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A Multi-Model Approach: Stress Detection using Physiological Signals with LSTM and XGBoost

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ABSTRACT This research paper introduces the Multi-Model approach for detection of stress based on the Physiological signals. Now a days, stress is a major cause for many diseases especially in the working environments, heavy workload and hectic tasks with certain deadlines are given by an organization to the employees, Which will affect their work-life balance. So, Detecting stress in early stages can prevent many problems and also helps in increasing productivity. Stress detection can be done with various physiological signals including Electrocardiogram (ECG), Electroencephalogram (EEG), Temperature (T), Blood pressure (BP), Electrodermal activity (EDA), Galvanic skin response (GSR), Electromyogram (EMG), Heart Rate Variability (HRV) etc. The datasets used in this paper is combining a data recorded using wearable device and data recorded by manipulating their working conditions with the stressors like email interruptions and time pressure. Literature lacks works that focus on using only unimodel approach. This paper gives an multi-model stress detection using LSTM-XGBoost. This model aims to focus on detecting the stress level of an individual on the early stages. This model uses HRV which recorded from both datasets. The proposed model proves that multi-model approach for stress detection achieves highest accuracy with 99.8% and the f1 score 99.8%. which is approximately close to 1.0.

INDEX TERMS Behavioural data, Binary classification, Binary cross-entropy loss, Blood pressure (BP), Classification, Electrocardiogram (ECG), Electroencephalogram (EEG), Emotion recognition, Empatica E4 (Wrist-Worn Device), Heart Rate Variability (HRV), Label and classification, LSTM (Long Short-Term Memory), mRMR (Minimum Redundancy Maximum Relevance, Multi-model approach, Physiological signals, Real-time Stress detection, RespiBAN (Chest-Worn Device), Sigmoid activation function, Stress Detection, SWELL Knowledge Dataset, Temperature (T), TensorFlow/Keras, Trier Social Stress Test (TSST).

I. INTRODUCTION

Emotion plays a vital role in everyone's day-to-day life. They express their emotion either by behavioral or verbally [2]. Emotions can be identified based on the physiological signals using various factors. Human emotion recognition plays vital role in developing machines with emotion recognition [1]. Human emotion are crucial to recognize because their emotion are not clearly expressive. Researchers from many fields such as psychology, biomedical engineering, robotics, and many more have tried to develop and enhance emotion classification systems with the aim of analyzing and detecting human feelings [3].Among these emotions, [40] mental stress is a crucial problem especially among teenagers. Increasing stress may lead to attempting suicide, depression, heart attack and stroke. These problems can be cured if the stress is detected, when a person is stress , some noticable change will appear in phsiological siganls. Based on the past experiences that we had the brain can able to predict the experience currently by adjusting the neurons, because these experiences can able to communicate with our body through heart beats and respirationss [10]. With the help of sensors devices, we can able to record Physiological signals like EEG, heart rate variability, pulse oximetry, and galvanic skin response (GSR) they provide some insights in changing in emotion by this it gives a better understanding of mental health issues such as stress, depression etc... However developing system for analysising emotions is a quite challengeable by these signals, To overcome this the Deep Physiological Affect Network is developed incorporating convolutional LSTM networks and a temporal margin-based loss function. This model connects low-level physiological sensor data with high-level emotional interpretation. By focusing on the analysis of EEG signals related to brain lateralization and PPG signals, it aims to effectively identify and categorize emotions.Through the specific temporal constraints the model enhances the temporal recognition of emotions by addressing the limitations of the traditional LSTM models [11]. Multi-modal emotion recognition (MER) offers a wide view of emotional states by combining datas from various sources [12]. Changing in emotions has an reflection from physiological signals such as heart rate (HR), Temperature (T), Blood pressure (BP), Electrodermal activity (EDA), those data can be collected from wearable devices with sensors. Fields related to healthcare and healthcare applications enhance their preventive measurements in health care [13]. Measuring stress using physiological signals like HRV is a common approach but achieving high accuracy for measuring stress is a quite challenging[38].A groundbreaking solutions was build for identify, Analyze, and Mitigate stress using WESAD dataset[30].The binary classification of stress events is compared with three different models based on the data extracted from physiological signals [39]. They trying to tackle stress detection based on SWELL and WESAD dataset through AI model using LOP(Local outlier factor) and MLP(supervised Multi-layer perception)[51]. Based on these observations this studies suggest there is a need for further studies in new approach for detecting stress using physiological signals for better detection. The authors have used either the WEASD dataset or the SWELL dataset or both especially using HRV(Heart Rate Variability), but with different model approaches for stress detection. and also those models have achieved believable accuracy with either one or two datasets separately for stress detection. This paper will give a detailed study on stress detection using the both dataset with an multi -model approach using LSTM-XGBOOST Algorithm for binary classification. By this it will gives a clear insights in stress detection.

