Neural Pulse: Advanced Stress Detection via Deep Learning and ECG Signals

Soham Sangwan
Department of Data Science
Manipal University Jaipur
Jaipur, India
sohamsang@gmail.com

Ashmit Sharma
School of Computing & Intelligent Systems
Manipal University Jaipur
Jaipur, India
sharmaashmit2327@gmail.com

Naina Sharma
School of Computer & Science Engineering
Manipal University Jaipur
Jaipur, India
nainashrm77@gmail.com

Shubham Dahatonde
School Of Computing & Intelligent Systems
Manipal University Jaipur
Jaipur, India
shubham2262v@gmail.com

***Abstract*—This paper presents a deep learning-based method for stress detection using ECG features from the WESAD dataset. The proposed model shows significant advancements in accuracy and F1 score compared to existing state-of-the-art techniques, indicating its potential for practical applications in stress detection. The model achieved an average accuracy of 0.920, precision of 0.804, recall of 0.845, and an F1 score of 0.818. Additional testing on new data validated the model's robustness, resulting in an accuracy of 0.957, precision of 0.851, recall of 1.00, and an F1 score of 0.920. These outcomes suggest that our deep learning approach is highly effective and promising for emotion recognition using ECG signals, surpassing traditional methods such as Linear Discriminant Analysis.**

***Index Terms*—ECG, Stress Detection, Deep Learning, Neural Network, Feature Extraction, Cross-Validation**

I. Introduction

A. Background

Stress is a common problem that has an impact on both physical and mental health. Early stress detection can result in better health outcomes and early interventions. Because physiological signals, such electrocardiograms (ECGs), can represent the autonomic nervous system's reaction to stress, they have been investigated as potential stress indicators. Developments in deep learning techniques in recent times present intriguing avenues for building reliable and precise models for stress detection from ECG signals.

B. Objective

This study's main goal is to create and assess a deep learning model that can use an individual's ECG data to predict their emotional state (stress or no stress). The WESAD dataset, which was created especially for stress detection using physiological measurements, is used to train and assess the model. The research attempts to:

> Utilizing cutting-edge techniques, extract pertinent information from the ECG data. Create a classification model based on deep learning to forecast a person's emotional state. Utilize cross-validation to assess the model's performance and contrast it with the most recent techniques documented in the literature.

C. Significance of the Study

The proposed deep learning-based strategy may offer a low-cost, non-invasive way to identify stress that may be included into wearable technology for continuous monitoring. By showing notable gains in accuracy and F1 score over the most advanced techniques, the study adds to the body of literature and emphasizes the technology's potential for real-world stress detection applications.

II. literature Survery

Philip Schmidt et al [1]goals to pick out someone's emotional kingdom to decorate human-computer interaction. however, the dearth of general datasets for wearable strain detection with multimodal, 86f68e4d402306ad3cd330d005134dac facts and more than one affective states has been a undertaking. To address this hole, the WESAD dataset was brought, proposing physiological and motion records from wrist- and chest-worn devices of 15 subjects at some point of a lab study. The dataset consists of diverse sensor modalities: blood quantity pulse, electrocardiogram, electrodermal interest, electromyogram, respiration, body temperature, and three-axis acceleration. It also encompasses 3 affective states (neutral, pressure, entertainment) and self-reports acquired from hooked up questionnaires. using standard features and device learning strategies for benchmarking, the dataset executed up to

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eighty% accuracy for a 3-magnificence classification (baseline vs. stress vs. entertainment) and as much as 93% for a binary strain vs. non-stress classification. consequences propose the chest-primarily based device offers the pleasant type, but the wrist-primarily based device suggests promising effects with minimum intrusion. The dataset is publicly to be had and encourages similarly research for set of rules improvement and benchmarking

T. Lin and W. Zi introduces a novel feed-through intelligent sensor device (FTISD) designed for pressure detection and tension manage in pre-harassed concrete systems, consisting of long-span bridges and homes. This era at once applies anxiety control to the pre-stressed reinforcement, enabling actual-time tracking of strain variations at some point of the shape's lifecycle. Engineering software effects exhibit the device's accuracy and performance in pressure detection and tension manipulate, making sure the pleasant and sturdiness of pre-careworn concrete structures. The approach enhances creation great, will increase protection, and offers big social and financial advantages for pre-burdened concrete packages[2].

