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Heart Rate Variability Based LSTM Model for Stress Detection with Explainable AI Insights

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Abstract: In today's busy world, stress is common because people must think about many things simultaneously. To effectively deal with the harmful effects of worry on your health, a person needs to notice them as soon as they appear. This study supports recognizing stress as a helpful method. It shows how critical physiological signs are as a reliable way to detect stress, mainly because these signals cannot be changed purposefully. Heart Rate Variability (HRV), a physiological signal, is used in this study to investigate how stress can be detected using the SWELL knowledge work (SWELL-KW) dataset of 25 Subjects. PCA (Principal Component Analysis) and IQR (Interquartile Range) Preprocessing techniques are applied to select 26 features and detect outliers. The proposed model used a long short-term memory (LSTM) model to sort stress levels from biosensors in real-time and gives 98% accuracy. This study goes even further by using explainable artificial intelligence (XAI) models to explain their performance by pointing out the factors the model thought were important when making a decision. The SHAP (SHapley Additive Explanations) model is used to understand results by making them easier to interpret. It also promotes acknowledging stress as a beneficial method for managing mental health, highlighting the significance of early identification and intervention for a proactive and comprehensive approach to mental well-being. The contributions provide significant insights and techniques for resolving stress-related difficulties and developing mental health awareness and resilience.

Keywords: *Explainable -AI, HRV, LSTM, Stress Detection, SWELL Dataset*

1. Introduction

An individual's mental well-being reflects their overall state of mind and temperament. It encompasses various emotions, including positive, negative, inspired, and stressful feelings. Positive psychological well-being leads to a more positive outlook on life. Several factors contribute to psychological health, such as depression, personality disorders, and more. Therefore, detecting high-level stress and conducting laboratory tests is essential. Stress management methods are essential for determining how much stress affects our social and economic lives. According to the World Health Organization (WHO), about one in four people in the world deal with stress [1]. Stress in people causes emotional and social problems, as well as confusion at work and bad work. A relationship, sadness, and finally, committing suicide in the worst cases. This means that people who are stressed need to get counselling to help them deal with their worries. It's impossible to avoid worry, but taking steps to stop it can help you deal with it [2]. At the moment, only medical and physiological professionals can tell if a person is depressed or worried. Questionnaires [3] are one of the old ways to find out if someone is stressed. It will be hard for people to say whether they are stressed or not with this method because it depends on their answers. Automatically detecting stress lowers the chance of health problems and makes society better off. This makes it clear that we need a scientific tool that uses physiological signs to figure out how stressed and automatically.

Person is. For professional growth [4], research emphasizes stress management as a crucial soft skill because of its impact on health and well-being. Additionally, stress negatively impacts working memory and cognitive flexibility, thereby decreasing the performance of students and professionals. Measuring stress is challenging, and validated questionnaires need users to provide direct feedback on their stress levels over time. Social Safety Theory appears to be a framework [5] that integrates knowledge from stress biology with social experiences to understand their impact on human health and well-being. The goal seems to be leveraging our understanding of stress biology to identify which social experiences are most crucial to focus on, considering the sophisticated regulatory mechanisms of the human brain and immune system.

This process is inconvenient due to self-bias and the time commitment involved. Affective computing is a developing solution that creates machine systems that identify emotions, such as stress. A prevalent method for automatically detecting stress involves affective computing using biometric data, as some biometric data are closely associated with stress [6] and can be derived from a photoplethysmography (PPG) sensor commonly

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used in smartwatches and wristbands. A new dataset was created during the presented research, and machine learning techniques were used to assess whether the two chosen bio-signals are strong indicators of human emotions [7]. Yet, some biometric data cannot be obtained without expensive, intrusive research-focused equipment. HRV-based features are elaborated on below.

