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ML BASED STRESS DETECTION VIA HEART RATE VARIABILITY

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ABSTRACT
Stress is a Natural response to Pressure, But when it becomes chronic, it can leads to Mental Health Issues. Stress is measured using physiological Parameter such as Heart Rate Variability (HRV).HRV is not equivalent to Heart Rate. HRV represents the variation of Time Interval Between successive Heart Beats. If a Person having Stress, it leads to increase in the Heart rate, which causes Risk to life. HRV Increases with Relaxation and decrease with stress. Indeed, HRV is usually higher when heart is beating slowly & vice versa. Our Project focuses on developing ML model capable of accurately detecting stress levels basedon the Indicator given to all types of stress levels.

Introduction

Machine Learning, often abbreviated as ML, is a subset of Artificial Intelligence (AI) that focuses on the development of computer algorithms that improve automatically through experience and by the use of data. In simpler terms, machine learning enables computers to learn from data and make decisions or predictions without being explicitly programmed to do so.
At its core, machine learning is all about creating and implementing algorithms that facilitate these decisions and predictions. These algorithms are designed to improve their performance over time, becoming more accurate and effective as they process more data.
In traditional programming, a computer follows a set of predefined instructions to perform a task. However, in machine learning, the computer is given a set of examples (data) and a task to perform, but it's up to the computer to figure out how to accomplish the task basedon the examples it's given.
For instance, if we want a computer to recognize images of cats, we do not provide it with specific instructions on what a cat looks like. Instead, we give it thousands of images of cats and let the machine-learning algorithm figure out the common patterns and features that define a cat. Over time, as the algorithm processes more images, it gets better at recognizing cats, even when presented with images it has never seen before.
This ability to learn from data and improve over time makes machine learning incredibly powerful and versatile. It's the driving force behind many of the technological advancements we see today, from voice assistants and recommendation systems to self-drivingcars and predictive analytics.

OBJECTIVE

The objective of using machine learning for stress detection via heart rate variability (HRV) is to develop a system that can accurately classify an individual's stress levels based on their HRV patterns. By analyzing HRV data using machine learning algorithms, the goal is to
create a model that can distinguish between different stress levels (e.g., low, medium, high) orclassify stress into specific categories (e.g., normal, acute, chronic).

Literature Review

S Sadruddin, VD Khairnar, DR Vora
Stress is recognized as a strong factor linked to severe health conditions like

hypertension, cardiovascular diseases, and diabetes. With the growing emphasis on wearable health monitoring, numerous investigations have been conducted into the feasibility of leveraging diverse physiological markers to detect stress. This research endeavors to conduct classification using physiological data, drawing from the readily accessible WESAD (WearableStress and Affect Detection) dataset. The primary goal is to employ this dataset to develop models capable of predicting stress based on physiological indicators. In this paper, amodel is designed to enhance the accuracy of stress level detection through the application of the Synthetic Minority Oversampling Technique (SMOTE). The purpose of SMOTE is to rectify the issue of imbalanced datasets by oversampling the minority class. To handle the imbalancednature of the data, this study adopted the SMOTE technique to effectively balancethe dataset groups.

Multi-Class Stress Detection Through Heart Rate Variability: A DeepNeural Network Based Study

Jon Andreas Mortensen; Martin Efremov Mollov; Ayan Chatterjee; Debasish Ghose

Stress is a natural response to pressure or demands, but chronic stress can lead to mental health issues. Measuring stress using heart rate variability (HRV) is common, but achieving high accuracy is challenging. HRV measures the variation in the time between heartbeats, not just the heart rate. In this study, we explored HRV features for stress detectionand developed a CNN-based model for multi-class stress detection (no stress, interruption stress, time pressure stress). Validated on the SWELL-KW dataset, our model achieved 99.9% accuracy, outperforming existing methods. We also highlighted the importance of key HRV features for stress detection using variance analysis.