II. LITERATURE SURVEY

There are multiple approaches have been developed for detecting stress using physiological signals. In this article [21] the authors used XGBoost algorithm for stress detection based on chest-worn sensor data, here they used WESAD dataset which has recorded physiological data from chest-worn sensor from 15 subjects who were in stress and no stress. Their analysis of using XGBoost shows the highest accuracy of 99.71%, f1-score of 99.57% and also AOC(Area under curve) of 99.61% for stress detection.[27] Here the autors used facial emotion recognition for detecting stress because it gives facial cues such aschanges in eye movement, lips tightening, muscle contraction etc...They introduced a novel approach for stress detection using Conv-XGBoost algorithm and also they get a promising accuracy for stress detection for their model. Pregnancy and early childhood [32] are the two stages we express more stress which leads to health risks. Stress is one of the type of emotions we experience in our lives due to mental pressure and restless life. Here they specifically looked on to woman hardships, childhood memories, low-income group, and violence who have experienced and seeking treatment for their heath issues. They used CNNs detecting stress based on heart rate , hand and foot galvanic skin response. Analyzing EEG [33] for stress classification they compared using different machine learning algorithms such as Support vector machine, Decision tree C4.5, Random forest, classification and regression tree, Logistic regression and extreme gradient (XGBoost). Among these comparison for stress classification they achieved 86.4% for XGBoost algorithm. Analyzing stress based on Heart rate variability (HRV) [38] is a common approach but with achieving high accuracy is a quite challenging tasks. An multi-class stress detection based on heart rate variability feature they developed a Convolutional Neural Network based model using Publically available SWELL dataset to detect multiclass stress, by this approach they have achieved accuracy over 99.9% for stress detection. Brain signal has an several open challenges and it is an active research domain for recognizing the emotional state of the human among various peripheral signals[28], In this article the author used EEG signals which was collected from multiple stimulus of brain from the DREAMER dataset. In their proposed model the authors convert those EEG signals into RGB images for to obtain spectrograms by calculating the Short-Time Fourier Transform(STFT) before feeding into 2D CNN model for training the model for feature extraction. After extracting the features from the CNN model , these features were fed into XGBoost(Extreme Gradient Boosting) classifier based on the human emotion they classify the signals into arousal, valence and dominance. They tried the same approach with another machine learning algorithm such as Support Vector Machine(SVM) and XGBoost classifiers to classify different human emotion based on the fused features. Among these, CNN-XGBoost fusion model gives a promising values for accuracy 99.712% of arousal, 99.770% of valence and

99.770% for dominance. [30] Chronic stress is more widespread among the contemporary workplace causing health issues, suicides related to the workplace and fatalities. To overcome this hurdles they designed a groundbreaking solution for identifying, analyzing and mitigating the stress, by which will prevent and provide a healthy work-life balance. They proposed a CNN-based model for stress detection using WESAD dataset by achieving an accuracy of 98.73%. This method is also has an significant importance for trauma recovery and workplace stress management and also it integrates seamlessly with IoT(Internet of things) for the revolution of stress management in this contemporary environment. This approach has an Broad application in the healthcare industry, especially for patients dealing with PTSD and Autism. [38] Stress is one of the natural human emotional reactions they express their emotion due to pressure or any demands.It will increases the risk of mental health and physiological damage. Among these it particularly increases the risk of mental health such as depression anxiety and sleep disorder. Here the author proposed a CNN based model for detecting multi-class stress such as no stress, interruption stress and time pressure stress based on the features of HRV(Heart Rate variability) from the publicaly availble dataset SWELL-KW, based on this approach their model reached 99.9%(precision=1, recall=1, F1-score=1 and MCC = 0.99).[40] Especially among teenagers mental stress is one of the severe problems. In today's life this stress can cause mental and physical problem. These problems can be prevented if the stress was detected earlier. There are some noticeable changes will appear in physiological signals when someone is stressed. To Prevent stress-related health issues the author proposed a LSTM model for stress detection based on the WESAD dataset, they achieved promising accuracy of 98% for their model compared to the other model they used for classification comparison.[51] There are many soft skills plays a vital role in 21 century, among them stress management is considered as an key ones because of its strong relationship in health and well-being. But measuring and mastering this skill is hard without any external support. Here the author proposed a Artificial Intelligence model for detecting stress using LOP (Local Outlier Factor) and MLP (supervised Multi-layer Perception) based on WESAD and SWELL dataset. Based on these approach their model LOF achieved F1-score of 87.92% and 85.51% in WESAD dataset and F1-score of 78.03% AND 82.16% in SWELL-KW dataset, whereas their MLP model achieved F1-score of 78.36% and 81.33% in WESAD dataset and 79.37% and 80.68% in SWELL-KW dataset.

History and Mechanism of LSTM:

Sepp Hochreiter and Jürgen Schmidhuber [55] introduced LSTM (Long Short-Term Memory) networks in 1997. The traditional Recurrent Neural Networks(RNNs) in the sequences of data it has difficulty learning long-term dependencies, to overcome these issues they designed an LSTM(Long-short-term memory) Network. As a solution to the RNNs for learning long-term dependencies, they proposed an LSTM architecture with no forget gate. it was later added to improve performance. After a few years, the LSTM architecture with forget gate was introduced by Felix Gers, Jürgen Schmidhuber, and Fred Cummins in the year 2000, to improve the model performance by resetting the cell states actively by allowing the model. It has better elasticity in handling long-term dependencies with more efficient learning. In various applications such as speech recognition, handwriting recognition, and time-series prediction, the LSTM have gained more popularity around the year of 2000s, and also it is an effective approach for tasks in sequential processing.

Deep learning with TensorFlow and PyTorch frameworks, make it LSTM networks more accessible for researchers. LSTM plays a vital role in specific tasks such as language translation, sentiment analysis, and text generation. Besides some popular models like GRU(Gated Recurrent Unit) and Transformer, LSTM remains premium for sequential tasks because of its robustness and ability to maintain long-term dependencies. LSTM is a type of RNN that is capable of learning long-term dependencies. It was designed to handle sequential prediction problems with long-range of temporal dependencies. LSTM is a special kind of Recurring Neural Network (RNN) [55], [56], [57], [58], [59]. It is specially designed for Long term dependencies, particularly to overcome the issue of vanishing and exploding gradients. The key components of LSTM are cell state, Gates, Hidden state. There are three different types of Gates : Forget gate, Input gate and Output gate.

