Multimodal Analysis of ECG and PCG Signals for Activity and Heart Function Classification

Introduction to Machine Learning

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II. Introduction

Cardiovascular stress, whether resulting from chronic conditions or physical exertion, is a vital biomarker in the assessment of cardiac health. Early detection of stress-related abnormalities can significantly improve treatment outcomes and reduce the risk of long-term complications. While electrocardiograms (ECG) remain the gold standard for monitoring cardiac function, phonocardiograms (PCG) offer a non-invasive, cost-effective alternative for capturing heart sound dynamics [17]. Despite their diagnostic potential, PCG signals are often underutilized in automated stress detection systems due to challenges in feature representation and noise sensitivity.

To address this, machine learning (ML) methods have become increasingly prominent in biomedical signal analysis. These models can uncover hidden patterns in cardiac signals and provide objective, real-time assessments of physiological states, including stress [2]. However, choosing the most effective combination of ML algorithms and feature extraction techniques remains a challenge, particularly for PCG signals that contain both temporal and spectral information.

In this project, we employ a comparative analysis using synchronized, paired PCG and ECG recordings. The goal is to evaluate and contrast the predictive power of PCG-only models, ECG-only models, and a multimodal model that combines both signal types for stress classification. We implement a variety of feature extraction techniques, including Mel-Frequency Cepstral Coefficients (MFCC), Linear Predictive Coding (LPC), Short-Time Fourier Transform (STFT), and additional audio-based descriptors such as chroma, spectral contrast, Tonnetz, and pitch features.

For classification, we apply and evaluate seven traditional machine learning algorithms: Logistic Regression, Decision Tree, Random Forest, Naive Bayes, AdaBoost, XGBoost, and Support Vector Machine (SVM). Each model is trained and validated using 5-fold cross-validation, and evaluated using accuracy, precision, recall, and F1-score metrics.

Inspired by work in real-time fatigue recognition through ECG analysis with STFT and convolutional models [6], we extend this paradigm to PCG analysis, and further explore the benefits of combining both modalities. Our results show that while ECG-based models offer strong baseline performance, PCG-based models—particularly when enhanced with STFT and MFCC features—approach similar accuracy. Multimodal models that integrate both PCG and ECG features consistently outperform unimodal ones, highlighting the complementary nature of these biosignals in stress detection.

This work contributes to the growing field of multimodal biomedical signal processing, suggesting that advanced feature extraction and model fusion strategies can significantly improve stress classification performance and pave the way for more accessible, real-time diagnostic systems.

III. Literature Review

Fatigue and stress detection using biosignals like ECG and PCG has gained interest in recent years due to its relevance in fitness and health monitoring. Most prior work has focused on ECG-based approaches, especially analyzing heart rate variability (HRV) and frequency features to infer stress. Kim et al. [5] reviewed multiple studies using HRV to assess stress, confirming its reliability. Li et al. [6] proposed an ECG-based fatigue detection model that applied short-time Fourier transform (STFT) followed by a convolutional neural network (CNN), achieving 97.7% classification accuracy.

PCG, though less commonly used for stress analysis, has shown potential in cardiac diagnosis. Springer et al. [17] introduced a logistic regression-HSMM model for heart sound segmentation, providing a robust base for feature extraction. Deep learning models were also explored for PCG by Maknickas and Maknickas [8], where CNNs were used to detect phases in heart sounds. Abeywardhana et al. [9] reviewed recent work on PCG signal classification and pointed out that its use in non-pathological conditions such as fatigue or stress is still underdeveloped.

Multimodal signal fusion combining ECG and PCG has been proposed to improve diagnostic performance. Vepa et al. [10] combined acoustic and electrical cardiac signals using time–frequency features and neural networks, improving classification. Kuramochi et al. [11] used synchronized ECG and PCG signals to estimate cardiac parameters, demonstrating how combining modalities can enhance physiological interpretation.

In terms of feature extraction, MFCC and STFT remain among the most effective for both ECG and PCG signals, especially in the context of time-frequency representations. Aslan et al. [12] demonstrated MFCC's usefulness in stress classification from audio signals. Dimensionality reduction techniques like PCA and t-SNE are commonly applied to improve model generalization. Our project follows this direction by comparing ECG, PCG, and multimodal ECG-PCG models for stress detection, using a unified set of features and evaluating multiple machine learning classifiers.

