systems provides a more comprehensive and reliable stress detection profiling compared to single channel systems.

2 USE CASES OF STRESS ANAYSIS USING MACHINE LEARNING

This stress analysis model uses machine learning to analyse speech-based features and classify emotions into different stress levels. Below is an in-depth explanation of how this model can be applied in various industries and real-world applications.

1. Mental Health Monitoring & Early Intervention
2. Workplace Stress Management
3. Call Centre & Customer Service Analysis
4. Education & Student Stress Tracking
5. High-Risk Professions (Military, Aviation, Healthcare, etc.)

2.1 Mental Health Monitoring & Early Intervention

The model processes speech data, extracts frequency-based features, and classifies the emotional state into negative (high stress), neutral (moderate stress), or positive (low stress)..It can be integrated into mental health applications to monitor users' emotions over time. Helps in early detection of stress, anxiety, and depression. Provides data-driven insights to mental health professionals for better patient care.

2.2 Workplace Stress Management

The model can be used to monitor employees' stress levels through voice-based interactions during meetings, calls, or check-ins. HR teams can analyze collective stress trends and make data-driven workplace improvements. Improves employee well-being and productivity. Helps prevent burnout and workplace dissatisfaction.

2.3 Call Centre & Customer Service Analysis

The model can analyse customer service call recordings to detect stress levels in both employees and customers. If high stress is detected in employees, breaks or training programs can be recommended. If high stress is detected in customers, the system can escalate the call to a human representative with special skills. Enhances customer satisfaction by detecting and responding to stress signals.
Reduces employee burnout by managing high-stress interactions.

2.4 Education & Student Stress Tracking

Teachers and education platforms can use stress analysis to track students' emotional well-being during virtual or in-person classes.

Stress levels can be analysed to adjust teaching methods and exam difficulty. Helps prevent academic burnout and anxiety. Improves teaching strategies based on real-time student feedback.

2.5 High-Risk Professions (Military, Aviation, Healthcare, etc.)

The model can monitor stress in high-pressure professions like pilots, surgeons, soldiers, and emergency responders. It can detect stress levels from voice-based communication and alert supervisors when stress levels are dangerously high. Reduces human errors and accidents in critical operations. Improves mental resilience and decision-making in high-risk environments.

3 RELATED WORK

Stress response is defined as an evoked response when our body perceives any stimuli that exceeds an organism's adaptive capacity and disrupt homeostasis.

This paper (J. Lee et al., 2024) analysed the impact of the personal Physical stress factor Stress response and recovery and one operated one Comparative analysis of stress reactivity and Recovering between HRV and EDA parameters Group. Stress situation may begin Human body is identified and measured Represented for stress with a defence mechanism (A. Ferrarotti et al., 2024) by physical variation.

This paper (A. Ferrarotti et al., 2024) mainly relies on invasive systems and infrequently focuses on AR/VR applications. this work investigates whether the head movements of a user wearing an AR HMD vary due to the presence of a stress factor while performing static tasks. In order to induce stress, the SCWT has been used.

This paper (S. Santhiya et al., 2024) indicates how audio-based Stress detection system can be used to improve systems General welfare and preventive health measures. To make accurate production and Trusted results, this study proposes a novel method of detecting stress from deep learning Algorithm with sophisticated signal processing Technology.

This paper (A. Singh et al., 2024) proposes a comprehensive approach which uses the ccombination of computational power, Software, technology and sympathy care to determine similarities in frequency pattern stress level. In our sharp world, stress is affected Countless people affect their mental Goodness. 48% gene z adults report Accepted, sad, depressed, (N. Oryngozha et al., 2024) experience Fofo (fear of disappearance), and reduced Self -esteem or insecurity.

This research N. Oryngozha et al., 2024) proposes ML and NLP to recognize and evaluate stress related posts and comments within Reddit's academic communities which can be used to analyze comments from text. Stress monitoring is a crucial component (Z. Lei el al., 2024) of any strategy used to intervene in the case of stress.

This study (H. A. Khan et al., 2023) proposes for an outline using a wearable sensor, safely an artificial intelligence driven in associated with Cloud-based server to initial detection High blood pressure and an intervention facility System.

This study (Mittalakod et al., 2023) improves sentiment and emotion analysis to measure the stress levels of people by analysing their social posts and comments using complex machine learning techniques and the deep learning model BERT.

This paper (J. G. Jayawickrama and R. A. H. M. Rupasingha, 2022) explores how we can detect human stress by analysing sleep patterns, using a technique called ensemble learning. In the first part of the research, five different machine learning algorithms were tested for classification, including Decision Tree, Logistic Regression, and Naive

Bayes. Then, in the second part, they applied an ensemble learning algorithm that combined the results of these five methods using an average probability approach. The findings were promising, with ensemble learning achieving an 94.25% accuracy in classifying the data. This suggests that using a combination of algorithms can significantly enhance our ability to understand and identify stress based on sleep patterns.