1.1. Heart Rate Variability

HRV Heart rate variability (HRV) is calculated by the time interval(R-R Interval) between consecutive heartbeats in milliseconds, known as heart rate variability. The supportive branch of the autonomic nervous system (ANS) controls the stress or reaction, preparing us to act, respond, and conduct in rebuttal to life's diverse needs. The time between heartbeats (R-R interval) varies from beat to beat, and this variation in HRV can reveal a lot about the body's physiological state. HRV should naturally rise during relaxing activities and fall during stressful situations when the body can take advantage of increased sympathetic action. Heart rate variability is higher when the heart beats slowly; when the heart rate increases, such as during stress or exercise, it decreases during relaxing activities. Heart rate and HRV are in the inverse relation.

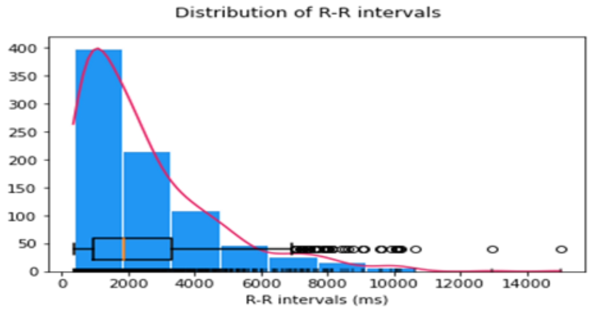

Fig 1. Distribution in the Time Domain

Heart rate variability level intuitively varies daily depending on activity, anxiety, and work-related stress. The duration between heartbeats (R-R interval) fluctuates from beat to beat and can give information about the body's physiological reaction [8]. The Time Domain defines how many beats are in the R-R interval. It is depicted in Figure 1 with a sampling Rate of 100.

Some basic time domain features are mentioned below,

• R-R interval: The time elapsed between two successive R-waves of the QRS signal on the electrocardiogram (and its reciprocal, Heart Rate)

• MEAN_REL_RR: Mean of all relative RR intervals

• SDRR: Standard deviation of R-R intervals.

• Min HR: lowest heart rate.

• Max HR: highest heart rate.

• NN50: The number of pairs of successive R-R intervals that differ by more than 50 ms. (regular R-R intervals are often called NN intervals).

• PNN25: Percentage of adjacent RR intervals differing by more than 25 ms.

• PNN50: The proportion of NN50 divided by the total number of R-R intervals.

• SDSD: The standard deviation of all intervals of differences between adjacent RR Intervals.

• RMSSD: Root mean square of successive RR Interval's differences.

Frequency Domain Features define the power distribution of signal and its ranges and also describe how the R-R interval is modulated. It is illustrated in Figure 2 with a sampling rate of 100 of the SWELL dataset.

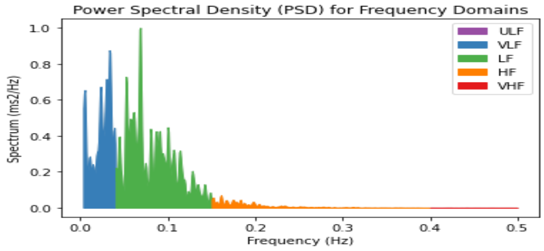

Fig 2. Distribution in the Frequency Domain

Some basic frequency domain features are mentioned below,

• High (HF.) Frequencies Between 0.15–0.40 Hz Are Associated With Parasympathetic Activity (Recovery).

• Lower Frequencies (LF.) Between 0.04–0.15 Hz Are Linked To Both Sympathetic And Parasympathetic Activity.

• The Ratio Of LF/HF Is To Measure the Autonomic Nervous System Balance. A Higher HF And A Lower LF/HF Ratio Indicate An Increased HRV, Which Means Your Body Is Recovering. Nonlinear Domain Features These features analyze the geometric shape formed by plotting each RR interval against its successive interval. In Poincaré, each RR interval is plotted against the next RR interval, as mentioned in Figure 3. The resulting shape of the plot is the essential feature and can be used to identify a person's stress level.