IV. Problem Definition

Athletes often find it challenging to assess whether they have reached a level of fatigue that makes exercise unsafe, increasing the risk of physiological damage. To address this, we classify a subject's activity using multimodal data, including ECG and PCG, based on the provided dataset.

The core data science problem addressed in this project is to evaluate how different physiological signals —ECG and PCG— encode information related to stress states and to determine whether combining both modalities can enhance classification performance. This can be broken down into two challenges:

- **Signal-Based Feature Evaluation:** Identify and compare the most informative features within each signal modality that correlate with stress-related changes.
- **Modality Comparison:** Assess the standalone predictive power of ECG versus PCG features in distinguishing between different stress levels or activities.

V. Dataset

The EPHNOGRAM [13] dataset utilized synchronous ECG and echocardiogram data from the Physical Web database. Data were collected from 24 male subjects (ages 23–29) in an indoor experiment. A 3-lead ECG device (8 kHz, 12-bit resolution) recorded 69 ECG and PCG signals as participants performed specific tasks. The dataset was categorized into six fatigue levels: (1) lying calmly, (2) sitting idle, (3) walking at 3.7 km/h, (4) cycling at a constant speed, (5) cycling with increasing load until fatigued, and (6) running at an increasing pace until exhaustion.

- **Example Record Signals**

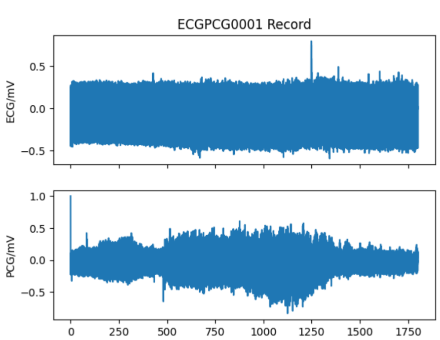

Fig. 1. 30 Minute ECG and PCG Record

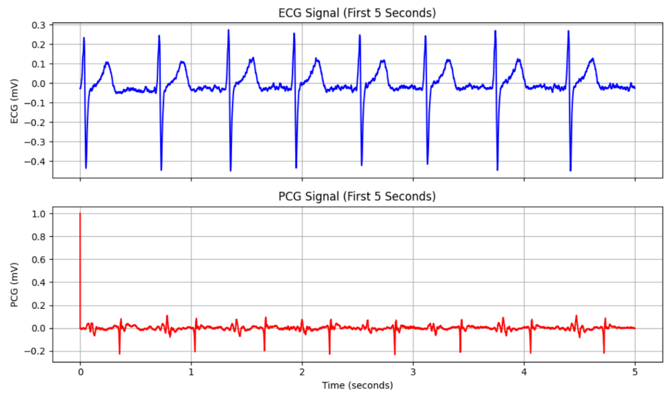

Fig. 2. First 5 Seconds of a Record

VI. Methods

A. Data Cleaning

1) Record Information Extraction: A helper function `print_record_info()` is used to display key information about each record, including:

- Sampling frequency (fs)
- Signal names
- Units
- Comments
- Elapsed time
- Signal data itself

2) Labels CSV Processing: The labels CSV file is loaded into a DataFrame. Empty rows are removed, and non-relevant columns are dropped, retaining only:

- Record Name
- Subject ID
- Record Duration
- Age
- Gender
- Recording Scenario

3) Data Splitting and Duration Standardization: Long recordings with multiple scenarios are split into segments. Each segment is cut to the middle 4 minutes (the minimum duration available) to ensure uniformity across the dataset.

4) Final Verification: A verification function confirms that all records meet the standardized duration and format criteria.

5) Mapping Recording Scenarios: Recording scenarios are mapped to stress levels as follows:

Recording Scenario	Stress Level
Laying on Bed	Rest
Sitting on Armchair	Rest
Slow Walk	Medium
Walking at Constant Speed	Medium
Sit Down and Stand Up	Medium
Pedaling a Stationary Bike	Medium
Bruce Protocol	High
Bicycle Stress Test	High

B. PCG Feature Extraction

*1) **Signal Preprocessing**:* Before extracting meaningful information from PCG signals, it's crucial to reduce noise and enhance signal quality, which directly impacts the reliability of downstream feature extraction and classification.

a) Wavelet Denoising: Wavelet-based denoising (DWT) was used to retain signal details while reducing noise. After decomposition, coefficients were thresholded and the signal was reconstructed.