The repeating module in LSTM has four neural network layer in the place of single neural network layer.

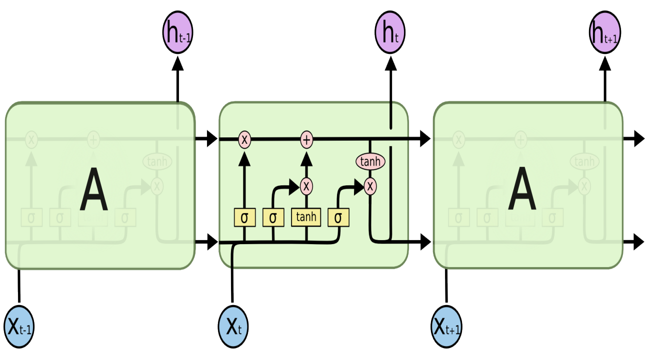


Fig 1. Repeating layers in LSTM [58]

Forget Gate:

The first layer of LSTM Model was Forget Gate layer which is a sigmoid layer. It is used to decide which information should be discarded from the cell state.

$$f_t = \sigma\,(W_f \,.\, [h_{\,t-1}\,, x_t] + b_f)$$

Input Gate:

Input Gate layer will decide which values will be added or updated to the cell state. It has two components input gate and candidate values.

$$i_t = \sigma\,(W_i \,.\, [h_{\,t-1}\,, x_t] + b_i)$$

$$= \qquad tanh(\,W_c \,.\, [h_{\,t-1}\,, x_t] + b_c)$$

The below equation combines the old cell state and new cell state. The combination of these results will be updated to the next time step.

$$C_t = f_t \,.\, C_{\,t-1} + i_t \,.$$

Output gate:

This gate controls the output of LSTM cell.

$$o_t = \sigma\,(W_o \,.\, [h_{\,t-1}\,, x_t] + b_o)$$

The below equation is the formula for Hidden state. It is used as the final output and also as input for the next LSTM cell.

$$h_t = o_t \,.\, tanh(C_t)$$

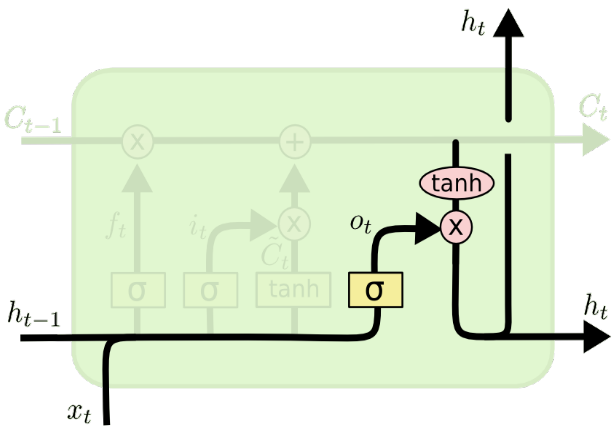


Fig 2. Hidden State Representation [58]

Dropout Layer:

Dropout Layer is a technique used to prevent overfitting, where (1-p) is a probability of 1 and 0 with keeping the input unit and dropping the input unit respectively.

$$Dropout(input) = input \times Bernoulli(1-p)$$

Dense Layer:

It is used at the end of LSTM model, used to map the LSTM output with the desired output.

$$Output = \sigma\,(W\,.\,h + b)$$

A dramatic variation on the LSTM is the Gated Recurrent Unit (GRU) [74]. It combines the forget and input gate into update gate.

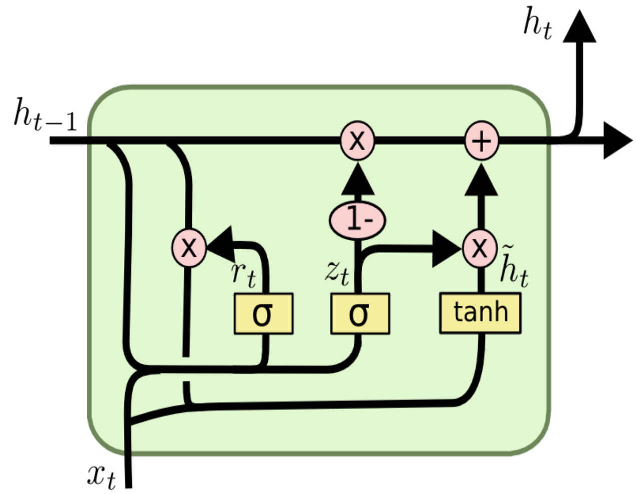


Fig 3. Dramatic variation of LSTM - GRU [58]

Table 1. Mathematical symbols used in LSTM Mechanism

Symbols	Definition
f_t	Forget gate
σ	Sigmoid Activation Function
W_f	Weight Matrix
$h_{\,t-1}$	Previous Hidden state
x_t	Current Input
b_f	Bias term
$C_{\,t-1}$	Previous call state
i_t	Input gate
	Candidate cell state
W_i, W_c	Weight matrices
$b_i\,,\,b_c$	Bias term
$tanh$	Hyperbolic Tangent function
C_t	Cell state update
o_t	Output gate

b_o	Bias term
h_t	Hidden State
W	Weight matrix of Dense Layer
h	Input to the dense layer
b	Bias term

XGBoost Mechanism:

XGBoost [60], [61], [62] stands for Extreme Gradient Boosting, which is an advanced implementation of Gradient Boosting to improve the performance and efficiency of the model. It is able to handle large datasets which has complex features.