. N. Kim, W. seo, S. Kim and S. -M. Park explores the feasibility of the usage of electrogastrogram (EGG) along-side electrocardiogram (ECG) and respiratory sign (RESP) for multi-modal intellectual strain assessment. Twenty-one members underwent relaxation and strain levels based on re-sponsibilities. extensive correlations had been observed among EGG capabilities and mental stress tiers, corresponding to RESP functions. Incorporating EGG stepped forward device getting to know model accuracy by using up to eight%, with logistic regression attaining 70.15% accuracy. The examine shows EGG tracking could decorate real-time and personalized mental stress assessment.[3]

M. P, S. S. J, J. P.k, R. R. Chandran, S. Krishnan and S. bright addresses the increasing incidence of stress-associated illnesses by presenting a machine mastering-based totally method to hit upon stress using Electrocardiogram (ECG) signals. The proposed algorithm classifies ECG signals as stressed or everyday by mechanically detecting heart fee variability from R peaks through the Discrete Wavelet transform (DWT) technique. The machine's reliability can be better by means of incorporating additional sensors like Galvanic pores and skin reaction, Electromyogram, and respiratory rate. numerous gadget gaining knowledge of classifiers were tested, with Logistic Regression and Naïve Bayes accomplishing the very best accuracy of ninety%. This approach offers a promising technique for early prognosis of strain-related illnesses, doubtlessly contributing to life-style improvement.[4]

M. A. B. S. Akhonda[5], S. M. F. Islam, A. S. Khan, F. Ahmed and M. M. Rahman focuses on detecting the stress levels of computer customers in an office-like environment to permit the improvement of smart, affective computing systems[6]. Physiological statistics from 12 topics had been accrued for the duration of diverse laptop-mediated duties in the course of the day. A three-layer lower back propagation neural[7] community became hired to correctly determine stress degrees. The take a look at found out that pressure tiers fluctuated with pc usage time and the issue's effort. intense eye work and intellectual pressure have been identified as the number one individuals to induced strain. despite the fact that other factors like intellectual condition and absence of sleep can also influence strain[8], similarly studies is needed to account for individual physiological differences and context awareness. The proposed[9] machine goals to offer real-time pressure monitoring for computer users, improving computer-person interplay by thinking about the user's affective country.[10]

III. Methodology

A. Data Pre-processing

1) Dataset Extraction and Organization: The WESAD dataset, a benchmark dataset for wearable stress and affect detection, is extracted and organized into individual folders corresponding to each subject (S2, S3, ..., Sk). The raw ECG data for each subject is contained in .pkl files. This organization ensures easy access and systematic management of the extensive data, streamlining the preprocessing and subsequent analysis. article

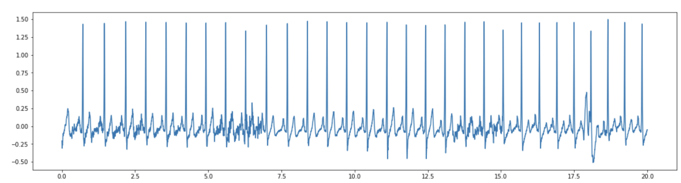

Fig. 1. Dataset Organization

2) ECG Signal Pre-processing: The raw ECG signals are pre-processed using the . notebooks facilitate the initial cleaning and transformation of the ECG signals, ensuring they are in a suitable format for further analysis.

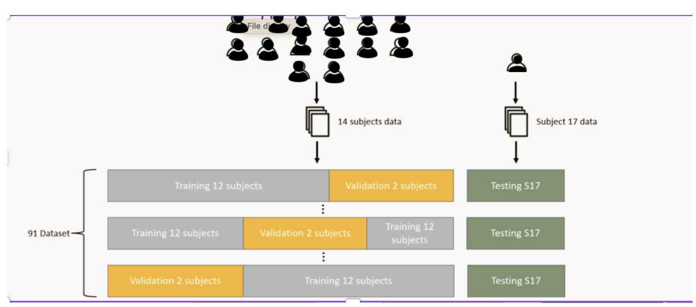

Fig. 2. ECG Signal Pre-processing Workflow

B. Feature Extraction

1) ECG Peak Detection: HeartPy, a comprehensive Python tool for heart rate analysis, is employed for ECG peak detection. HeartPy offers a robust method for handling variations in peak amplitude, ensuring accurate and consistent detection across all subjects and recordings.