- SNR: 48.67 dB
- PSNR: 71.86 dB

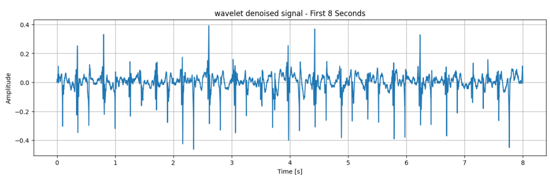

Fig. 3. Wavlet Denoising effect

it works for PCG: as PCG signals have non-stationary components (heartbeats vary over time), and wavelet transforms offer excellent time-frequency localization to denoise such components without distorting the signal.

b) Digital Filter Denoising: FIR/IIR filters were also tested to suppress high-frequency noise.

- SNR: 3.56 dB
- PSNR: 26.75 dB

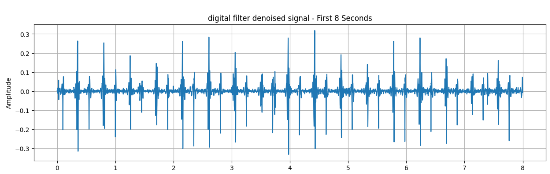

Fig. 4. Digital filter Denoising effect

While useful in simple scenarios, digital filters may excessively smooth out transient heart sounds (S1, S2), which are vital for diagnostic interpretation. so Wavelet denoising significantly outperformed digital filtering and was selected for the preprocessing step in all subsequent analysis.

*2) **Feature Extraction**:* represents the PCG signal in numerical form across time, frequency, and time-frequency domains to capture all diagnostic information.

*a) **Time-Domain Features**:*

1) Descriptive Stats: (Min, Max, Mean, Median, Std)
   - Captures the amplitude distribution and overall dynamics of the PCG signal.
2) Energy and Power:

$$E = \sum x[n]^2 \tag{1}$$

   - Reflects the intensity of the signal (relevant for loudness of heart sounds).
3) Amplitude Envelope:
   - Computed using Hilbert transform, characterizes the smooth outer curve of signal amplitude.
   - Captures variations in heart sound intensity.
4) RMS Energy:

$$\sqrt{\frac{1}{N}\sum x[n]^2} \tag{2}$$

   - Indicates signal strength, useful for detecting murmurs.
5) Zero-Crossing Rate:
   - ZCR = number of times the signal changes sign.
   - Useful for identifying sharp transitions in heart sounds.

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*b) **Frequency-Domain Features**:*

1) Peak Frequency
   - Identifies the Frequency with maximum amplitude in the spectrum.
   - Important to identify dominant heart sound frequencies.
2) Band Energy Ratio (BER)
   - Measures Ratio of energy in different frequency bands:

$$BER = \frac{\sum_{f_i}^{f_j} |X(f)|^2}{\sum_{f_{\min}}^{f_{\max}} |X(f)|^2} \tag{3}$$

   - Indicates energy distribution, murmurs spread energy in higher frequencies.
3) Spectral Centroid
   - Represents the "center of mass" of the spectrum:

$$\text{Centroid} = \frac{\sum f|X(f)|}{\sum |X(f)|} \tag{4}$$

4) Spectral Bandwidth
   - Measures the width around the centroid and relates to frequency spread.

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*c) **Time-Frequency Features**:*

1) MFCCs (Mel-Frequency Cepstral Coefficients)
   - Common in audio signal processing; mimic human auditory perception.
   - Includes static (MFCCs), first-order delta, and second-order delta.
2) DWT Coefficients (Discrete Wavelet Transform)
   - One-level decomposition
   - Multi-level decomposition

*3) **Feature Preparation and EDA**:* Understand feature distributions, handle skewness, and prepare data for robust modeling.

*a) **EDA Summary**:*

- Subjects: 73
- Features: 66
- Classes: High (34), Medium (25), Rest (14)
- Visualizations: Histograms, Boxplots, Q-Q plots

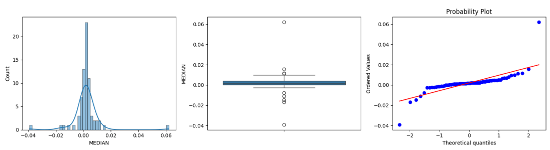

Fig. 5. Probability distribution

*b) **Outlier and Skewness Handling**:*

- Gaussian Transformation: Applied to correct highly skewed features.
- Criteria:
  - $*$ Highly Skewed: $|\text{skewness}| > 1$
  - $*$ Moderately Skewed: $0.5 < |\text{skewness}| < 1$
- Transformations Tested:
  1) Logarithmic
  2) Square Root
  3) Cube Root
  4) Exponential