This paper (F. J. Ming et al., 2023) proposes to develop a Facial Emotion Recognition System designed to help identify mental stress among university students. The goal is to provide support both to the students themselves and to the counselling departments within institutions. The system will analyse facial expressions to recognize various emotions, including happiness, sadness, anger, and fear.

4 EXISTING SYSTEM

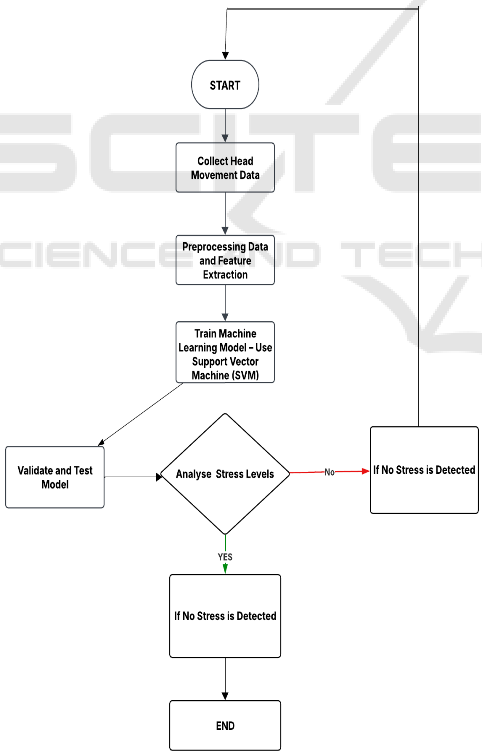

Figure 1: Existing Stress Analysis model.

The following study presents a non-invasive means of detecting stress within Augmented Reality (AR) applications based on head movement during the use of Head-Mounted Displays (HMDs). Using this system, engaged with various AR tasks, stress levels were identified using machine learning with the main algorithm being Support vector machines (SVMs). Headset data is logged and converted to be analysed to identify similarities across participants. Using a weighted decision model, an SVMs training process is initiated in an effort to enhance their classification accuracy in predicting stress levels. However, it is worth mentioning that there are some limitations to this system. The figure 1 shows the Existing Stress Analysis model. For one, the study had a relatively small number of people, meaning its results may not be generalizable to everyone. There isnt a lot of diversity among participants, either, in terms of age and gender and backgrounds — which could affect how the model performs across various groups of people.

5 PROPOSED SYSTEM

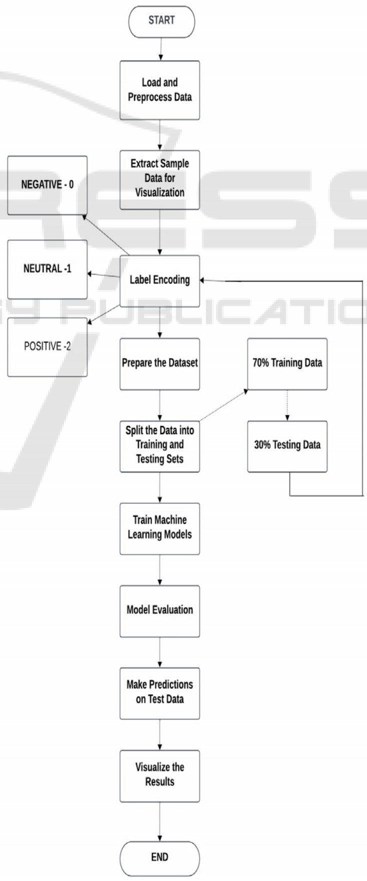

Figure 2: Proposed System for stress Analysis.

The existing system relies on a fairly limited sample size, which really holds it back from being as effective as it could be. In contrast, our new system takes a big step forward by including a larger and more diverse group of participants, significantly boosting our data set. One of the key differences is that while the existing approach only analyses head movement data after tasks are completedessentially looking at it afterward we've developed an innovative solution that detects stress in real time. We leverage streaming machine learning models to continuously analyse head movement data, allowing us to gain immediate insights and react promptly. The figure 2 shows the Proposed System for stress Analysis.In our evaluation process, we closely compared Support Vector Machine (SVM) and K-Nearest Neighbours (K-NN) to see which method fits our goals best. We ultimately decided to go with K-NN because of its strength in classification.