Deep Learning Approach for Detecting Work-Related Stress Using Multimodal Signals

Wonju Seo; Namho Kim; Cheolsoo Park; Sung-Min Park

Work-related stress has significant negative effects on employees, making timely detection crucial for effective stress management. This study proposes a deep learning approachthat accurately detects work-related stress using multimodal signals. Electrocardiogram (ECG), respiration (RESP), and video data were collected from 24 subjectsin simulated stressful situations. Signals were pre-processed, and ECG, RESP, and facial features were fed into a deep neural network. Facial landmarks' coordinates and textures were extracted, and signals were fused at feature and decision levels. The feature-level fusion using RESP and facial landmarks showed an average accuracy of 73.3% in two-level stress classification. In three-level stress classification, using ECG, RESP, and coordinates resulted in 54.4% accuracy. Weight analysis in decision-level fusion revealed varying importance of information items across stress classifications. The study suggests that fusing multimodal signals with DL can improve stress detection, despite challenges like overlapped samples causing performance degradation.

ECG Heart-Beat Classification Using Multimodal Image Fusion

Zeeshan Ahmad; Anika Tabassum; Ling Guan; Naimul Khan

In this paper, we present a novel Image Fusion Model (IFM) for ECG heart-beat classification to overcome the weaknesses of existing machine learning techniques that rely either on manual feature extraction or direct utilization of 1D raw ECG signal. At the input of IFM, we first convert the heart-beats of ECG into three different images using Gramian AngularField (GAF), Recurrence Plot (RP) and Markov Transition Field (MTF) and then fusethese images to create a single imaging modality. We use AlexNet for feature ex-traction and classification and thus employ end-to-end deep learning. We perform experiments on PhysioNet's MIT-BIH dataset for five different arrhythmias in accordance with the AAMI EC57 standard and on PTB diagnostics dataset for myocardial infarction (MI) classification. We achieved an state-of-an-art results in terms of prediction accuracy, precision and recall.

A Review on Mental Stress Detection Using Wearable Sensors andMachine Learning Techniques

Shruti Gedam; Sanchita Paul

Stress is a heightened state of the body in response to challenging events or conditions, known as stressors, which can negatively impact mental and physical health if prolonged. Earlydetection is crucial, and wearable devices offer real-time monitoring. This paper reviews stress detection using wearables and machine learning, focusing on sensors like ECG, EEG, and PPG in various environments. It highlights approaches, results, and issues, aiming to guide future research. Additionally, a proposed multimodal stress detection system uses wearable sensors and deep learning.

High-Resolution Physiological Stress Prediction Models based on Ensemble Learning and Recurrent Neural Networks

Flavio Di Martino; Franca Delmastro

High-resolution stress detection is crucial for mobile sand e-health systems supporting personalized treatments, but existing solutions often focus on binary or few-class stress detection, limiting their utility. This paper presents an approach using ensemble learners and recurrent neural networks (RNNs) for time series regression in stress detection. Models were trained and tested on the WESAD dataset, using stress scores from validated questionnaires asground truth. Results indicate that Nonlinear AutoRegressive network with eXogenous inputs (NARX), Random Forest (RF), and Least-Squares Gradient Boosting (LSBoost) offer high- resolution personalized stress predictions. These models could be integrated into a Decision Support System (DSS) for online stress monitoring, aiding in designing personalized stress management strategies.

Cross Dataset Analysis for Generalizability of HRV-Based StressDetection Models

Mouna Benchekroun, Pedro Elkind Velmovitsky

Stress is a widespread mental health issue globally, with significant costs for treatment. While self-reporting is common for stress monitoring, AI-based approaches using physiological signals are emerging. This study focuses on the generalizability of Heart Rate Variability (HRV)-based ML models for stress detection. Logistic Regression and Random Forest models were trained and tested on two datasets with different protocols and stressors. Results show that the Random Forest model achieved better generalization, with an F1 score of 61%. This suggests that HRV-based stress detection models can be improved by integrating different models, benefiting mental health and medical research.

A survey of machine learning techniques in physiology based mentalstress detection systems

Suja Sreeith Panicker, Prakasam Gayathri

Automated and semi-automated medical diagnosis systems based on human physiology are gaining popularity, offering reliability, accuracy, and robustness. Research has focused on detecting positive and negative emotions using physiological features after presenting stimuli. This paper surveys physiological data collection, the role of machine learning in emotion andstress detection, evaluation measures, challenges, and applications. It also explores links between biological features and emotions/stress. The paper highlights research gaps, guidingfuture studies in the field.