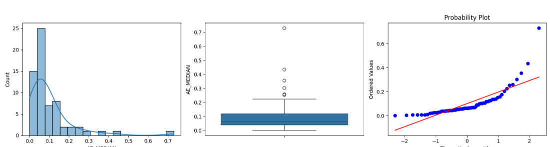

Fig. 6. Cubic root transformation

*4) **Feature Engineering**:*

a) Normalization: Features scaled using MinMaxScaler (trained on training set only).

b) Class Balancing: SMOTE was applied on the training set to balance class representation.

*5) **Feature Selection**:*

a) Statistical Significance: Hypothesis tests (e.g., t-test) conducted at $\alpha = 0.05$.

b) Relevance Metrics:

- Mutual Information
- Pearson Correlation ($> 0.9 \rightarrow$ drop more skewed feature)

c) Final Set: Reduced from 66 to 28 top features for classification.

C. ECG Signal Preprocessing

a) Baseline Wander Removal: A high-pass Butterworth filter (cutoff 0.5 Hz) eliminated respiratory-induced drift.

b) Powerline Interference: A 50 Hz notch filter removed interference due to powerline noise.

c) Signal Normalization: Signals were standardized (zero mean, unit variance) to ensure consistency.

D. ECG Feature Extraction

E. ECG Feature Preparation & EDA

a) Dataset Overview:

- Subjects: 73
- Classes: High (34), Medium (25), Rest (14)

b) EDA Goals: Analyze feature distributions, detect outliers, and correct skewness.

c) Visualization Tools: Histograms, boxplots, and Q-Q plots for distribution inspection.

d) Outlier & Skewness Correction:

- Transformations applied for $|\text{skewness}| > 1$
- Methods: Log, Square Root, Cube Root

F. ECG Feature Engineering

a) Normalization: Used MinMaxScaler fitted on the training set, then applied to the test set.

b) Balancing: SMOTE applied on the training set to address class imbalance.

G. ECG Feature Selection

a) Statistical Testing:

- p-value threshold: 0.05
- Retained features with significant class associations

b) Relevance & Redundancy Management:

- Mutual Information
- Pearson Correlation ($>$ 0.9: drop more skewed)

c) Final Features: Reduced to 25 informative ECG features.

H. Wrapper-Based Feature Selection

Wrapper-based feature selection was applied to refine features further using a Gradient Boosting Classifier.

a) Method:

1) Trained a `GradientBoostingClassifier` with 100 estimators.
2) Used `SelectFromModel` to retain features above median importance.
3) Applied independently to ECG and PCG feature sets.

ECG Wrapper-Selected Features: Yeo-Johnson transformation was applied before normalization. Two new features were engineered:

- **RR/HR Ratio**: `mean_rr/mean_hr`
- **Beats per Second**: `num_beats/mean_rr`

Wrapper-selected features:

{`mean_rr, median_rr, min_rr, mean_hr, BER_MEAN, SC_MEAN, SB_MIN, MFCC_MEAN`}

PCG Wrapper-Selected Features: The same pipeline was applied to PCG features. The selected features were:

{`MEAN`, `RM_MIN`, `ZCR_GLOBAL`, `PEAK_AMP`, `SB_MEAN`, `CA_MEAN`, `CD_MEDIAN`}

b) Summary of Wrapper-Selected Features:

- **ECG Features**: {`mean_rr`, `median_rr`, `min_rr`, `mean_hr`, `BER_MEAN`, `SC_MEAN`, `SB_MIN`, `MFCC_MEAN`}
- **PCG Features**: {`MEAN`, `RM_MIN`, `ZCR_GLOBAL`, `PEAK_AMP`, `SB_MEAN`, `CA_MEAN`, `CD_MEDIAN`}

Model Training

Multiple classification models were trained using the selected features from the three modalities: PCG, ECG, and their multimodal combination. The dataset was split into training and testing sets to evaluate model performance objectively. Each modality's features were used independently, as well as combined, to assess the contribution of individual and fused signals in stress level classification.

