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REAL-TIME MENTAL STRESS PREDICTION USING MACHINE LEARNING MODELS TRAINED ON STREAMING DATASETS

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ABSTRACT
Mental stress presents a pervasive challenge affecting individuals across all age demographics in contemporary society, with profound implications extending beyond psychological well-being to encompass chronic ailments such as depression, cancer, and cardiovascular diseases (CVD). Effective management and prevention of mental stress are critical for promoting overall health and mitigating associated risks. This paper addresses the pertinent issue of mental stress in modern society, emphasizing the importance of early prediction and intervention. Leveraging the Random Forest (RF) method enhanced by band-pass filtration on electrocardiogram (ECG) data, we propose a robust framework for stress level prediction. Achieving a high accuracy of 96.73% in stress categorization, our approach demonstrates significant advancements over existing methodologies. Crucially, validation with real-time datasets enhances the model's reliability and applicability in practical settings.

Keywords: Mental Stress, Random Forest, ECG Signals, Real-Time Dataset

I. INTRODUCTION

Stress, a common experience in contemporary society, arises when individuals perceive themselves unable to cope with demands placed upon them [1]. This condition not only affects mental well-being but also contributes to various chronic illnesses such as depression, cancer, and cardiovascular diseases (CVD) [2]. The American Physiological Association and American Institute of Stress reported that in 2014, a significant majority of individuals in the United States experienced physical and psychological symptoms due to stress [2]. Similarly, in the EU, a substantial proportion of employees felt their health was compromised by work-related stress, resulting in substantial healthcare costs and lost productivity [3] [4].

The autonomic nervous system (ANS) plays a pivotal role in the physiological response to stress, comprising sympathetic and parasympathetic branches that regulate bodily functions [5]. Stressful events often disturb the balance between these branches, leading to heightened sympathetic activity and reduced parasympathetic tone, notably impacting heart function as observed through electrocardiogram (ECG) signals [5]. Heart rate variability (HRV), derived from ECG R peaks, is a reliable metric for assessing stress due to its sensitivity to autonomic changes [6]. HRV analysis typically involves placing ECG electrodes on specific body locations to capture signals, followed by computation of HRV features over defined time windows [7] [8] [9].

Various physiological markers, including elevated heart rate and altered HRV patterns, have been proposed for stress detection, underscoring the diverse manifestations of stress responses among individuals [9] [10]. Integration of multiple features has been shown to enhance the accuracy of stress classification, reflecting individual variability in stress reactions [10]. Traditional classifiers like Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) have been commonly employed for stress detection using these features [12].

Convolutional Neural Networks (CNNs), originally developed for image processing, have shown promise in biosignal classification tasks including ECG analysis [13] [14]. CNNs have been successfully applied in various bioinformatics domains such as arrhythmia detection and biometric identification [17] [19], highlighting their potential for stress detection based on ECG data [14].

This paper introduces a novel application of the Random Forest (RF) method for real-time detection of mental stress using ECG signals. Unlike previous approaches, which primarily focus on offline analysis, our method aims to provide instantaneous stress assessment from specific ECG segments. Real-time stress detection is crucial for scenarios requiring immediate intervention, such as acute stress situations.

The primary objective of this study is to investigate the feasibility and efficacy of RF in identifying acute cognitive stress using real-time ECG datasets. We conducted a comparative analysis to evaluate the performance of RF against conventional ECG-based stress estimation methods. Our results demonstrate that RF outperforms traditional techniques in accurately predicting mental stress in real-time applications. By enhancing the practical implementation of ECG-based stress measurement, our approach offers expedited and reliable stress assessment outcomes.

This research contributes to advancing the field of stress detection by introducing a robust method capable of real-time monitoring, thereby facilitating timely interventions to mitigate the adverse effects of stress on individuals' health and well-being.

II. LITERATURE REVIEW

Stress, a prevalent condition in modern society, poses significant health risks affecting both mental and physical well-being. Understanding stress and its physiological manifestations through biosignal analysis has been a focal point in research aimed at early detection and management.

Neural Regulation of Stress Responses

Ulrich-Lai and Herman [1] emphasize the neural mechanisms underlying stress responses, highlighting the intricate interplay between the central nervous system and the hypothalamic-pituitary-adrenal (HPA) axis. They discuss how chronic stress can dysregulate these systems, leading to prolonged physiological alterations detrimental to health.