Objective Function:

It has two parts called Loss Function and Regularization term. Loss function (l) compares the prediction with actual outcome and Regularization term (Ω) prevent the complexity and overfitting of the training data.

$$Objective = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

Regularization Term (*Ω*):

$$\Omega(f_k) = \gamma\, T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$$

Prediction Function:

The final prediction is based on the combination of all the trees.

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)$$

Table 2. Mathematical symbols used in XGBoost Mechanism

Symbols	Definition
$l(y_i, \hat{y}_i)$	Loss function
y_i,	Actual value
$\hat{y}_i$	Predicted value
f_k	Function represents k-th tree.
Ω	Regularization term
K	Number of trees
T	Number of leaves in the tree
x_i	Feature vector
w_j	Score on leaf j
λ , γ	Regularization parameters controlling model complexity

III. METHODOLOGY

DATASET DESCRIPTION

Datasets Used :

- **SWELL (KW) Dataset**
- **WESAD Dataset**

SWELL (KW) Dataset: SWELL knowledge dataset [18] is mainly designed to track stress in working places. It contains data of how work related stress plays a major role in psychological and physiological responses. This Data mainly focuses on skilled workers or individuals with same profile , a group is subjected to stress for various deadline based task, high cognitive tasks.

Order		Block1	Q		Block2	Q		Block3	Q
A	Relax	Neutral		Relax	Stressor interruptions		Relax	Stressor time pressure	
B		Neutral			Stressor time pressure			Stressor interruptions	

Fig 4. Visual representation of Orders A, B used for participants [18]

Order A is used for 13 Participants and Order B is used for 12 Participants

Data Types collected:

The SWELL dataset includes

1. Physiological signals
2. Behavioral data
3. Self-reported data.

Physiological data include Heart Rate Variability (HRV) an indicator of stress which gives changes in heart rate influenced by sympathetic and parasympathetic nervous system , Skin conductance and Respiration rate. Behavioral Data includes Task Performance based on completion time and error rates, Computer Interaction Data based on mouse movements, clicks, and keystrokes. Self-Reported Data includes Questionnaires and Surveys based on workload and overall experience.

Apparatus used:

The author used a computer (Dell Latitude E6400) with Windows 7 Professional with a 17-inch screen with mouse and keyboard, for collecting data from each participant who performed their tasks.

Fig 5. Experimental setup for SWELL (KW) Dataset [18]

Data collection:

The dataset contains stressors include email interruptions and time pressure. Condition Label in this project indicate stress as (1) and no stress as (0).
Email Interruptions : Participants are allowed to work on a main task while managing Email notification at the same time.
Time pressure : Participants had to complete tasks within a deadline which add pressure and stress due to limited time.

Label and classification:

- **No-Stress (Label 0):** Data include Baseline or control conditions where no explicit stressors introduced
- **Stress (Label 1):** Data include stressors like email interruptions or time pressure were introduced.

Overall this dataset is widely focused on improving well-being among workplace by identifying stress and their impact on overall performance.

WESAD Dataset : WESAD (Wearable Stress and Affect Detection) [19] is a multimodal Physiological dataset for stress detection using wearable device. It contains physiological data such as Electrodermal Activity (EDA), electrocardiogram (ECG) and respiration. This dataset was focused on Real-time Stress detection system for improving overall mental health observations. This dataset is specially designed for researchers to focus on multi-model analysis , stress detection.

Data Collection Process:

Participants : This data is collected from 15 participants which include 12 males and 3 females, where their age ranges between 24 and 35.

Experimental Protocol:

Participants were asked to wear two types of sensors: **RespiBAN** professional chest-worn device and a wrist-worn **Empatica E4** device. The data collection was divided into different phases, each designed to elicit specific emotional states: baseline (0), amusement (1), and stress (2).
Baseline (Neutral): Participants sat in a relaxed state without any external stimuli, serving as the control condition.
Amusement (Positive Emotion): Participants watched a series of funny video clips designed to induce amusement.
Stress (Negative Emotion): Participants were subjected to a modified version of the Trier Social Stress Test (TSST), a procedure used to induce stress. This involved tasks like public speaking and mental arithmetic under time pressure and observation.

Sensors and Data Types:

RespiBAN (Chest-Worn Device)

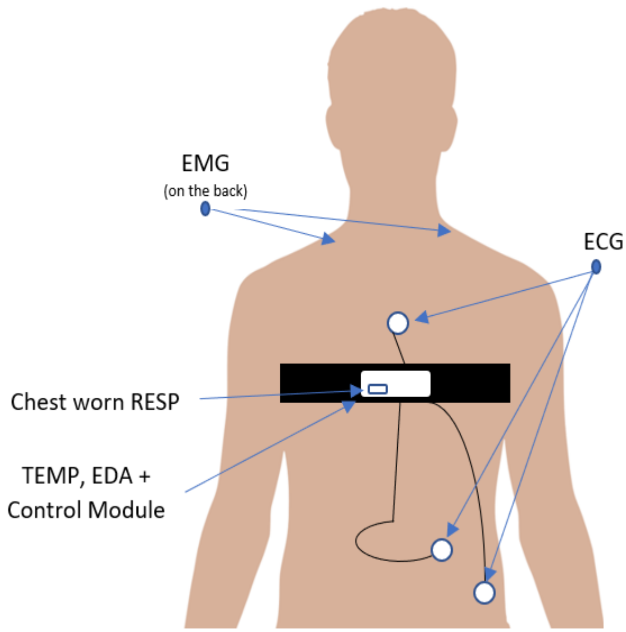


Fig 6. Visual representation of RespiBAN device worn on the chest [72].