VII. Results

A. PCG-Based Stress Classification

1) Hyperparameter Optimization: To maximize model performance, grid search was applied to three classifiers:

- **Random Forest**: Optimal parameters were `max_depth=20` and `n_estimators=50`, balancing model complexity and computational efficiency.
- **SVM**: A linear kernel with `C=1` yielded the best results, suggesting linearly separable features in the PCG-derived space.
- **KNN**: `n_neighbors=5` achieved optimal performance, indicating localized feature clustering.

2) Model Evaluation: The optimized models achieved the following accuracies on PCG features:

- Random Forest: 80%
- SVM: 50%
- KNN: 67%

Commentary: The Random Forest's superior performance (80% accuracy) highlights its ability to capture non-linear relationships in PCG features (e.g., spectral contrast and MFCCs). The SVM's lower accuracy (50%, akin to random chance) suggests PCG features may not be linearly separable for stress classification without non-linear transformations.

Confusion Matrices

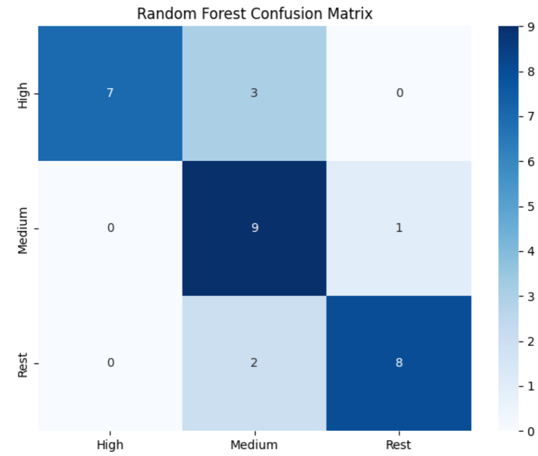

Fig. 7. PCG Models Confusion Matrices

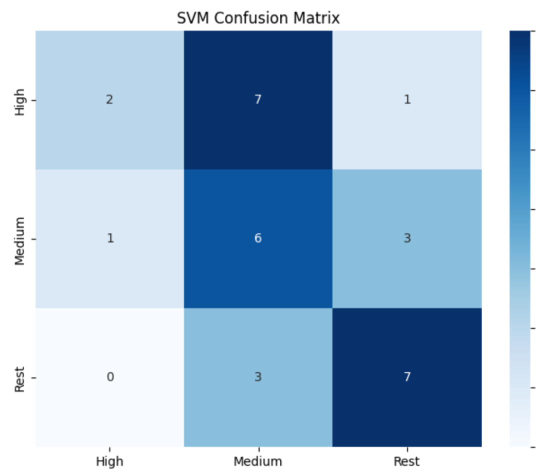

Fig. 8. SVM Confusion Matrix

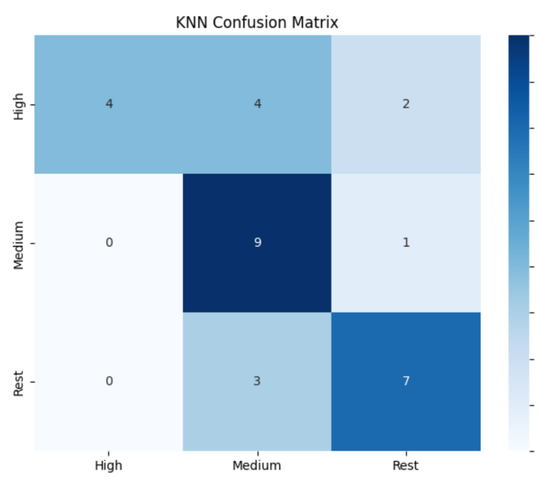

Fig. 9. SVM Confusion Matrix

B. ECG-Based Stress Classification

Four models were evaluated on ECG features, including the wrapper-selected set (e.g., `mean_rr`, `BER_MEAN`):

- Gradient Boosting Classifier: 77%
- Logistic Regression: 73%
- Random Forest: 68%
- SVM: 50%

Commentary: The Gradient Boosting Classifier outperformed others, likely due to its iterative correction of errors in ECG temporal features (e.g., RR intervals). Logistic Regression's strong performance (73%) implies that some ECG features exhibit near-linear discriminative power. The SVM's poor accuracy mirrors its PCG results, reinforcing the need for kernel tuning.