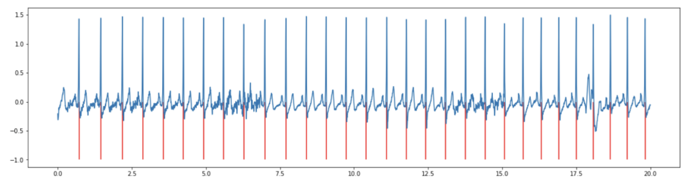

Fig. 3. ECG Signal Pre-processing Workflow

2) *Heart Rate and HRV Calculation:* After peak detection, various statistical features are computed from the detected peaks:

- **Mean Heart Rate (Beat/s)**: The average number of heartbeats per second.
- **STD Heart Rate (Beat/s)**: The standard deviation of the heart rate.
- **TINN (s)**: The triangular interpolation of the Normal-to-Normal intervals.
- **HRVindex**: A comprehensive HRV index.
- **#NN50**: Number of pairs of successive NN intervals that differ by more than 50 milliseconds.
- **pNN50**: Proportion of NN50 divided by total number of NNs.
- **Mean HRV (s)**: Mean of HRV values.
- **STD HRV (s)**: Standard deviation of HRV values.
- **RMS HRV (s)**: Root Mean Square of HRV values.

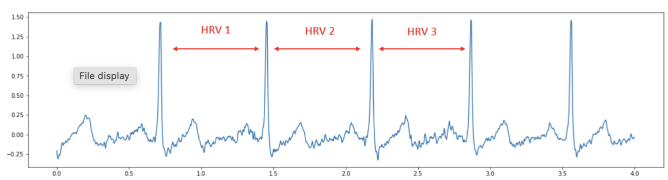

Fig. 4. HRV Calculation

3) *Triangular Interpolation on HRV:* A Gaussian distribution is fitted to the HRV data to perform a triangular interpolation. This process is crucial for revealing features relative to stress detection, such as TINN and HRVindex. It helps in smoothing out the data and highlighting the subtle variations in the HRV.

$$Y = \max(\text{distribution})$$

$$HRV_{\text{index}} = \frac{\text{total number of peak intervals}}{Y}$$

The TINN score is computed from the calculation of M and N which are such as a multi-linear function of time $q(t)$ is defined as $q(t) = 0$ for $t < N$ and $t > M$ and $q(\arg\max(\text{distribution})) = Y$ such as:

$$\int_0^{\infty} (D(t) - q(t))^2 \, dt$$

is minimum. Then

$$TINN = M - N$$

4) *Fourier Transform and Power Spectral Density (PSD):* Fast Fourier Transform (FFT) is utilized to extract the Power Spectral Density (PSD) from the HRV data. This provides insights into the frequency domain characteristics of the HRV, offering a more detailed and comprehensive view of the signal's properties.

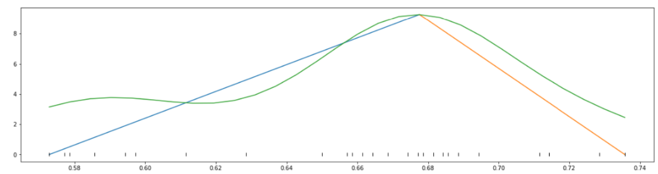

Fig. 5. Fourier Transform and PSD Calculation

C. Dataset Creation and Labeling

rohit.sharmarockstar0123@gmail.comFrom every recording, sampling of the 20sec with an one's step are taken out and paired with a label to show the emotional state: 1

- **1 denotes neutrality**
- **2 = stress**
- **3 = amusement**
- **4 = meditation**

A 90s baseline in a neutral state is selected as a reference. For every 20s sample, the features are normalized by the baseline features to facilitate comparison, ensuring a consistent and standardized analysis across all recordings.