TO CLASSIFY STRESS ON ECG DATA ANALYSIS THROUGH ML& DL ALGORITHMS

On the other hand, there have been a lot of recent research efforts on ECG data analysisto classify stress through ML and DL algorithms. Existing algorithms have focused mainly onbinary (stress versus nonstress) and multi-class stress classifications.

For instance, the authors in classified HRV data into stressed and normal physiological states. The authors compared different ML approaches for classifying stress, such as naive Bayes, knearest neighbour (KNN), support vector machine (SVM), MLP, random forest, and gradient boosting. The best recall score they achieved was 80%. A similar comparison study was performed in where the authors showed that SVM with radial basis function (RBF) provided an accuracy score of 83.33% and 66.66% respectively, using the time-domain and frequency-domain features of HRV.

Moreover, dimension reduction techniques have been applied to select best temporal andfrequency domain features in HRV. Binary classification, i.e., stressed versus not stressed,was performed using CNN in through which the authors achieved an accuracy score of 98.4%. Another study, Stress Click, employed a random forest algorithm to classify stressed versus notstressed based on mouse-click events, i.e., the gaze-click pattern collected from the commercialcomputer webcam and mouse.

In tasks for multi-class stress classification (e.g., no stress, interruption stress, and timepressure stress) were performed using SVM based on the SWELL−KW dataset. The highest accuracy they achieved was 90%. Furthermore, another publicly available dataset, WESAD, was used in for multi-class (amusement versus baseline versus stress) and binary (stress versusnon-stress) classifications. In their investigations, ML algorithms achieved accuracy scores upto 81.65% for three-class categorization. The authors also checked the performance of deep learning algorithms, where they achieved an accuracy level of 84.32% for three-class stress classification.

We have developed a novel 1D CNN model to detect multi-class stress status with outstanding performance, achieving 99.9% accuracy with a Precision, F1-score, and Recall score of 1.0 respectively and a Matthews correlation coefficient (MCC) score of 99.9%. We believe this is the first study that achieves such a high score of accuracy for multi-class stress classification.Furthermore, we reveal that not all 34 HRV features are necessary to accurately classify multi- class stress. We have performed feature optimization to select an optimized feature set to traina 1D CNN classifier, achieving a performance score that beats the existing classification models based on the SWELL-KW dataset.

- Our model with selected top-ranked HRV features does not require resource-intensive computation and it achieves also excellent accuracy without sacrificing critical information.

EXISTING SYSTEM

CNNs can analyze physiological responses such as facial expressions, body language, and vital signs captured through imaging techniques like thermal imaging or wearable sensors.These networks can extract features from images, such as changes in skin temperature, perspiration levels, or heart rate variability, which are indicators of stress.

CNN-based stress detection systems can be integrated into healthcare, workplace, and smart environment applications to monitor and manage stress levels effectively.

Convolutional Neural Networks (CNNs) have limitations, including their computationalcomplexity, lack of interpretability, data requirements, susceptibility to overfitting, and limited ability to capture long-range dependencies or contextual information.

Despite these drawbacks, CNNs are still widely used due to their capability to automatically learn features and capture complex patterns in HRV data.

Continuous research and development in CNN algorithms and applications are driving advancements in stress analysis, leading to more accurate and reliable detection methods.

PROPOSED SYSTEM

In machine learning-based stress detection via heart rate variability (HRV), a 1D convolutional neural network (CNN) can play a crucial role. HRV data, being a time-series signal, requires sophisticated analysis to extract relevant patterns associated with stress. A 1D CNN excels at this task by automatically learning features from the raw HRV signal, eliminating the need for manual feature engineering. This ability to capture both local and global patterns in the HRV signal is particularly advantageous, as it allows the model to discern subtle variations indicative of stress. Additionally, 1D CNNs are robust to noise, which is beneficial given that HRV data can be noisy. By learning hierarchical representations of the data, a 1D CNN can reduce the complexity of the model while maintaining its effectiveness instress detection. Furthermore, the end-to-end learning capability of 1D CNNs enables the modelto directly map raw HRV data to stress detection, simplifying the overall pipeline and potentially improving performance. Overall, the use of 1D CNNs in stress detection via HRV holds great promise for developing accurate and efficient models.