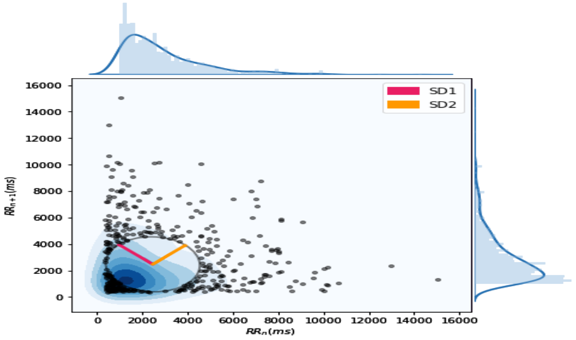

Fig 3. Poincaré Plot of SD1 and SD2

•Descriptors SD1 and SD2 represent this fitted ellipse's minor and significant semi-axes [9]. It described SD1 and SD2 in linear statistics. SD1 is the standard deviation of the distances of points.

From axis one. It determines the width of the ellipse (short-term variability), and SD2 equals the standard deviations from axis two and the length of the ellipse (long-term variability)

• The SD1/SD2 ratio represents the randomness in the heart rate variability time series. In one study [10], HRV signals obtained from a wristband-type wearable device with a photoplethysmography (PPG) sensor were used to predict daily mental stress levels. The study employed an autoregressive (AR) model to extract low-frequency (0.04Hz - 0.15Hz) and high-frequency (0.15Hz - 0.4Hz) features from HRV Data were collected from eight university students who self-evaluated their stress levels using the Perceived Stress Scale (PSS) three times a day for a week. Linear regression achieved an accuracy of 86.35%, but the use of additional machine learning algorithms and established PPG analytic tools could yield better results. Another study [11] aimed to identify physiological changes during a stressful task by recording ECGs and inter-second heart rates using a Fitbit device during resting and stress phases. However, further investigation with a larger sample size and stratified anxiety scores based on the Depression Anxiety Stress Scale is required to analyze the association with HRV in more detail. The study provides insights into the latest advancements in this field. Stress is commonly intertwined with a negative connotation, often regarded as a subjective sensation experienced by individuals that can potentially impact both emotional and physical well-being [12]. This phenomenon is a psychological and biological response to various internal or external stressors. The authors present a global stress detection framework combining a reduced HRV feature set with a Random Forest model [13].

Much research work is done to detect stress using HRV signals. Different authors applied various algorithms to achieve good accuracy using models. However, we have achieved good accuracy using the LSTM Model as well, and Explainable AI is used to interpret the visibility of the model achieved for better understanding.

1.2. Research Gap

Numerous research efforts have been dedicated to detecting stress using heart rate variability (HRV) signals. Various authors have applied diverse algorithms to achieve high accuracy in modelling stress levels. Among these approaches, the LSTM (Long Short-Term Memory) model has emerged as particularly influential. LSTM models, a type of recurrent neural network (RNN), excel in capturing temporal dependencies within time-series data. They are well-suited for analyzing HRV signals, which exhibit dynamic fluctuations over time.

Furthermore, recent studies have integrated explainable artificial intelligence (XAI) techniques to enhance model interpretability and facilitate a deeper understanding of the

Factors contributing to stress detection. By employing XAI methodologies such as SHAP (SHapley Additive Explanations), researchers can elucidate the decision-making process of the LSTM model, making the predictions more transparent and interpretable.

This combined approach of leveraging LSTM models for accurate stress detection and employing XAI techniques for model interpretability represents a significant advancement in the field. Not only does it enable the achievement of high accuracy in stress detection, but it also provides insights into the underlying mechanisms driving the model's decisions. Ultimately, this enhances the usability and trustworthiness of stress detection systems, paving the way for more effective interventions and management strategies in various contexts.

This study explores the generalizability of HRV-based machine learning models for stress detection. The contribution of this paper is threefold:

- The application of preprocessing techniques such as PCA and IQR.
- The utilization of an LSTM model.
- Implementing an explainable approach (SHAP) facilitates a deeper understanding of the model.

This study advocates acknowledging stress as a crucial Component of mental health management, emphasizing the significance of early detection and intervention. By offering Insights and techniques for addressing stress-related challenges, our research enhances mental health awareness and resilience. The integration of novel methodologies and Emphasis on interpretability distinguishes our work, paving the way for more comprehensive stress detection and management approaches.

This paper consists of several sections. Section 2 covers the data and methods used, including the extraction methods for features, outlining the purpose of the study. Section 3 presents the results and discussions derived from the experimental work. Finally, Section 4 concludes the paper and outlines potential avenues for future research.