Epidemiology of Stress

The American Psychological Association [2] reports on the pervasive impact of stress in American society, documenting its profound effects on physical and psychological health. The report underscores the need for effective stress management strategies to mitigate its adverse consequences.

Wearable Physiological Sensors

The integration of wearable physiological sensors for stress monitoring is explored in the study by IEEE [3], focusing on the evaluation of integrated systems that use biological markers to monitor stress levels in real-time working environments. This approach offers insights into continuous stress assessment beyond clinical settings.

Psychological Stress Detection Using Biosignals

Giannakakis et al. [7] review various methods for psychological stress detection using biosignals, highlighting the efficacy of heart rate variability (HRV) and electrocardiogram (ECG) signals in assessing stress levels. They emphasize the importance of robust feature extraction techniques and machine learning algorithms in enhancing detection accuracy.

Heart Rate Variability and Stress Assessment

Billman et al. [5] delve into the methodological considerations and clinical applications of heart rate variability (HRV) as a biomarker for stress assessment. Their review underscores HRV's sensitivity to autonomic nervous system modulation, offering valuable insights into its role in quantifying stress responses.

Machine Learning Approaches for Stress Detection

Recent advancements in machine learning have revolutionized stress detection methodologies. McDuff et al. [9] demonstrate remote stress measurement via HRV, utilizing machine learning techniques to correlate physiological responses with stress levels. Their study highlights the feasibility of real-time stress monitoring using non-invasive techniques.

Deep Learning in Stress Detection

The application of deep learning, particularly convolutional neural networks (CNNs), in stress detection is explored by various researchers [13], [14], [20]. These studies showcase CNN's effectiveness in analyzing ECG signals for automatic stress classification, paving the way for accurate and efficient stress monitoring systems.

Summary of Relevant Studies

The literature reviewed underscores the multifaceted nature of stress assessment, integrating neurophysiological insights with advanced computational techniques. Table 2.1 summarizes key studies and their contributions to stress detection using biosignals.

Table 2.1: Summary of Key Studies in Stress Detection Using Biosignals

Study	Key Findings and Contributions
Ulrich-Lai and Herman [1]	Neural regulation of stress responses and implications for chronic stress management.
American Psychological Association [2]	Epidemiological data on stress prevalence in American society and its impact on health.
IEEE [3]	Evaluation of wearable sensors for real-time stress monitoring in workplace environments.
Giannakakis et al. [7]	Review of biosignal-based techniques for psychological stress detection, emphasizing HRV and ECG analysis.
Billman et al. [5]	Methodological considerations and clinical applications of heart rate variability in stress assessment.
McDuff et al. [9]	Remote stress measurement using HRV and machine learning, enabling real-time stress monitoring.
Deep Learning Studies [13], [14], [20]	Application of CNNs in ECG-based stress classification, highlighting advancements in automated stress detection.

In conclusion, the integration of advanced biosignal analysis techniques with machine learning and deep learning approaches holds promise for enhancing the accuracy and efficiency of stress detection systems. These studies collectively contribute to the evolving landscape of stress research, emphasizing interdisciplinary collaboration and technological innovation.

III. System Architecture

In this part, we will go over the recommended techniques. Figure 3.1 depicts the total system architecture diagram.