ADVANTAGES OF PROPOSED SYSTEM

1D Convolutional Neural Networks (CNNs) offer several advantages for machinelearning-based stress detection via heart rate variability (HRV):

a. **Automatic Feature Extraction:** 1D CNNs can automatically learn relevant features from HRV signals, eliminating the need for manual feature engineering.
b. **Hierarchical Feature Learning:** CNNs can learn hierarchical representations of HRV data, capturing both local and global patterns in the signal, which are important for stress detection.
c. **Robustness to Noise:** CNNs are robust to noise and can learn to filter out irrelevant information from the HRV signal, improving the model's performance.
d. **End-to-End Learning:** With 1D CNNs, the entire model can be trained in an end-to-end manner, directly from the raw HRV data to stress detection output, simplifying theoverall pipeline.
e. **Scalability:** CNNs can be scaled to handle large datasets and complex HRV signals, making them suitable for real-world applications with varying data sizes.
f. **Interpretability:** While CNNs are often considered black-box models, techniques such as visualization of feature maps can provide insights into the features learned by the model, improving interpretability.
g. **State-of-the-Art Performance:** D CNNs have been shown to achieve state-of-the- art performance in various machine learning tasks, indicating their effectiveness for stress detection via HRV.

SYSTEM STUDY

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus, the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased

Methodology

Stress is a Natural response to Pressure, But when it becomes chronic, it can leads to Mental HealthIssues. Stress is measured using physiological Parameter such as Heart Rate Variability (HRV).HRV is not equivalent to Heart Rate. HRV represents the variation of Time Interval Between successive Heart Beats. If a Person having Stress, it leads to increase in the Heart rate which causes Risk to life. HRV Increases with Relaxation and decrease with stress. Indeed, HRV is usually higher when heart is beating slowly & Vice versa. Our Project focuses on developing ML model capable of accurately detecting stress levels based on the Indicator given to all types of stress levels.

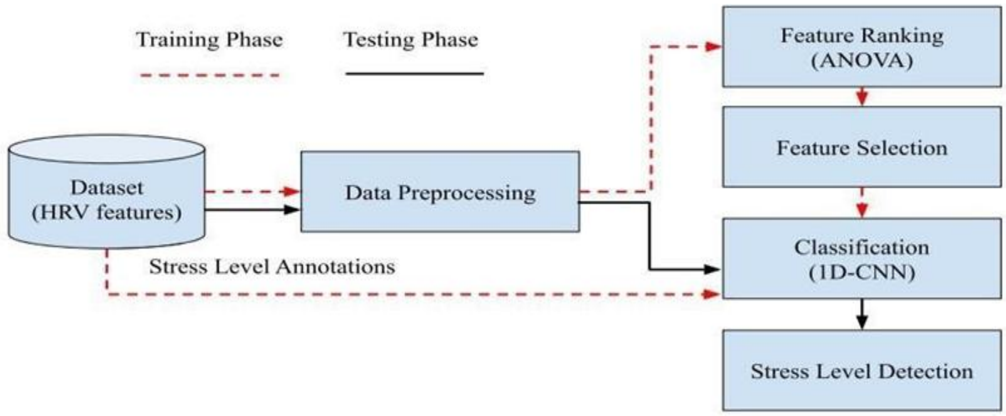

Fig.1. System Architecture

Multi-class stress classification (e.g., no stress, interruption stress, and time pressure stress) were performed using SVM based on the SWELL−KW dataset. The highest accuracy they achieved was 90%. Furthermore, another publicly available dataset, WESAD, was used in for multi-class (amusement versus baseline versus stress) and binary (stress versus non-stress) classifications. In their investigations, ML algorithms achieved accuracy scores up to 81.65% for three-class categorization. The authors also checked the performance of deep learning algorithms, where theyachieved an accuracy level of 84.32% for three- class stress classification.

Comparison of Models

A summary of the performance comparisons of the implemented models based on testingAccuracy, Precision, Recall, F-Score.