2. Methodology

The SWELL (Smart Reasoning for Well-being at Home and Work) dataset from [14] was collected at Radboud University. The authors requested participants not to smoke or drink caffeine 3 hours before the experiment, as these are possible confounders. Before the investigation started, the experiment and recordings were explained, and all participants signed a consent form to confirm that the recorded data may be used for research purposes. Body sensors were applied, and while the experimenter checked the recordings, the participant read the experiment instructions and filled in a general questionnaire. This research project included 25 people doing office tasks (such as writing reports, giving a presentation, reading emails, and seeking information) and were exposed to it daily. Work stress (e.g., being unexpectedly interrupted by an urgent email and pressure to complete work in a limited time). The researcher observed the subjects' computer usage patterns, facial expressions, body movements, electrocardiogram (ECG) signal, and Electrodermal activity (EDA) signal during the experiment.

The people involved participated in various environmental conditions:

No stress condition: The participants performed the assigned tasks for 45 minutes.

Time pressure condition: The time to complete each participant's job has been reduced to two-thirds of the time in a stress-free state.

Interruption condition: The participant received a suspension email during the assigned task. Some emails were related to their task, and participants were asked to take specific actions. The other emails were irrelevant, and the participants didn't have to do anything.

At the end of each experimental condition, each participant's perceived stress was assessed using various self-assessment questionnaires, including the NASA Task Load Index (NASATLX) by the author [15] S. G. Hart et al. The participants' body postures were recorded with a Kinect (for Windows, model 1517) depth camera. The body sensors, the lab's ceiling camera, and microphones were used to make lab records during the experiment. The ECG was recorded using a Mobi device (TMSI) with self-adhesive electrodes. The electrodes were placed across the heart, one below the participant's right collarbone, the other left below the chest, with a grounding electrode below the left collarbone. In addition, some preprocessing was programmed into the recording software Portilab2. Mobi was used with finger electrodes to record skin conductance. These were fixed with Velcro tape around the lower part of the thumb and ring finger of the participant's non-dominant hand. The recording frequency was 2048 Hz. All signals (raw and preprocessed ECG and skin conductance) were stored in an S00 file. Feature Extraction Figure 4 depicts a heatmap that shows the relationship between HRV time and frequency domain features.

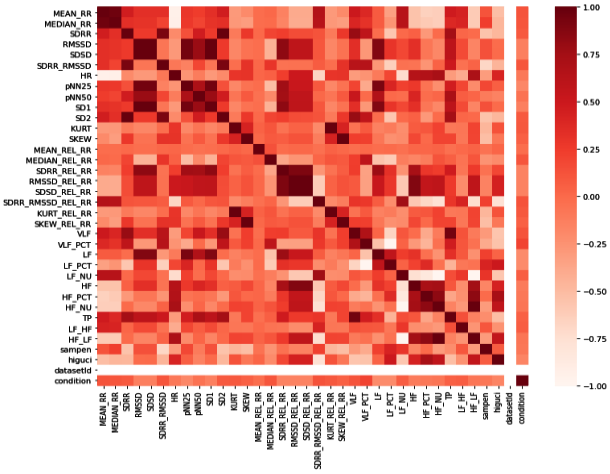

Fig 4. Heatmap of HRV Features

Author [16] extracted the Dataset's HRV features using statistical methods. They computed the HRV feature according to the standards and algorithms proposed by the Task Force of the European Society. [17] Each HRV feature was calculated on a five-minute moving window as follows: The author extracted an Inter-Beat Interval (IBI) signal from the peaks of the Electrocardiogram (ECG) signal of each subject. Each HRV index was then computed on a 5-minute IBI array. Different sample features were utilized in this work, including the mean of the R-R interval, the median of the R-R interval, and the standard deviation of the interval differences between R-R intervals that differ by more than 50 ms (known as pNN50).

