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A Machine Learning Framework for Stress Detection Using Photoplethysmography (PPG) Signals

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***Abstract*—Stress detection using machine learning has gained significant consideration due to its potential applications in mental health monitoring and well-being assessment. This study presents an efficient framework for stress classification, incorporating preprocessing, feature extraction, and model training techniques. Initially, raw signal data undergoes preprocessing, including bandpass filtering and segmentation, to enhance data quality. Features are extracted and labeled, followed by the dataset being split into training and testing sets. Multiple machine learning models, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naıve Bayes, and AdaBoost, are evaluated for classification, with the Gradient Boosting Classifier (GBC) as the proposed model. Experimental results demonstrate that GBC outperforms other classifiers, achieving an accuracy of 99.77%, precision of 99.76%, recall of 99.76%, F1-score of 99.77%, mean squared error (MSE) of 0.0046, and root mean squared error (RMSE) of 0.0962. These results demonstrate how well our method works to differentiate between stressed and non-stressed states, providing a viable way to identify stress in real time.**

***Index Terms*—Stress Detection, Machine Learning, Feature Extraction, Signal Processing, Mental Health Monitoring.**

I. INTRODUCTION

Stress is the bodies and mind's reaction to external pressures, frequently harming mental and physical health [1]. In today's fast-paced world, stress has become a significant health concern due to shifting lifestyles, social pressures, and increasing workloads [2]. Chronic exposure to stress can result in serious health issues, including anxiety, depression, cardiovascular diseases, and weakened immune function [3]. These adverse effects highlight the need for early stress detection, which can help mitigate health risks and improve overall well-being [4]. Traditional stress detection techniques rely on clinical evaluations and self-reported questionnaires, which are often time-consuming, subjective, and prone to bias. As a result, researchers have turned their attention to ma- machine learning (ML)-based automated stress detection systems, which leverage advanced computational models to analyze various forms of data efficiently [5]. ML techniques have gained significant attention due to technological advancements that allow accurate stress detection using diverse datasets, including physiological, behavioral, and textual data [6]. The physiological approach to stress detection focuses on analyzing biological signals such as heart rate variability (HRV), electrodermal activity (EDA), blood pressure, and cortisol levels. HRV, a crucial biomarker, measures fluctuations in heartbeats and reflects the autonomic nervous system's response to stress [7]. The integration of deep learning (DL) has significantly enhanced stress detection accuracy. Deep learning models excel in feature extraction and pattern recognition, making them highly effective in complex classification tasks, including medical diagnostics and stress analysis [8]. Convolutional neural networks (CNNs) have demonstrated impressive results in extracting spatial features from images and physiological data, while recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are well-suited for capturing temporal dependencies in sequential data. Hybrid architectures that combine CNNs with sequential models can simultaneously capture both spatial and temporal features, improving stress classification performance [9]. Our work proposes an efficient framework integrating preprocessing, feature extraction, and model training techniques. Various classifiers, including KNN, SVM, Naive Bayes, and AdaBoost, are evaluated, with GBC demonstrating superior performance. GBC achieves 99.77% accuracy, precision 99.76%, recall 99.76%, and F1-score, with an MSE of 0.0046 and RMSE of 0.0962. These results validate the effectiveness of our approach in distinguishing stressed and non-stressed states, making it a promising solution for real-time stress detection. The key contributions are as follows: Implemented a tailored Butterworth bandpass filter (0.5–5 Hz) to effectively retain heart rate-related fre- frequencies while minimizing motion artifacts and noise, ensuring high-quality input for stress classification.

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- Extracted and analyzed key cardiovascular metrics, including RR intervals, heart rate, and heart rate variability (HRV), providing a comprehensive representation of autonomic nervous system activity linked to stress responses.
- Conducted a rigorous evaluation of diverse machine learning algorithms (AdaBoost, Gradient Boosting Classifier, SVM, KNN, and Naive Bayes) to identify the most effective model for stress prediction, offering valuable insights into algorithm suitability for physiological data.
- Translated raw model predictions into intuitive stress categories ('Stressed' and 'Not Stressed'), enhancing real-world usability in digital health applications and wearable-based stress monitoring systems.

II. Problem Statement

Stress is a significant public health concern, affecting mental and physical well-being. Chronic stress has been linked to various health issues, including anxiety, depression, cardiovascular diseases, and weakened immune function. Traditional stress assessment methods, such as self-reported questionnaires and clinical evaluations, are subjective, time-consuming, and prone to bias. With advancements in sensor technology and machine learning, there is an increasing demand for automated, objective, and real-time stress detection systems. However, existing machine learning approaches often suffer from limited accuracy, a lack of generalization across different datasets, and inefficient feature extraction techniques. Furthermore, selecting an optimal classifier for stress prediction remains a challenge due to variations in physiological signals and external influencing factors. Therefore, developing a robust, high-accuracy stress classification framework that leverages advanced preprocessing, feature extraction, and ma- machine learning techniques is crucial for improving real-time stress monitoring and intervention strategies. This study aims to address these limitations by proposing an efficient machine learning-based stress detection framework.