Models: The performance metrics that are considered in our proposed works are as follows:

Precision: The ratio of the number of correctly predicted observations (true positives) to thetotal number of positive predictions (true positives + false positives).

Recall: The ratio of correctly predicted observations (true positives) to all observations in that class (true positives + false negatives).

F-Score: F-Score is a metric used to evaluate the performance of a Machine Learning model. It combines precision and recall into a single score. F-measure formula: F-score = 2 * (precision * recall) / (precision +recall)

Accuracy: The total number of correctly classified images to the total number of images.

MEAN_RR	82.50	100	90.41	89.39
MEDIAN_RR	86.84	100	92.95	92.42
SDRR	84.61	100	91.66	90.90
RMSSD	89.18	100	94.28	93.93

MODULES USED

Data Collection & Data Processing:

Once the data is collected, it undergoes preprocessing steps such as cleaning, handlingmissing values, and normalizing features to ensure data quality.

Feature Engineering (Feature Ranking & Feature Selection) :

Next, feature engineering techniques are applied to extract relevant features from the HRV signals that can effectively capture stress patterns. This step is crucial in enhancing the predictive power of machine learning models for stress detection.

Classification:

Following feature engineering, appropriate machine learning models, such as Support Vector Machines (SVM) are selected based on their suitability for stress detection tasks. These models are then trained using labeled HRV data to learn the patterns associated with stress.

Random Forest Classifier:

This Classifier is essential to ensure their accuracy and reliability. This Project is predicting the stress through medical data of the Patients Using “Random Forest Classifier”.

Stress Level Detection:

In real-world scenarios, the trained models are deployed for real-time monitoring of stress levels. This involves integrating the models with real-time data streams and implementing the system forpractical stress management applications.