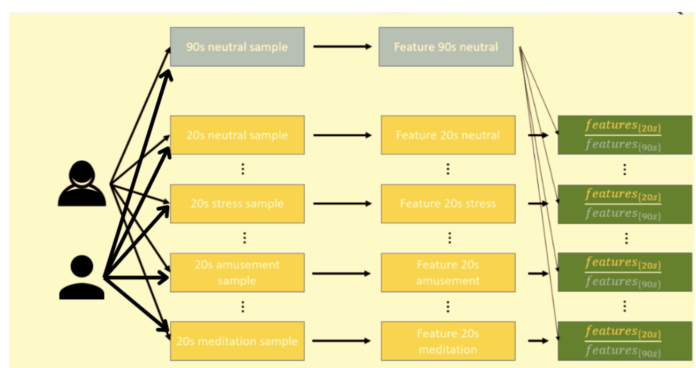

Fig. 6. Dataset Creation and Labeling

D. Model Architecture and Training

1) *Neural Network Architecture:* The deep learning model adopted for this study is a Fully Connected Neural Network. The architecture comprises:

- **Input size**: 12
- **FC Layers**: 128 $\rightarrow$ 64 $\rightarrow$ 16 $\rightarrow$ 4 $\rightarrow$ 1
- **Output size**: 1
- **Activation Function**: Sigmoid

To improve the model's robustness and performance, each FC layer is supplemented with a Batch Normalization layer, a Dropout (p=0.5) layer, and a LeakyReLU (a=0.2) layer.

2) Training Parameters: For each fold (out of the 91-fold cross-validation), the model is trained with the following parameters:

- **Loss Function**: Binary Cross Entropy
- **Epochs**: 15
- **Batch Size**: 32
- **LR**: 0.0001
- **Optimizer**: Adam (lr, b1=0.9, b2=0.999)

The best model, determined based on the validation set's loss value, is saved for each fold to compute the outcomes of cross-validation.

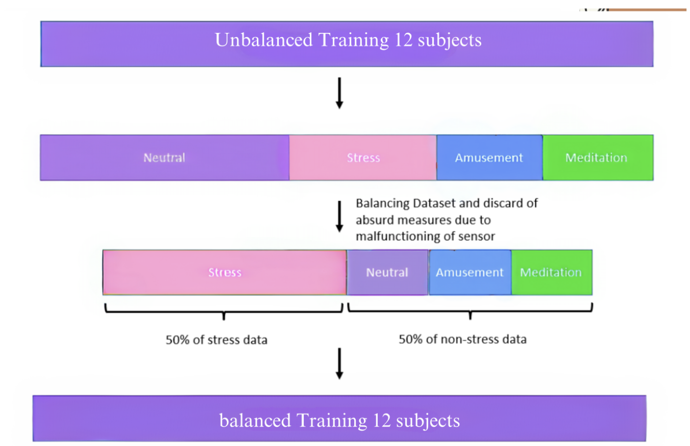

Fig. 7. Training Parameters

IV. Results and Discussion

A. Cross-Validation Results

1) Evaluation Metrics: 0.5 was chosen as the threshold value to be used in predicting the output's emotional state. There were two kinds of confusion matrices used:

- A 2×2 confusion matrix when the prediction is Stress/No stress and the ground truth is Stress/No stress.
- A 2×4 confusion matrix where the prediction is Stress/No Stress and the ground reality is Emotional state (Neutral, Stress, Amusement, Relax).

2) Average Model Performance: The average metrics of the model are as follows:

Metrix	Mean ± Stdevi
ACC	0.920 ± 0.06
Pre	0.804 ± 0.132
Recall	0.845 ± 0.183
F1 score	0.818 ± 0.148

B. Comparison with Previous Work

The best result using simply ECG data from the chest using Linear Discriminant Analysis, as reported in the WESAD publication [1], provides:

Metrix	Mean val
ACC	0.8544
F1-score	0.8131

An ACC gain of 6.56% and an F1-score increase of 0.49% were attained by the suggested deep-learning model.