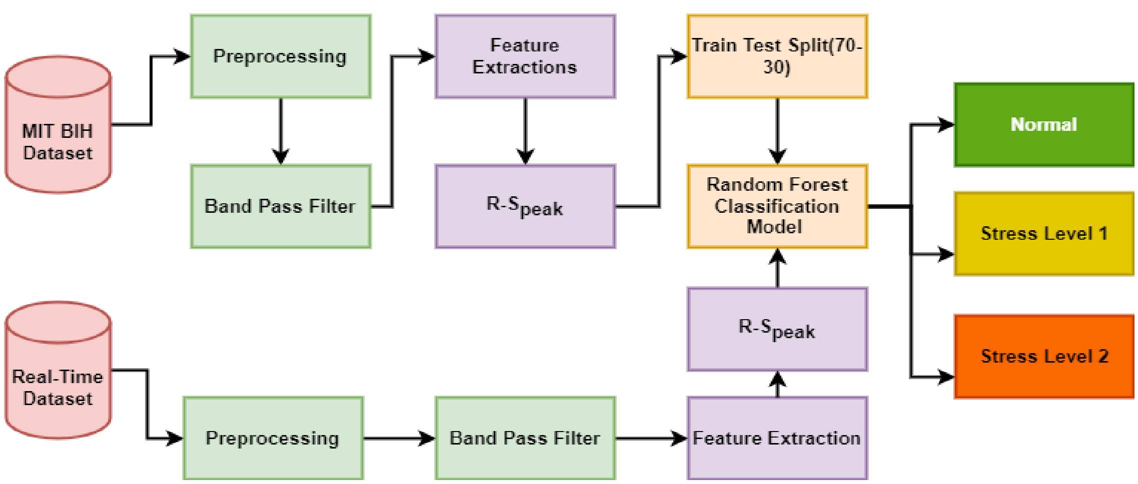

Figure 3.1: System Architecture

DATASET DESCRIPTION

Training Dataset:

The proposed study utilizes the MIT-BIH Database for training, consisting of ECG recordings from 47 patients. The database includes 23 recordings randomly selected from a collection of 4000 24-hour mobile ECG recordings gathered at Boston's Beth Israel Hospital. These recordings encompassed approximately 60% inpatients and 40% outpatients. The ECG signals were digitized at 360 bits per second per channel with an 11-bit resolution, spanning a range of 10 mV. Each record underwent individual annotation by two or more cardiologists, resolving discrepancies to provide computer-readable reference annotations for approximately 110,000 heartbeats in total.

Testing Dataset:

For real-time stress analysis, we acquired ECG signal data from renowned cardiologists in the Mumbai, India region. The dataset comprises ECG signals from 11 patients specifically for stress classification and prediction in our research. Due to space constraints, detailed data from all 11 patients cannot be included in this paper. However, Figures 3.2 and 3.3 show data from two representative patients.

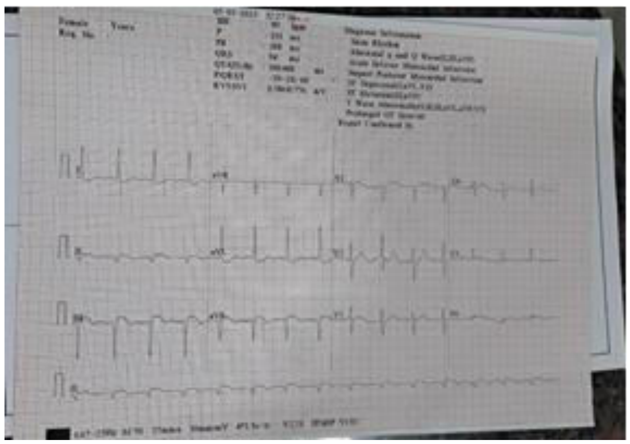

Figure 3.2: Patient 1 ECG Signal

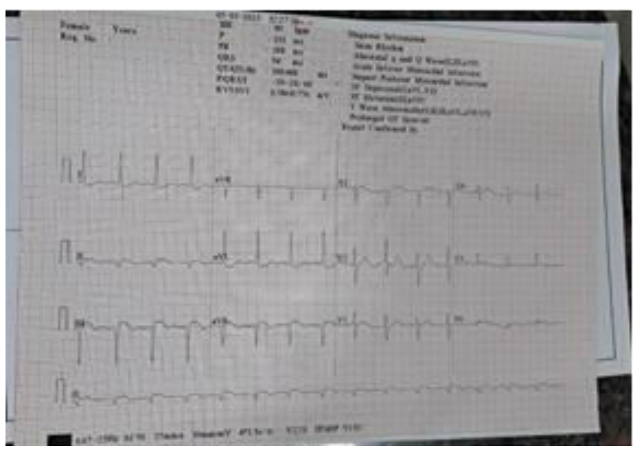

Figure 3.3: Patient 2 ECG Signal

Preprocessing and Feature Extractions

Electrocardiography (ECG) provides a non-invasive method to assess cardiac health by examining the heart's electrical activity. However, ECG signals are susceptible to noise, which can significantly degrade classification accuracy. To mitigate this, we applied a band-pass filter with a sample rate of 360 Hz and a cutoff frequency of 0.15 Hz to remove 90.89% of the noise.

Figure 3.4 illustrates R-peak values extracted from the ECG waveforms. Segmenting these data during both stressed and unstressed conditions facilitates a more robust analysis of ECG features. R-peak and S-peak values were derived from the ECG after applying a threshold. During stress, the heart exhibits irregular and rapid beats, narrowing the R-R interval and increasing the R-peak amplitude. Conversely, in non-stressful conditions, the heart typically beats steadily, resulting in a widened R-R interval and lower R-peak amplitude. The standard deviation (SD) of R-peak amplitudes during stress was 1.47 mV, whereas it was 4.25 mV during non-stressful conditions.