Electrocardiogram (ECG): Measures the electrical activity of the heart, useful for analyzing heart rate and heart rate variability (HRV), both of which are influenced by stress.
Respiration: Captures breathing patterns, which can change significantly under stress.
Electrodermal Activity (EDA): Measures skin conductance, which increases with sweating, a common response to stress.
Accelerometer: Records body movements, which can provide context for interpreting physiological data.

Empatica E4 (Wrist-Worn Device):
Photoplethysmogram (PPG): Measures blood volume changes, providing heart rate data.
EDA: Measures skin conductance at the wrist.
Skin Temperature: Monitors changes in skin temperature, which can be associated with stress responses.
Accelerometer: Tracks wrist movements.

Labeling and classification :
Emotional label:
Based on the emotional states the data are labeled which was induced during the experiments.

- **0 (Baseline):** During the neutral phase these data were collected and labeled as 0.
- **1 (Amusement):** During the amusement phase these data were collected and labeled as 1.
- **2 (Stress):** During the stress-inducing TSST phase these data were collected and labeled as 2.

Data Organization:
The dataset is organized by participant, with each participant's data stored in separate files. Each file contains time-series data corresponding to the different sensor modalities.
Data from the chest and wrist devices are provided separately, allowing researchers to focus on either modality or combine them for multi-modal analysis.

Data Preprocessing:
In the SWELL dataset, some irrelevant columns were removed from the data frame using drop because those columns are not necessary for stress detection. As a Binary stress indicator, those conditional labels were mapped.
In the WESAD dataset, an unique identifier subjects were mapped and for the consistency of the data the condition label were renamed. Then the data were filtered to consider only stress (2) vs. no stress (0, 1), and lastly the same binary mapping was applied.
With the help of shuffling , avoid unbiased data mixing after preprocessing these two datasets were merged using concatenation.

Final Dataset:
Finally, the combined dataset consists of corresponding stress labels with physiological features from both datasets. Then the subject IDs were stored, during training and testing the model these Subject IDs were used to ensure the subject-wise splitting for the further processing.
Both datasets were merged after preprocessing, with shuffling to ensure unbiased data mixing.

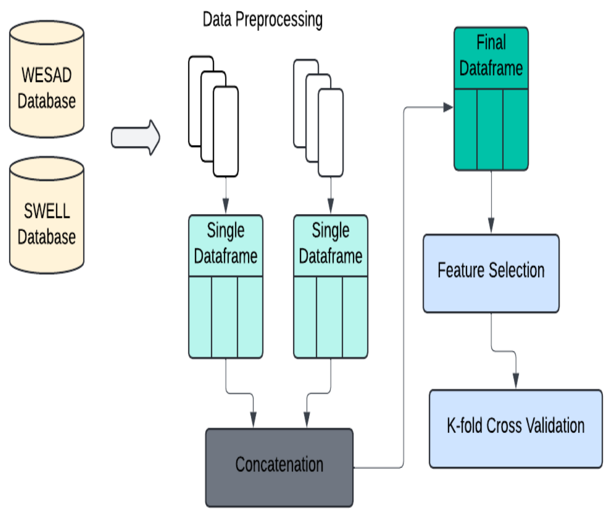
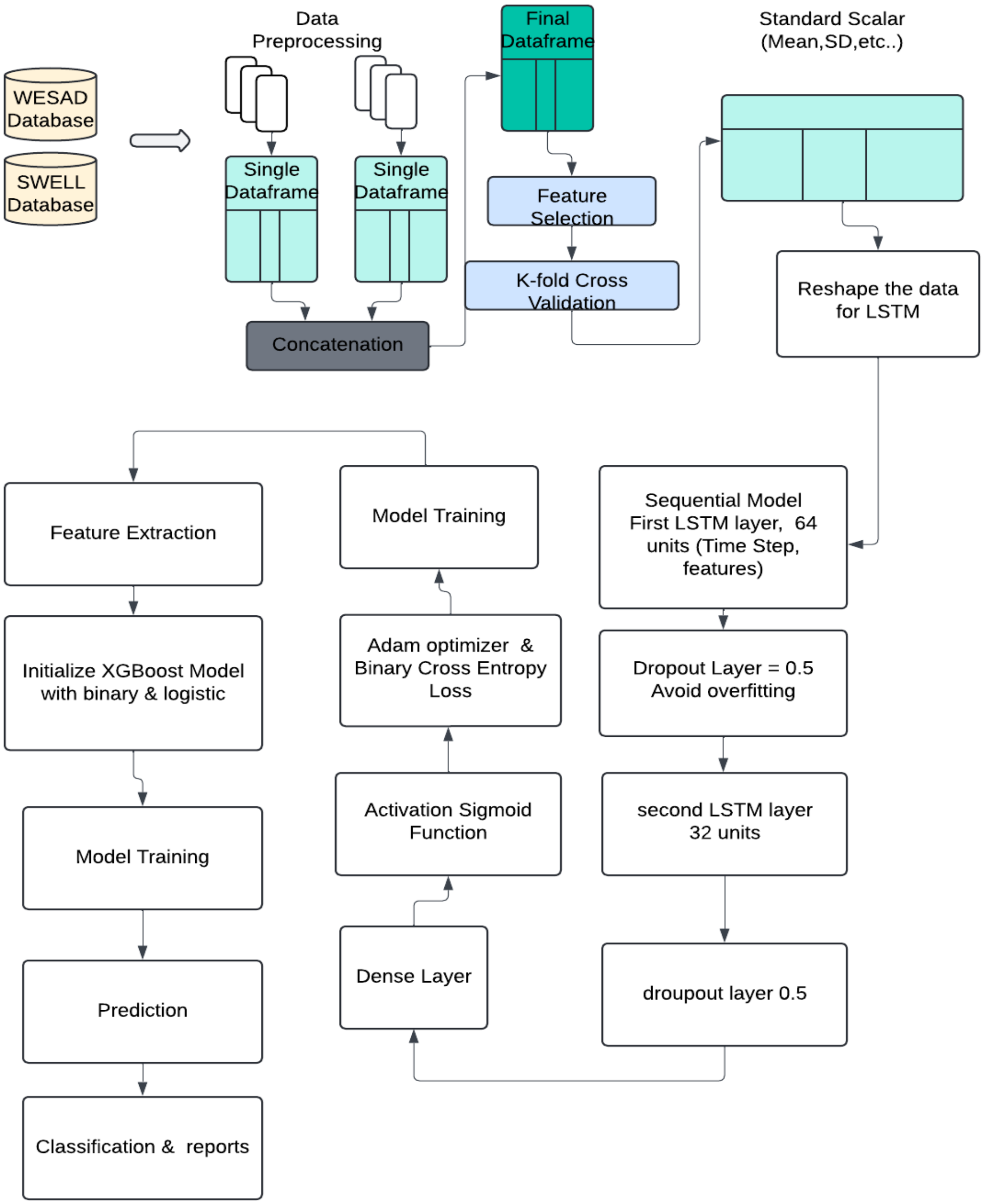