III. Literature Review

Stress detection research has evolved from traditional sta- statistical methods to advanced ML-based approaches utilizing physiological signals. Selvam et al. used EEMD and Hilbert Huang Transform on HRV and EDA signals with SVM, achieving 98.44% accuracy, but faced computational complexity limiting real-time application [10]. Paul et al. classified stress using respiratory signals from PPG with a threshold-based method, achieving 98.43% accuracy, though reliance on PPG alone limited other stress indicators [11]. Sara Pour Mohammadi et al. developed a fuzzy-based model using ECG and EMG, achieving 96.7% accuracy for two-level and 75.6% for three-level stress classification, but struggled with multi-level stress detection [12]. Zubair et al. proposed a multilevel stress detection system using ultra-short PPG recordings, achieving 94.33% accuracy with SVM, but faced generalization issues across stressors [13]. Sharma et al. ap- applied entropy-based features with stationary wavelet transform and SVM, achieving 97.26% accuracy, though reliance on EEG signals limits real-time wearable applications [14]. Can et al. used smart bands for HRV and EDA signals, achieving 81% and 72% accuracy, respectively, improved to 79.66% and 76% with contextual data, yet struggled with real-world stress detection [15]. Md. Rashed et al. used an SVM and GBC combined model through a Stacking Classifier and refining final decisions with a Random Forest-based Fusion Model, achieving 99.09% accuracy, 100% precision, and 98.53% sensitivity, highlighting the effectiveness of hybrid models in early diagnosis [16]. Pramod et al. used multimodal wearable sensor data with ML and DL models, achieving 81.65% (three-class) and 93.20% (binary) accuracy, improved to 84.32% and 95.21% using deep learning, but faced challenges in generalizing multimodal stress classification- tion [17].

IV. Proposed Methodology

Stress detection using machine learning has gained substantial attention due to its applications in mental health

monitoring. This study presents an efficient framework that integrates data acquisition, preprocessing, feature extraction, and model training to ensure accurate classification of stress levels. The proposed approach follows a structured pipeline consisting of Dataset Acquisition, Data Preprocessing, and the Proposed Classification Framework described in detail below:

A. *Dataset Acquisition*

The dataset [18] consists of PPG (Photoplethysmogram) recordings from 200 critically ill patients (100 adults and 100 neonates) during routine clinical care. The data was collected using a bedside monitor at a frequency of 125 Hz, primarily capturing finger PPG signals. The reference beats for this dataset are derived from ECG-based QRS detections, also sampled at 125 Hz. Each recording has an average duration of 5.7 minutes, with a range between 3.6 to 7.8 minutes. In total, the dataset includes 115,941 individual heartbeats, providing valuable insights for analyzing cardiovascular health in critically ill patients.

B. *Data Preprocessing*

Data preparation is a critical component of the machine learning pipeline that transforms raw PPG signals into a usable format for model training and testing. Preprocessing entails filtering, segmentation, feature extraction, feature labelling, and data splitting.

Filtering: A Butterworth bandpass filter is applied to enhance signal quality and remove extraneous noise, leaving only frequency components between 0.5 and 5.0 Hz. Filtering in this way means that only the physiologically relevant portions of the signal remain.

Segmentation: The filtered signals are divided into 100-sample overlapping windows with a 50-sample overlap to enable localized analysis.

Feature Extraction: On each of the specified windows, a peak detection procedure is carried out to identify the unique features of the PPG waveform, and then the intervals between successive peaks (RR intervals) are calculated. From these intervals, two basic features are calculated: the mean heart rate, by dividing 60 by the average RR interval, and heart rate variability (HRV), as the standard deviation of the RR intervals.

Feature Labeling: Each distinct segmented window is provided with a specific label denoting its stress level according to predefined rules, thereby allowing the models to be trained on appropriately labelled data. Data Splitting: The ultimate dataset is divided into a training subset, comprising 75% of the data, and a testing subset, comprising 25% of the data, to allow the models to learn to identify generalizable patterns and to prevent overfitting issues.

C. *Proposed Classification Framework*

The proposed classification framework aims to evaluate and classify stress levels based on physiological data by leveraging various machine learning classifiers. This study explores a diverse set of classification algorithms, including AdaBoost.