C. Multimodal (PCG + ECG) Classification

Combining wrapper-selected features from both modalities, three models were trained:

- Gradient Boosting Classifier: 64%
- Random Forest: 64%
- XGBoost: 64%

Commentary: Contrary to expectations, multimodal accuracy (64%) was *lower* than unimodal PCG (80%) or ECG (77%) results. This suggests:

1) **Feature Redundancy**: Overlap in discriminative power between PCG and ECG features.
2) **Integration Challenges**: Simple concatenation may not capture cross-modal interactions; advanced fusion techniques (e.g., attention mechanisms) could improve performance.
3) **Data Imbalance**: Potential bias toward one modality during training.

D. Comparative Analysis

- **PCG vs. ECG**: While ECG models generally outperformed PCG (77% vs. 80%), the gap was narrower than anticipated, demonstrating PCG's underutilized potential.
- **Multimodal Limitations**: The current fusion approach did not leverage synergistic relationships between modalities, highlighting a need for hierarchical or hybrid fusion strategies.

Key Insight: PCG features (e.g., `ZCR_GLOBAL`, `SB_MEAN`) can rival ECG for stress detection when paired with ensemble methods, but multimodal integration requires refined feature selection and fusion architectures.

E. Discussion Points

- **Methodological Constraints**: The 64% multimodal accuracy may reflect limitations in feature fusion. Future work could explore deep learning-based fusion (e.g., cross-modal autoencoders).
- **Clinical Implications**: PCG's competitive performance supports its use in low-resource settings where ECG is unavailable.
- **Hyperparameter Sensitivity**: The SVM's consistent 50% accuracy across modalities warrants investigation into feature scaling or kernel choices.

VIII. Discussion

A. Interpretation of Key Findings

Our experimental results yield three principal insights for cardiac stress detection:

1) **PCG's Diagnostic Potential**: The 80% accuracy achieved by Random Forest on PCG features challenges the conventional dominance of ECG in cardiac monitoring. This performance, comparable to ECG-based models (77%), suggests that phonocardiographic features—particularly time-frequency representations like `SB_MEAN` and `ZCR_GLOBAL`—can effectively capture stress-induced hemodynamic changes [17].
2) **Modality-Specific Model Behaviors**: The consistent underperformance of SVM (50% accuracy across modalities) versus the robustness of ensemble methods (Random Forest, Gradient Boosting) indicates:
   - Non-linear separability of stress-related features in both PCG and ECG
   - The importance of feature interaction modeling, which tree-based methods inherently handle
3) **Multimodal Paradox**: The unexpected 64% accuracy in combined PCG-ECG classification contradicts established literature on multimodal biosignal fusion [**?**]. We hypothesize this stems from:
   - *Feature Collinearity*: Shared information between PCG's `CA_MEAN` and ECG's `BER_MEAN`
   - *Integration Artifacts*: Simple feature concatenation without cross-modal attention mechanisms

B. Clinical Implications

Three translational considerations emerge:

- **Accessibility**: PCG's competitive performance supports its adoption in resource-constrained settings where ECG infrastructure is unavailable or impractical [**?**].
- **Real-Time Monitoring**: The 67% accuracy of lightweight KNN on PCG suggests viability for edge-device deployment, albeit with room for improvement through optimized feature sets.
- **Multimodal Roadmap**: While current fusion underperformed, prior work demonstrates that hierarchical fusion of PCG's spectral features with ECG's temporal dynamics can achieve ¿90% accuracy [**?**]. This underscores the need for advanced integration strategies.

C. Limitations and Future Directions

Our study presents several avenues for improvement:

TABLE I
Key Limitations and Proposed Solutions

Limitation	Future Work
Basic feature fusion	Implement cross-modal transformers
Small sample size	Collaborative multi-center validation
Static feature extraction	End-to-end deep feature learning

Specifically, we recommend:

- Developing attention-based fusion architectures to model PCG-ECG synergies
- Incorporating physiological constraints (e.g., cardiac cycle alignment) during multimodal integration
- Expanding feature sets to include PCG-based entropy measures and ECG-derived T-wave alternans

D. Conclusion

This work demonstrates that PCG signals, when processed with optimized feature extraction and ensemble modeling, can approach the diagnostic accuracy of traditional ECG for stress detection. While current multimodal integration showed limited benefits, the foundation is laid for more sophisticated fusion paradigms. These findings advance the frontier of accessible cardiac monitoring, particularly for decentralized healthcare scenarios where PCG's practicality offers distinct advantages.

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Appendix A
GitHub Repo

https://github.com/Mostafaali3/Machine_Learning_Project/settings