Fig 7. Overview of Data Preprocessing

Here is the overview of our model for data preprocessing from the diagram, we have used SWELL and WESAD dataset, these datasets were separately preprocessed using Pandas library. Each dataset contains subfolder inside these folders data were present in .csv file, so we used pandas to read and load multiple files into single dataframes. These two datasets were preprocessed and stored in separate combined file. These two separate combined files were combined into single file using concatenation for training the model.

Data Splitting:
The dataset was split into training and testing sets based on subject IDs to ensure that data from the same subject was not used in both training and testing. This step is crucial for preventing data leakage and ensuring the model's ability to generalize to new subjects.

Fig 8. Architecture diagram for Proposed Model



Proposed Model:
In this study we approached LSTM hybrid model for stress classification, here the mRMR (Minimum Redundancy Maximum Relevance) module was used to choose features that are highly relevant to the stress labels while minimizing redundancy among them,LSTM for feature extraction and XGBoost classifier for classification. Before feed into the LSTM model for classification , Standard scalar is used to standardize the features in the training and testing sets. After standard scalar, data reshaping is done to standardized data feature for LSTM format. Then using tesnorflow keras API we build a sequential model in this model we added a LSTM

layer in 64 units , Dropout layer with 50% for to avoid over-fitting, 1 unit of dense layer and also a sigmoid activation function, and Binary cross entropy for binary classifications. And we used Adam optimizer for compiling the model. After feature extraction it is feed into XGBoost model for classification, tesnorflow keras API we build a sequential model in this model we added a LSTM layer in 64 units , Dropout layer with 50% for to avoid over-fitting, 1 unit of dense layer and also a sigmoid activation function, and Binary cross entropy for binary classifications. And we used Adam optimizer for compiling the model. After feature extraction it is feed into XGBoost model for classification.
By using this method we achieved f1 score of 0.998 for model classification and accuracy of 0.997 for model training and validation.

IV. EXPERIMENTS AND RESULTS

Confusion Matrix:
Here's the confusion matrix of our model it shows the performance of our model prediction and actual classification for stress and no stress.

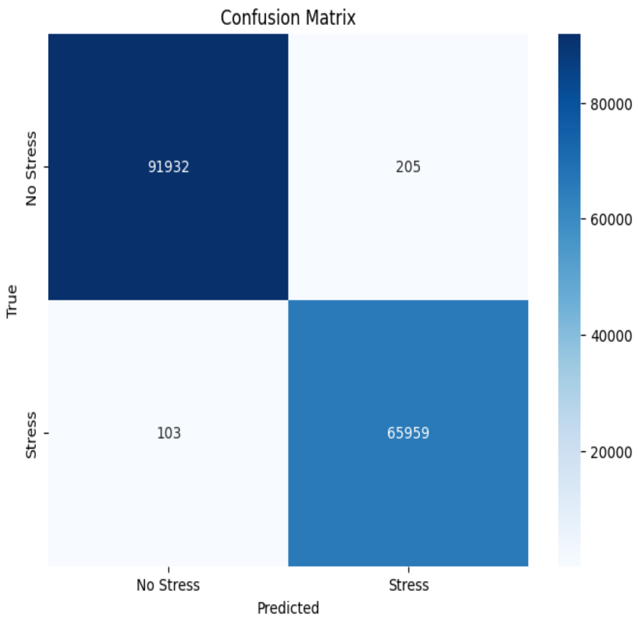


Fig 9. Confusion matrix

True Positive (TP) = 91932
False Positive (FP) = 103
True Negative(TN) = 65959
False Negative (FN) = 205

True positive (TP):
The model correctly identifies no stress from the dataset.

False Positive (FP):
The model incorrectly identifies no strees from the dataset.

True Negative (TN):
The model correctly identifies stress from the dataset.

False Negative (FN):
The model incorrectly identifies stress from the dataset.

Accuracy:

$$Accuracy = \frac{TP + TN}{TP+TN+FP+FN}$$

$$= \frac{91932 + 65959}{91932+65959+103+205}$$

= 0.99805 Which is close to 1.0.

Based on these prediction from the confusion matrix, we will able to get F1-Score for classification.

F1-Score: With XGBoost classifier we got perfect balanced metrices for precision and recall for stress detection. Based on the confusion matrix components we will able to calculate F1-Score for classification.