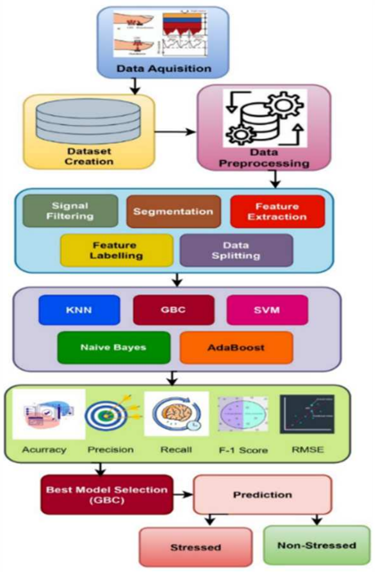

Fig. 1. Suggested architecture for mental stress classification

Algorithm 1 Gradient Boosting Classifier

Data: Training set $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$
Result: Trained model $F_M(x)$
Initialize model with a constant value:
$F_0(x) \leftarrow \arg\min_\gamma \sum_{i=1}^{N} L(y_i, \gamma)$
for $m = 1$ to M **do** ▷ Number of boosting iterations
  Compute negative gradient:
  $r_{im} \leftarrow -\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}$
  Fit a weak learner (decision tree) to residuals: $h_m(x)$
  Compute optimal weight γ_m for $h_m(x)$:
  $\gamma_m = \arg\min_\gamma \sum_{i=1}^{N} L(y_i, F_{m-1}(x_i) + \gamma h_m(x_i))$
  Update model:
  $F_m(x) \leftarrow F_{m-1}(x) + \gamma_m h_m(x)$
end for

GBC, SVM with radial basis function (RBF) kernel, KNN, and Naive Bayes. Each classifier is independently trained on a preprocessed training dataset, utilizing features extracted from physiological signals such as PPG and ECG. The goal is to identify the unique patterns that characterize different stress levels in critically ill patients, ensuring that each classifier effectively captures the complexities of the data. For comprehensive model evaluation, we assess the performance of each algorithm on a test set using a variety of performance metrics, including accuracy, precision, recall, F1 score, MSE, and RMSE. These metrics provide a well-rounded view of model performance, taking into account not just overall accuracy but also the ability to handle class imbalances and minimize prediction errors. Furthermore, the framework includes a comparative analysis of the advantages and limitations of each classifier, considering factors such as interpretability, training time, and computational complexity. This analysis guides the selection of the most appropriate model for real-world stress detection applications, where precision, reliability, and efficiency are paramount.

V. Results and Discussion

Table 1 presents the relative performance of several ML algorithms for stress classification. Naıve Bayes demonstrates modest classification ability, achieving 76.38% accuracy, 78.57% precision, 76.38% recall, and an F1-score of 74.46%. AdaBoost radically enhances classification performance with 96.76% accuracy and balanced precision, recall, and F1-score measures of 96.76%. SVM also enhances predictive performance, with an accuracy of 98.61%, precision of 98.15%, recall of 98.61%, and F1-score of 98.38%. KNN performs better than SVM, with an accuracy of 99.30%, a precision of 99.84%, a recall of 99.30%, and an F1-score of 99.07%. GBC performs the best, with an accuracy of 99.77% and precision of 99.76%, recall of 99.76%, and F1-score of 99.77%. Apart from classification measures, error assessment measures like MSE and RMSE also give important information regarding the credibility of the model. All the models gave an MSE of 0.0046 and an RMSE of 0.0962, suggesting very little error in predictions Figure 2 presents the confusion matrix for the GBC displays model's performance in classifying three categories: LS, HS, and Unknown. The matrix shows that 168 LS samples were correctly classified, with only 1 misclassified as HS. Similarly, 261 HS samples were correctly predicted with no misclassifications. The "Unknown" category had 2 correctly classified samples. The model exhibits high accuracy with minimal misclassifications, especially for LS and HS categories. The matrix highlights strong performance with clear distinctions between classes, making GBC an effective classifier for this dataset with a negligible error rate. The ROC curve compares the performance of five classifiers: AdaBoost (AUC = 0.99), SVM (AUC = 0.99), KNN (AUC = 1.00), Naive Bayes (AUC = 0.96), and GBC (AUC = 1.00). A higher AUC value indicates better classification performance, with GBC and KNN achieving perfect discrimination (AUC = 1.00), while AdaBoost and SVM also perform excellently (AUC = 0.99). Naive Bayes, though slightly lower (AUC = 0.96), still performs well. Since all models have high AUC values, they effectively distinguish between classes, with GBC being the most accurate.