This algorithm is great at categorizing data based on class membership, which means it can effectively decide whether a data point belongs to group A or group B. K-NN works by looking at the nearest neighbours, with 'k' representing the number of closest points considered—usually a small, positive integer. We also looked into Decision Trees (DT), which create classification models in a way that's easy to understand by forming a tree structure. This technique breaks down the dataset into smaller pieces while building a corresponding decision tree. The result is a model that's clear and interpretable, showing decision nodes and leaf nodes that represent the underlying class data. Our approach not only pushes the limits of what can be achieved in real-time stress detection but also establishes a new benchmark in the field.

Working of Stress Analysis

The Stress analysis project is structured into multiple functional steps based on its working

1. Data Acquisition Module
2. Data Pre-processing Module
3. Feature Visualization Module
4. Model Training Module
5. Prediction Module

5.1 Data Acquisition Module

The Data Acquisition Module plays a crucial role in gathering the data needed for stress analysis. It uses a CSV file that includes speech recordings along with their associated stress labels. This dataset features numerical characteristics extracted from the speech recordings, alongside labels that indicate various levels of stress. Essentially, this module makes sure that we have all the necessary information at hand for the next steps in processing and analysis.

5.2 Data Pre-Processing Module

pre-processing is an inevitable procedure in any machine learning process Similar to the way in that we are working out the Functions here now is the data cleaning, feature selection or label encoding. First, we handle any non-existent values to ensure uniformity of the data. And then we will replace the categorical one like NEGATIVE, NEUTRAL and POSITIVE into numbers (0,1,2) that will help us to becoming compatible with different machine learning algorithms. Lastly, we ready the data for exploration and modelling.

5.3 Feature Visualization Module

Understanding the characteristics of the features is critical before you start training the model. In this module we utilize Matplotlib to plot sample distributions of the features so that we can visualize the variation of the frequency domain features with stress levels. Visualizing this data allows us to identify patterns and trends that may not be so obvious, which greatly improves our feature selection and increases the performance of the model.

5.4 Model Training Module

Module 4 Training ML models to classify the level of stress These features are fed to algorithms (Decision Tree Classifier, K-Nearest Neighbours (KNN)) capable of recognising patterns in the training data. These classifiers generate predictive models based on the correlation between the features of head movement over the three different levels of stress labels seen in Figs. It's a cool example of how to use data and technology to sharpen knowledge about human emotions.

5.5 Predicting Module

When the training phase is complete, the system uses the models it learned from the training data to assess stress on new data that was not seen in the training phase. These trained classifiers determine whether a certain sample is NEGATIVE, NEUTRAL or POSITIVE stress level when the testing set is provided. These predictions are then checked against the actual stress levels to measure classifier accuracy.

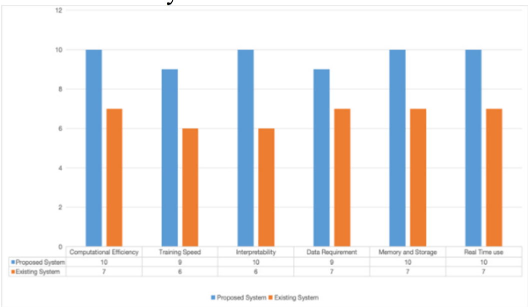

Figure 3: Comparison between Existing system VS Proposed system.

Figure 3 shows a comparative graph that clearly depicts the performance improvement between the existing system and the system that is proposed in this work. The model showed the best computational efficiency, training speed, interpretability, data intelligence, memory sage, and real-time performance. More specifically, the proposed system achieves high scores for computational efficiency, interpretability, memory, and real-time use, whereas the existing system performs low in these aspects. Further, compared to other systems that require large amounts of data but achieve similar accuracy rates, the proposed system is more optimized and requires less data to train on. Once again, the training speed is better, allowing the model to learn faster. In this way, these developments contribute to the proposed system to be used in real time stress analysis applications where speed and efficiency of data acquisition and decision making are critical.

6 CONCLUSIONS

By analysing how we move our heads, we can have a contemporary and more useful method of assessing level of stress using machine learning. The system can classify stress into 3 types: NEGATIVE, NEUTRAL, POSITIVE using smart algorithms like Decision Tree Classifier and K-Nearest Neighbours (KNN). It is also structured into multiple components data collection, data cleaning, visualization, model training, and model evaluation so it’s also accurate and reliable. Its most notable benefit, compared to current solutions, is that there are no physiological sensors required, making it more practical for usage in real-life scenarios, particularly in Augmented Reality (AR) environments. Tools such as confusion matrices and performance metrics help boost the model’s strength over time, so that its predictive power can continue improving. As for the future, there are exciting potential upgrades, including real-time stress monitoring, more physiological indicators, and even advanced deep learning techniques to boost accuracy.

In short, this machine learning system is a considerable step towards stress analysis in real-time. It has potential use in the fields of health care, workplace efficiency, and communication between humans and computers. You know, with a few more nudges and improvements it can be a powerful tool to help better understand and cope with stress in our lives.

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