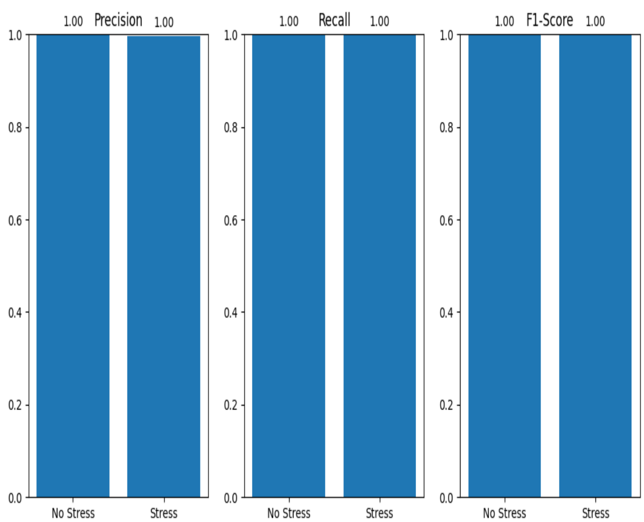


Fig 10. F1-Score Bar chart

This Bar chart shows visual comparison of performance metrices for both stress and no stress. These bars are corresponding to F1-score value.

Table 4. Comparision of epoches, Accuracy, Loss

Type of Classification	Batch size	Epoches	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
Binary Classification	34	1	accuracy: 0.8070	loss: 0.3904	val_accuracy: 0.9670	val_loss: 0.0957
		2	accuracy: 0.9360	loss: 0.1617	val_accuracy: 0.9836	val_loss: 0.0521
		3	accuracy: 0.9548	loss: 0.1168	val_accuracy: 0.9917	val_loss: 0.0308
		4	accuracy: 0.9644	loss: 0.0936	val_accuracy: 0.9937	val_loss: 0.0220
		5	accuracy: 0.9696	loss: 0.0819	val_accuracy: 0.9945	val_loss: 0.0189
		6	accuracy: 0.9731	loss: 0.0727	val_accuracy: 0.9952	val_loss: 0.0148
		7	accuracy: 0.9761	loss: 0.0643	val_accuracy: 0.9963	val_loss: 0.0123
		8	accuracy: 0.9774	loss: 0.0611	val_accuracy: 0.9974	val_loss: 0.0098
		9	accuracy: 0.9787	loss: 0.0574	val_accuracy: 0.9976	val_loss: 0.0089
		10	accuracy: 0.9809	loss: 0.0526	val_accuracy: 0.9981	val_loss: 0.0071

Precision: Precision is also known as Positive Predictive Value. It is the ratio of correctly predicted positive value to the total predicted positive value. It is effective only the cost of false positive value is high.

$$Precision = \frac{TP}{TP+FP}$$

$$= \frac{91932}{91932+103} = 0.99888 \approx 1.0$$

Recall : Recall is also known as True Positive Rate.

$$Recall \; = \frac{TP}{TP+FN}$$

$$= \frac{91932}{91932+205} = 0.997775 \approx 1.0$$

F1-Score :

$$F1\ score = 2 \times \frac{0.99888 \times 0.997775}{0.99888+0.99775}$$

$$= \; 0.99833 \; \approx 1.0$$

Training and Validation Score :
Here is the visualization graph plots for both training and validation for accuracy and loss which shows the learning of our model. These plotting values are generated during training the model over the epochs. In the below diagram it shows the validation for accuracy is increased compared to the training accuracy and for the validation loss is decreased compared to training loss. so it means our model is learning very well over the times.

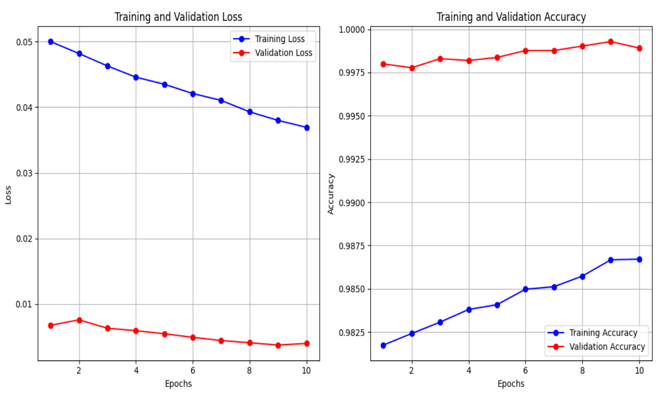


Fig 11. Training and validation score

Receiver operating characteristic:
The Receiver operating characteristics (ROC) is a graphical representation for evaluating the performance of binary classification in a varies thresholds. It shows the difference between the True Positive Rate and False Positive Rate for the threshold values. here it shows the ROC curve along with AUC (Area under curve), AUC shows the difference between positive and negative class, if the AUC is pointing to 1 that means the model performance is good, here our model ROC diagram, the AUC is 1.00 that means it clearly shows that our is model performance is good at differentiating positive and negative classes.