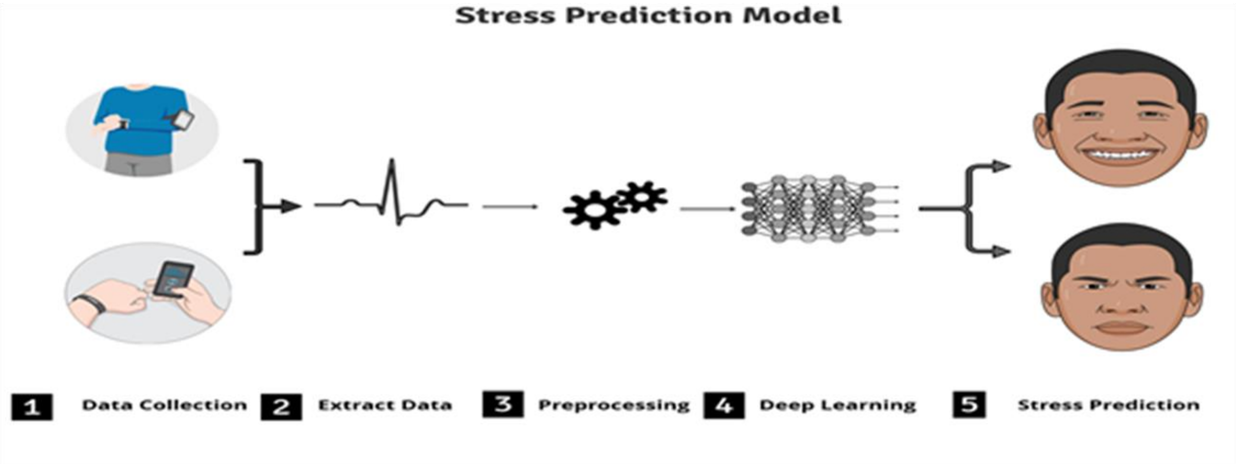

Fig 5. A framework of the proposed stress Prediction model

The proposed workflow in Figure 5 for stress prediction using wearable devices involves a systematic approach to harness physiological data for accurate stress level assessments. The summary of the workflow is as follows:

Step 1: Data Collection The initial phase of our workflow focuses on gathering data through wearable devices like smart watches or fitness trackers. These devices come equipped with sensors capable of capturing physiological signals, notably Heart Rate Variability (HRV) for stress prediction. Users wear these devices during their daily activities, enabling continuous monitoring and collection of relevant biometric data, which forms the foundation for subsequent analysis.

Step 2: Data Extraction HRV analysis involves extracting features from the time, frequency, and nonlinear domains to gain insights into the activity of the autonomic nervous system and overall cardiovascular health.

Step 3: Preprocessing Techniques Following the data collection phase, the next step involves applying various preprocessing techniques to enhance the data's quality and relevance. This stage comprises two crucial processes:

Feature Selection: The Interquartile Range (IQR) method selects the most informative features.

$IQR = Q3 - Q1$ (1)

Where:

Q1 is the first quartile (25th percentile)

Q3 is the third quartile (75th percentile)

Data points that fall above Q3 + 1.5 * IQR or below Q1 - 1.5 * IQR are considered outliers. Additionally, Principal Component Analysis (PCA) is employed for feature selection, aiming to reduce dimensionality and computational complexity while retaining essential information for stress prediction. 26 HRV features were selected using preprocessing methods.

Normalization: Standard Scalar Normalization ensures consistency and comparability across diverse features. This process scales the selected features to a standardized range, preventing certain features from dominating solely based on their more significant scale. Normalization enhances fair contributions from all relevant variables.

Step 4: Deep Learning Techniques The final stage involves applying advanced deep learning techniques, explicitly leveraging Long Short-Term Memory (LSTM) networks for stress prediction. This phase is designed to capture temporal dependencies within time-series data. The processed and normalized features serve as inputs to the LSTM model, enabling it to learn intricate patterns and relationships embedded within the data.

LSTM Model: Long Short-Term Memory Networks are highly

Effective in handling sequential data, making them particularly

Suitable for analyzing time-series information like HRV, The LSTM model's unique ability to retain and selectively update information over extended sequences enhances its capacity to capture nuanced patterns indicative of stress conditions.