C. Testing Results

The model was evaluated on fresh data (subject 17 data) and retrained using the entire cross-validation dataset (training + validation). The following are the test results:

Metrix	Val
ACC	0.957
pre	0.851
Recall	1.00
F1 score	0.920

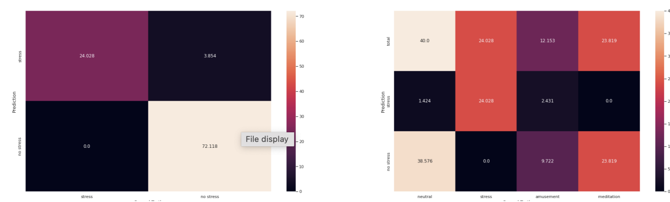

Fig. 8. Confusion Matrix on Testing Set

V. Future Work and Challenges

A. Real-time Monitoring

Future work will focus on implementing the model for real-time stress monitoring applications using wearable devices. The development of a real-time monitoring system will involve optimizing the model for low-latency inference and integrating it into wearable devices to provide continuous and immediate feedback to users.

B. Feature Exploration

Exploring additional features and their combinations for improved stress detection accuracy will be considered. Future research will investigate the potential of incorporating additional physiological signals, such as Electrodermal Activity (EDA) and Photoplethysmography (PPG), along with ECG to enhance the model's performance.

C. Generalization

Further investigation will be conducted to assess the model's performance on a larger and more diverse dataset to enhance its generalization capability. The inclusion of data from a more diverse population and different stress-inducing scenarios will help in evaluating the model's robustness and applicability in real-world settings.

D. Interpretability and Explainability

Enhancing the interpretability and explainability of the model will be another focus of future work. Techniques such as feature importance analysis and attention mechanisms will be explored to provide insights into the model's decision-making process, which is crucial for building trust and facilitating the adoption of the model in clinical and non-clinical settings.

E. User-Centric Design

Future work will also involve incorporating user feedback and preferences to tailor the model's predictions and recommendations to individual users, enhancing the user experience and engagement with the stress monitoring system.

F. Challenges

1) **Data Quality and Sensor Variability**
One of the major challenges faced in this study was the quality and variability of the data collected from different sensors. Future research will focus on developing robust preprocessing and data cleaning techniques to handle data inconsistencies and sensor variability effectively.
2) **Overfitting and Generalization**
Despite employing cross-validation and data balancing techniques, the risk of overfitting remains a challenge, especially when dealing with highly person-dependent ECG signals. Future work will involve exploring advanced regularization techniques and data augmentation methods to mitigate overfitting and improve the model's generalization capability.
3) **Real-world Deployment**
The deployment of the developed model in real-world settings, particularly in wearable devices, presents challenges related to power consumption, computational efficiency, and user acceptance. Future research will focus on optimizing the model architecture and developing efficient inference algorithms to enable real-time monitoring with minimal computational resources.
4) **Ethical and Privacy Concerns**
Addressing ethical and privacy concerns related to the collection, storage, and sharing of personal health data will be crucial in the development and deployment of the stress monitoring system. Future work will involve implementing robust data security and privacy-preserving techniques to ensure the confidentiality and integrity of the users' data.

VI. Conclusion

This study presents a deep learning-based approach for stress detection using ECG features from the WESAD dataset. The proposed model demonstrates significant improvements in accuracy and F1 score compared to the state-of-the-art methods, highlighting its potential for practical applications in stress detection.

- The average metrics of the model showed an Accuracy of 0.920, Precision of 0.804, Recall of 0.845, and an F1 score of 0.818.
- When compared to the best result from the WESAD paper [1], our model demonstrated a significant improvement with an accuracy increase of 6.56% and an F1 score increase of 0.49%.
- The model's robustness was further validated through testing on new data, yielding an Accuracy of 0.957, Precision of 0.851, Recall of 1.00, and an F1 score of 0.920.

These results suggest that our proposed deep learning approach is effective and promising for emotion recognition using ECG signals, outperforming traditional methods such as Linear Discriminant Analysis.

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