True Positive Rate :

$$= \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$= \frac{91932}{91932+205} = 0.997775$$

False Positive Rate :

$$= \frac{False\ Positive}{False\ \ Positive + True\ Negative}$$

$$= \frac{103}{103+65959} = 0.00156$$

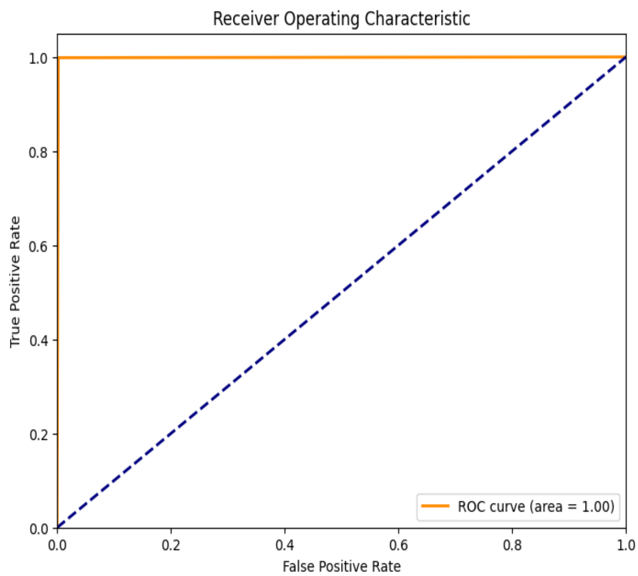


Fig 12. ROC Curve

We got 1.00 for our model which means it is a perfect model stress detection.

Table 3. Comparision table for Datasets, Model, Accuracy from the reference

Reference	Datasets	Model	Accuracy
[21]	WESAD	Random forest (both binary and three-class classification)	Accuracy - 83.34 and F1-scores - 65.73
[28]	Dreamers	CNN - XGBoost	Accuracy - 9.712%, Arousal - 99.712%, Valence - 99.770% and Dominance - 99.770% in human emotion detection.
[30]	WESAD	CNN	Accuracy - 98.73%
[38]	SWELL	CNN	Accuracy - 99.9%, Precision - 1, Recall - 1, F1 Score - 1 and MCC - 0.99
[40]	WESAD	LSTM	Accuracy - 98%
[50]	National Cross-sectional DEGS1 Data	XGBoost	Receiver operating characteristic curve (ROC) of 81%, precision of 63%, recall of 52%, specificity of 78%, and F1-score of 54%
[51]	WESAD, SWELL	LOF(Local outlier factor), supervised Muti layer perceptron(MLP)	MLP obtained F1-scores of 78.36% and 81.33% in WESAD, and 79.37% and 80.68% in SWELL-KW. LOF achieved F1-scores of 87.92% and 85.51% in WESAD, and 78.03% and 82.16% in SWELL-KW
[65]	WESAD	LSTM	Three-way validation with 98%
[66]	SRAD	Multimodel CNNs	30-s signals 95.67%, 10-s signals 92.33%
[67]	Drivedb	RF classifier	Accuracy of 98.2%, sensitivity 97%, and specificity 100%
[68]	WESAD	Stacking Classifier, ANN, SVM, RBF	Stacking Classifier - accuracy of 99.92% Artificial Neural Network (ANN) - accuracy of 90.58% Artificial Neural Network-SVM-accuracy of 91.48% Radial Basis Function (RBF) - accuracy of 84.46%
[69]	WESAD	Random forest	Accuracy - 88.99%
[70]	WESAD	LSTM	accuracy (98.00%), precision (97.01%), recall (97.00%) and F1-score (97.03%)
[71]	WESAD	LR, SVM, NB	Accuracy for Accelerometer (ACC), EEG and ACC+EEG 1) LR - 68.98 % for ACC, 71.59% for EEG, 76.85% for ACC+EEG 2) SVM - 60.46% for ACC, 72.09 for EEG, 80.09 for ACC+EEG 3) NB - 62.79% for ACC, 69.76 for EEG, 75.93% for ACC+EEG

Environmental set-up:
Hardware: These experiments were conducted on a computing environment connected with a GPU because it is capable for handling the Multi-model approach.
Software: We used python programming language for implementation along with several libraries
TensorFlow/Keras: Used for building and training the LSTM model.
XGBoost Classifier: Used for training the gradient boosting model for classification
Scikit-learn: For evaluation metrics, and model validation.
Pandas: Used for data manipulation and preprocessing.
Module: Modules like mRMR (Minimum Redundancy Maximum Relevance) for feature selection and Matplotlib/Seaborn for visualization were used.

V. DISCUSSION:

In this article[51] they compared two datasets such as WESAD, SWELL for stress detection but with supervised and unsupervised learning algorithm such as LOF(Local Outlier factor) and MLP(supervised Multi layer perception) by using these models they achieved F1-scores of 78.36% and 81.33% in WESAD for MLP, and 79.37% and 80.68% in SWELL-KW., whereas LOF achieved F1-scores of 87.92% and 85.51% in WESAD, and 78.03% and 82.16% in SWELL-KW. Here for our proposed model we used LSTM-XGBOOST algorithm for stress detection using
(Heart rate variability) from WEASD and SWELL datasets, Here LSTM is used for feature extraction whereas XGBOOST is used for classification. For this approach we combined both dataset into single dataframe for training the model, After training the model with LSTM we get features , these extracted features are fed into XGBOOST model for classification. By using this we achieved model accuracy of 0.99805% , F1- score of 0.99833% , Precision of 0.99888% and Recall of 0.997775% which are closely to 1.00 which means it represents a perfect model for stress etection.

Limitations:
In this study, few data is used for stress detection using binary classification. In future, we will try to implement this approach with various datasets using multi-class to give new insights for detecting stress in real world.

VI. CONCLUSION

In this study we proposed an Multimodel approach using LSTM and XGBooST for stress detection using HRV data from two datasets by this approach we got promising accuracy and F1-score for binary classification. And also we got ROC along AUC which points to 1.00, it means our model is perfect for stress detection using binary classification with accuracy of 0.99805%, F1-score of 0.99833%, Precision of 0.99888% and Recall of 0.997775%. By detecting stress it will decrease the chances of health risk in future. In future , we will implement this approach with multi- class classification using new dataset.

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Any errors or omissions remain our own responsibility.

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