Step 5: Stress Prediction The ultimate output of the deep learning model is a prediction of the individual's stress condition based on the input features. This prediction provides valuable insights into an individual's stress levels, facilitating early detection and proactive management of stress-related issues. Overall, this comprehensive workflow integrates wearable device data, preprocessing techniques, and advanced deep-learning methodologies to enhance the accuracy and effectiveness of stress assessment, ultimately contributing to improved well-being and proactive stress management.

3. Results and Discussion

This section provides a background on the deep learning algorithm utilizing two key components: (a) RNN (Recurrent Neural Network) and (b) LSTM (Long Short-Term Memory) cell. RNN was initially developed to detect and categorize temporal data. It is designed to process sequential data, retaining and utilizing information from previous steps to influence subsequent steps. RNNs find applications in various fields, including speech recognition [18]. However, a significant limitation of RNNs is the difficulty in handling long sequences, as highlighted by [19]. To address the challenges associated with prolonged sequences, the author [20] proposed LSTM as an alternative type of RNN. The LSTM network incorporates a specific internal structure to mitigate the problem of vanishing and exploding gradients during training. This enables the LSTM to effectively capture and utilize information over long sequences, thus overcoming the limitations of traditional RNNs.

Researchers [21] focus on stress detection in automobile drivers using Long Short-Term Memory (LSTM) networks based on ECG data. LSTM networks are a type of recurrent neural network (RNN) suitable for sequence data like ECG signals.

We designed a sequential LSTM network with one hidden layer using Python Libraries [22]. 75% of data are allocated to the training set, and 25% of data are given in the

Table 1. Comparison of the results with other state-of-the-art models

References	*Dataset*	*No. of features*	*Model*	*Accuracy*	*Precision*	*Recall*	*F1-score*
[25]	SWELL−KW	17	SVM	92.75%	NA	NA	NA
[26]	SWELL−KW,AMIGOS [5]	NA.	CNN	98.30%	96.00%	96.30%	95.80%
[27]	SWELL−KW	NA.	SVM	90.00%	N.A	N.A	N.A
[28]	SWELL−KW	34	MLP	88.64%	93.01%	92.68%	82.75%
[29]	SWELL-KW+ WESAD	64	ANN+NB	95.75%	95.75%	95.75%	95.75%
This Study	SWELL-KW	26	LSTM	98%	98%	97.33%	97.66%

Testing set. Relu activation function is used. Depending on how many stress and baseline samples each subject has, we are setting different batch sizes of 4,8,16, and 32 one at a time.

The algorithm uses the training. The network is then trained again with a set of 32 samples. Furthermore, the epoch sizes chosen are 4, 8, 16, and 32. The exact procedure is repeated until each model has spread throughout our network. It helps to prevent the blending of samples from different subjects. Early stopping is used to avoid over-training the model. After some time, the number of epochs is limited based on specific criteria. They minimize the validation loss while training in each epoch, the criterion used to determine when to stop training a model early.

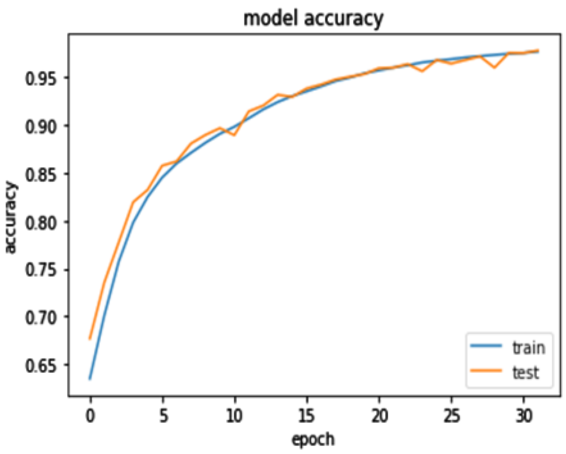

Fig 6. Accuracy vs. epoch of training and testing

Figure 6 visually represents the relationship between the accuracy of a machine learning model on both the training set and testing set across different epochs. The x-axis corresponds to the number of epochs, which are iterations over the entire dataset during the training process. The y-axis denotes the accuracy achieved by the model on both the training and testing datasets and shows the confusion matrix of the predicated and actual stress labels. Overall, 98% accuracy was gained using the LSTM Model.