Table 2 compares various stress detection models based on different physiological signals and machine learning techniques. Studies utilizing SVM (e.g., in HRV and EDA signals) and threshold-based methods on respiratory signals achieved high accuracy, with SVM performing particularly well in several cases, such as in short-duration EEG and ultra-short PPG recordings. Other models, like fuzzy-based and LSTM-based classifiers, also showed strong results, with accuracy ranging from 72% to 96.7%. Notably, our model, using a Gradient Boosting Classifier (GBC) with PPG signals, outperforms all others with an impressive accuracy of 99.77%, highlighting the potential of GBC for precise stress detection from physio-logical data. This suggests that, among the methods presented, GBC with PPG signals offers superior performance, making it a promising approach for stress classification applications. The comparison table of existing work shows our GBC model outperforms in terms of accuracy and consistency, highlighting its potential for use in practical, real-time healthcare applications. The simplicity of the model, coupled with high accuracy, emphasizes its suitability for personal health monitoring and stress management. By focusing on PPG signals, our approach also circumvents the complexities associated with other physiological signals, providing a more efficient and scalable solution for stress detection and intervention.

TABLE I
PERFORMANCE EVALUATION OF DIFFERENT MACHINE LEARNING MODELS

Algorithms	Accuracy	Precision	Recall	F-1 Score	MSE	RMSE
Naive Bayes	76.38%	78.57%	76.38%	74.46%	0.0046	0.0962
AdaBoost	96.76%	96.76%	96.76%	96.76%	0.0046	0.0962
SVM	98.61%	98.15%	98.61%	98.38%	0.0046	0.0962
KNN	99.30%	99.84%	99.30%	99.07%	0.0046	0.0962
GBC	99.77%	99.76%	99.76%	99.77%	0.0046	0.0962

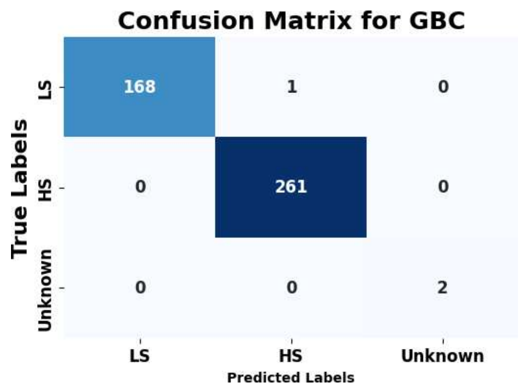

Fig. 2. Confusion Matrix for GBC Model

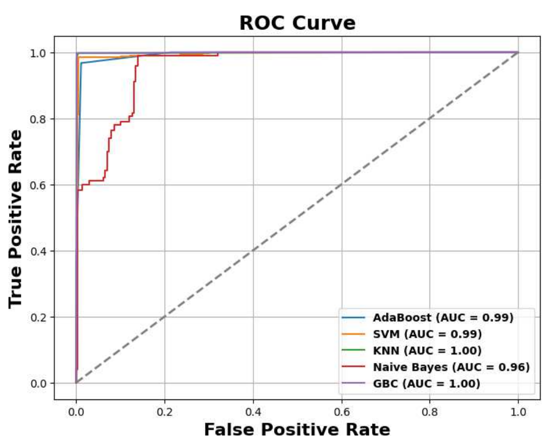

Fig. 3. ROC curve for classifier evaluation

TABLE II
PERFORMANCE COMPARISON AMONG EXISTING MODELS AND OUR MODEL

Ref.	Research Work	Model	Accuracy
[10]	Stress detection	Support Vector Machine (SVM)	98.44%
[11]	stress classification	Threshold-based techniques	98.43%
[12]	stress classification	Fuzzy-based model	96.7% (2-level), 75.6% (3-level)
[13]	Multi-level stress detection	SVM	94.33%
[14]	Stress detection	SVM	97.26%
[15]	Automatic stress detection system	MLP	81% (HRV), 72% (EDA)
[19]	Stress detection	LSTM	89.20%
Our	**Stress Detection**	**GBC**	**99.77%**

A. Conclusion and Future Work

This study demonstrates the effectiveness of using machine learning for stress detection, with a focus on preprocessing, feature extraction, and model training. The Gradient Boosting Classifier (GBC) outperformed other classifiers, achieving exceptional accuracy and other performance metrics, making it a promising approach for real-time stress detection. The results suggest that GBC can reliably differentiate between stressed and non-stressed states, offering potential applications in mental health monitoring and well-being assessment.

Future work will focus on exploring more advanced feature extraction techniques, such as deep learning models, to enhance detection accuracy further. Additionally, the framework will be tested on more diverse datasets, including different stress levels and populations, to assess its generalizability. Incorporating real-time data from wearable devices could also enable continuous stress monitoring and intervention in practical applications.

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