Python Libraries

Results

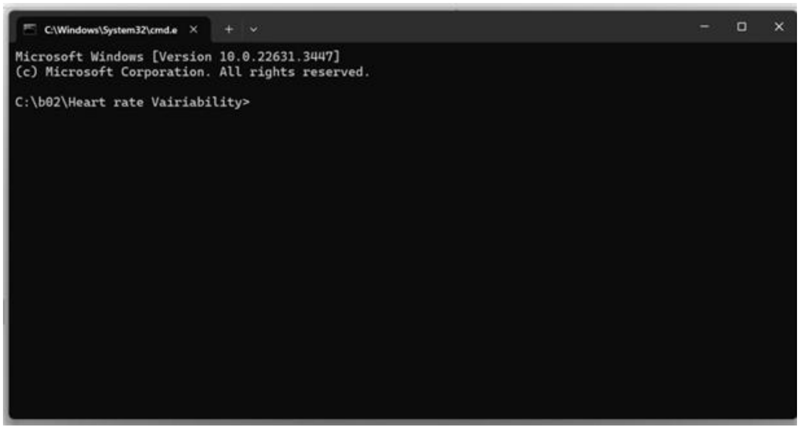

Figure.2. Command Prompt

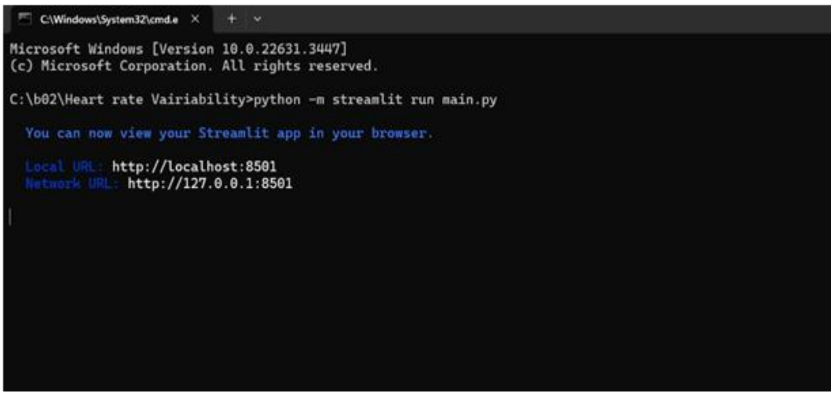

Figure.3. Enter the Command

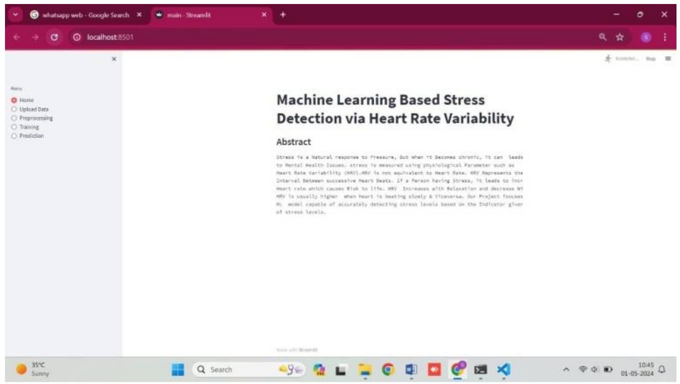

Figure.4. Home Page

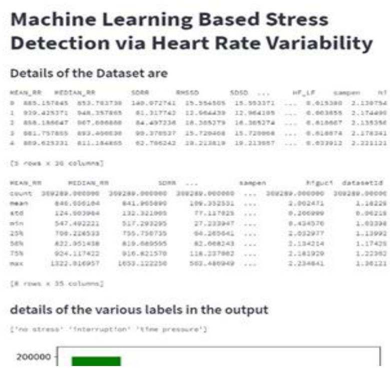

Figure.5. Upload Data

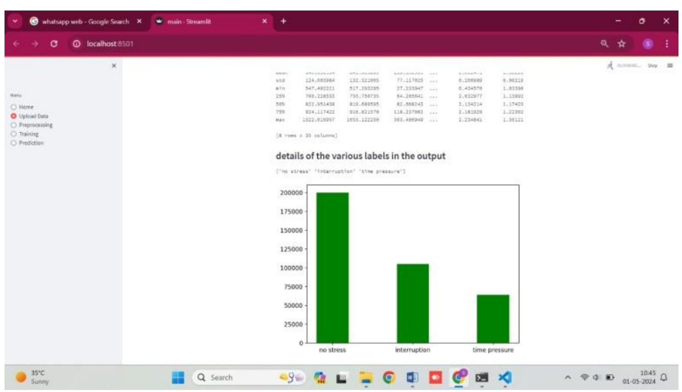

Figure.6. Types of Stress

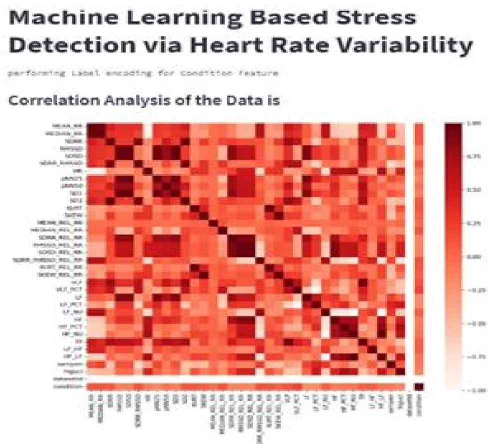

Figure.7. Data pre-processing

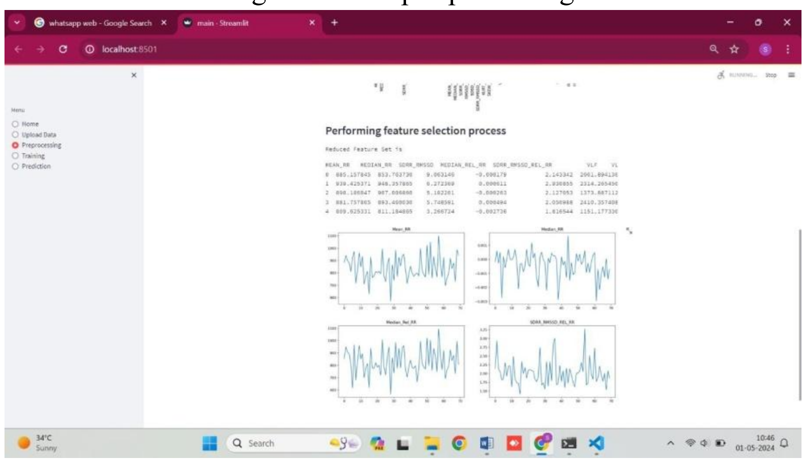

Figure.8. Feature Selection

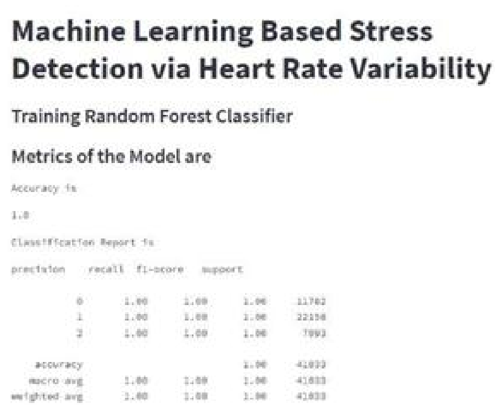

Figure.9. Random Forest Classifier

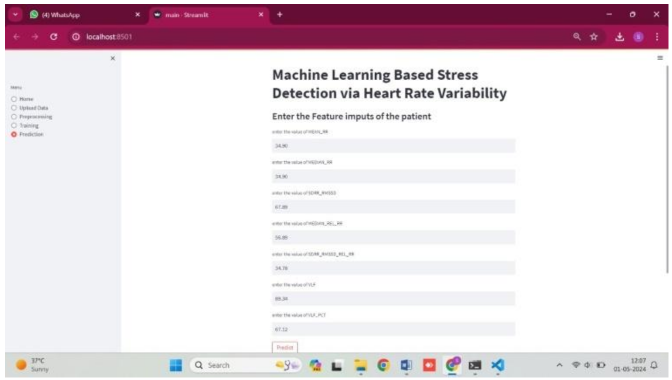

Figure.10. Prediction Phase

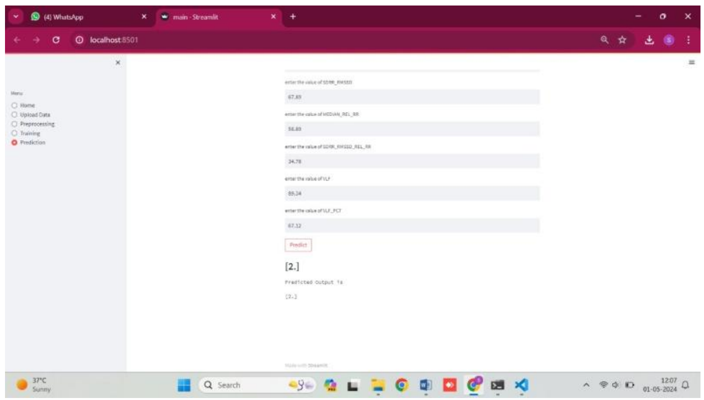

Figure.11. Prediction Output Accuracy

Conclusion

Implementing Machine Learning-based stress detection via HRV analysis involves using advanced computer algorithms to understand how our heart's activity changes with stress. By analyzing data from devices like ECG monitors, these algorithms can detect patterns that signal stress levels. This information can help individuals and healthcare professionals better manage stress and improve overall well-being. Machine Learning-based systems can provide real-time feedback, making it easier to track stress levels and take appropriate actions. This approach combines technology and health to create personalized solutions for stress management, potentially leading to healthier lifestyles and improved mental well-being for many people.

Future Enhancements

Integrating our stress detection system with smart watches equipped with HRV sensors.

Explanation: This integration will allow individuals to monitor their stress levels in real-time throughout the day. The smartwatch will continuously collect HRV data and provide feedback on stress levels, prompting users to take proactive measures such as deep breathing exercises or mindfulness activities when stress levels rise.

Fitness Tracker Integration:

Future Enhancement: Integrating our system with fitness trackers that track physical activity andsleep patterns.

Explanation: By combining HRV data with activity and sleep data from fitness trackers, our systemcan provide holistic insights into factors influencing stress levels. For example, it can identify correlations between high stress levels and lack of physical activity or poor sleep quality, enabling users to make lifestyle changes for better stress management.

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