The performance of the LSTM model for multiclass stress classification has been evaluated through Classifier Evaluation Measures based on the SWELL−KW dataset. (eq. (2)), Recall (eq. (3)), Accuracy (eq. (4), F1-score (eq. (5)), classification report, and confusion matrix. It is a 2-dimensional table (actual versus predicted), and both dimensions have four options, namely, true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).TP is an outcome where the model estimates the positive class accurately; TN is an outcome in which the model correctly predicts the negative class. FP is an outcome where the model estimates the positive class inaccurately; and FN is an outcome in which the model forecasts the negative class incorrectly. Accordingly, the performance metrics for a given class are expressed as follows [23] [24].

Precision = TP/TP + FP (2)

Recall = TP/ TP + FN (3)

Accuracy = TP + TN / TP + TN + FP + FN (4)

F1-score = 2 × Recall * Precision /Recall+ Precision (5)

This study demonstrates promising results compared to previous studies that have utilized the SWELL-KW dataset. A comparative analysis mentioned in Table 1 reveals the strengths of the LSTM model employed in this study: The LSTM model achieved an accuracy of 98.00%, which outperforms several other models such as SVM, MLP, CNN and ANN+NB.

4. Explainable AI- SHAP Model

Interpretability is a critical part of the machine-learning workflow. However, a machine learning model can no longer be maintained in a "black box".Stress levels are explained based on their HRV by using explainable machine learning (XML) [30]. ML systems are sometimes called "black boxes." ML models, like XML, help end users understand their goals, decisions, and thinking.

Stress detection was achieved by obtaining physiological sensor data from 32 participants during Baseline, Stress, Recovery, and cycling sessions. The outcomes of every wearable device were compared by classifying four stress classes with machine learning algorithms. Subsequently, an advanced explainable artificial intelligence technique was implemented to elucidate the predictions made by our models and examine the impact that various features exert on the outputs of the models [31].To implement XAI analysis in Multiclass classification difficulties and use it to improve the model, we described how to apply SHAP via a deep learning approach. A method for explaining individual predictions based on the optimal Shapley values for games was developed by [32] and is known as SHAP (Shapley Additive Explanations). However, the Shapley value calculation required to determine feature contributions is computationally intensive. KernelSHAP, TreeSHAP, and DeepSHAP are the primary techniques for approximating SHAP values to increase computation efficiency. Adapting the Deep SHAP equation for the LSTM model involves considering the sequential nature of the data. The adapted Deep SHAP equation (6) for LSTM models can be expressed as follows:

$$\phi j, t(x) = \sum_{S\subseteq\{1,\ldots,p\}\setminus\{j\}} \frac{|S|!(p-|S|-1)!}{p!}[f(x_{S,t}\cup\{j\}) - f(x_{S,t})](6)$$

Where

ϕj,t(x) is the SHAP value of feature j at time step t.

S represents a subset of features excluding feature j.

p is the total number of features.

xS,t denotes the input sequence with only the features in subset S at time step t.

f is the LSTM model's prediction function.

The summation is performed over all subsets S of features excluding feature j. The difference in model predictions between the input sequence with and without feature j at time step t is computed for each subset. The weighted average of these differences is then calculated to obtain the SHAP value for feature j at time step t.

SHAP offers global and local interpretation methods based on aggregations of Shapley values. SHAP gives each feature a relevance value for a specific prediction. It discovers a new class of additive feature importance measures. shap. The shap.DeepExplainer is used in the SHAP library to compute SHAP values.

Summary of the steps involved in using the shap.DeepExplainer.

- Initialize the DeepExplainer with your trained model and a background dataset.
- Compute SHAP values for specific input sequences using the initialized explainer object.
- Interpret the SHAP values to understand the importance of each feature in the model's predictions.

4.1. The dependency plot

The dependency plot, as defined in Figure 7, is a visualization tool within the SHAP (Shapley Additive exPlanations) framework that helps understand the relationship between a feature and its corresponding SHAP values. It illustrates how changes in the value of a specific feature influence the prediction made by a machine learning model. The vital plot in this plot is created by stacking the effects of a feature on the classes. Therefore, that is the plot where you can see if you created features to set a particular class apart. In other words, you can see what the Computer learned from the characteristics by looking at the multiclass classification summary in a graphical Way.

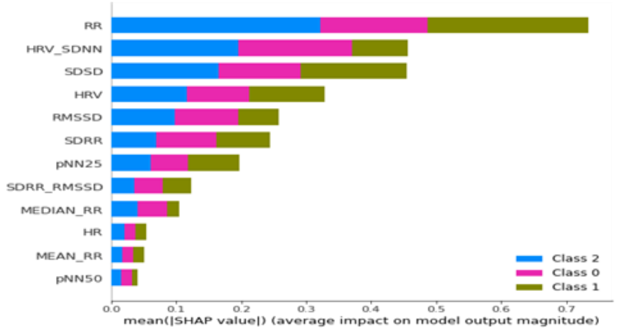

Fig 7. Feature Importance Plot using SHAP a)

a) https://shap.readthedocs.io/

B. The waterfall model

The waterfall model in SHAP is a visualization technique that displays the contribution of each feature to the final prediction in a step-by-step manner. It provides a clear and intuitive representation of how each feature affects the prediction and the cumulative effect of adding or subtracting features. The waterfall model starts with a baseline value, which represents the expected average prediction of the model. Then, each feature's contribution is shown as a series of bars, with positive or negative values indicating whether the feature increases or decreases in Figure 8. Each plot provides a unique perspective on feature importance,

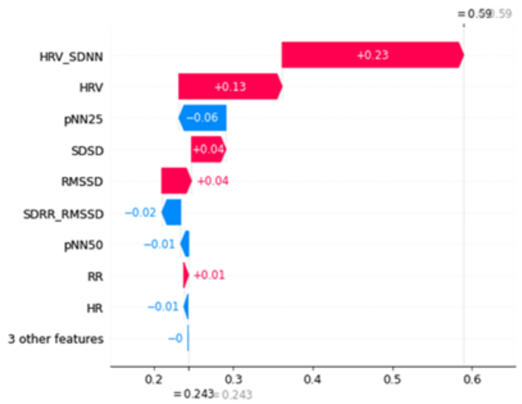

Fig 8. Water Fall Plot using SHAPa)

a) https://shap.readthedocs.io

relationships, interactions, and contributions, aiding in the interpretability and explainability of machine learning models. The plot choice depends on the Specific requirements and characteristics of the model and the insights sought by the user.

5. Conclusion

This study demonstrated the potential of using physiological HRV signals for stress detection in human physiological sensing. By incorporating different time domain features, frequency domain features, and nonlinear features, we have developed an LSTM-based stress prediction model. The model was trained and tested on the SWELL-KW dataset, consisting of physiological signals from 25 subjects. The results have been promising, with the LSTM model achieving a testing accuracy of 98% using stress level classification states. Furthermore, we have employed the Explainable AI technique SHAP to gain insights into the model's decision-making process and attribute importance. The SHAP analysis has contributed to the interpretability and transparency of our model, enhancing our understanding of the underlying factors driving stress predictions. In future work, we aim to investigate the evolution of stress patterns over time by focusing on various emotional transition states and try to incorporate time-series analysis techniques and advanced modelling approaches to achieve this. These methods will enable us to capture and predict emotional transitions, allowing for a deeper understanding of stress dynamics. In addition, we will develop real-time stress monitoring systems to make our research more practical and applicable. It will involve integrating the LSTM model, known for its effectiveness in handling time-series data, with wearable devices or mobile applications. Doing so allows us to continuously monitor and assess an individual's stress levels in real time.

Furthermore, the real-time stress monitoring systems will provide immediate feedback and interventions for effective stress management. For instance, if the system detects high-stress levels, it can deliver personalized recommendations for stress reduction techniques or suggest calming activities. By providing real-time support, individuals can manage their stress levels and promote overall well-being.

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