Figure 3.4: Feature Extraction by Threshold Values

Model Designing

We evaluated various machine learning classification models for stress categorization and selected Random Forest based on key performance metrics such as accuracy, precision, recall, and F1-Score.

Random Forest

Random Forest employs a bagging approach to enhance prediction accuracy by aggregating multiple decision trees. Each tree is trained on a different subset of data samples, and during construction, tree characteristics are chosen randomly. Predictions from multiple trees are combined via majority voting. Fine-tuning parameters such as the number of trees, minimum node size, and the number of attributes used for node partitioning can further improve the accuracy of the Random Forest model.

IV. Experimental Results

After applying the random forest model for classification of stress on 11 patients real time dataset, we found the analysis of the patient's records based on ECG signals of 30 sec ultrashort wavelength into the 3 classification stages as Normal (Stress Level 0), Moderate (Stress Level 1) and High (Stress Level 2). The results arediscussed in table 4.1.

Table 4.1: Real Time Data Stress Prediction

	BPM	P(s)	PR(s)	QRS(s)	ExecutionTime	Prediction
Patient1	90	0.111	0.188	0.04	0.17	Moderate
Patient2	91	0.102	0.186	0.099	0.21	Moderate
Patient3	86	0.115	0.185	0.089	0.19	Moderate
Patient4	64	0.101	0.159	0.092	0.14	Moderate
Patient5	48	0.116	0.18	0.09	0.28	High
Patient6	64	0.094	0.198	0.093	0.15	Normal
Patient7	86	0.081	0.152	0.067	0.21	Moderate

Patient8	106	0.072	0.151	-0.05	0.2	High
Patient9	103	0.101	0.145	0.103	0.277	Moderate
Patient10	68	0.094	0.157	0.084	0.207	Moderate
Patient11	59	0.107	0.164	0.144	0.2477	High

Out of 11 patient's ECG prediction for stress, we found only 1 patient as normal,3 patients with high stress and rest 7 patients having moderate level of stress. The Random Forest model has produced 96.73% accuracy for the stress classification and prediction when tested on real time dataset which is higher comparative with other studies with real time classification of the stress using ECG Signals.

Figure 4.1 show the stress prediction pie chart for real time dataset of 11 patients. We found that 64% patients are under moderate stress, 27% are under high stress and 9% are under normal stress.

When we done the comparative analysis with our research work with most recent research work then we found

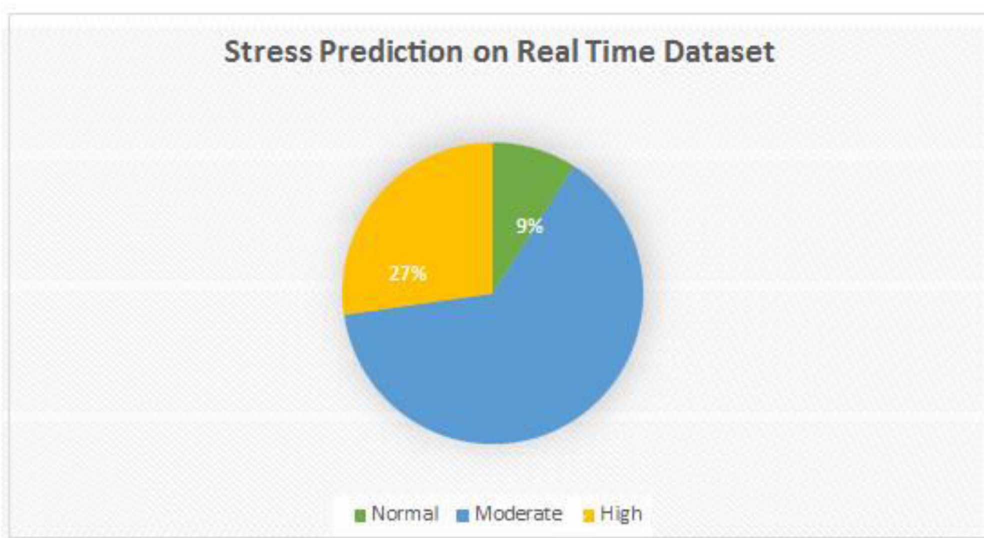

Figure 4.1: Stress prediction pie chart for real time dataset

that our model has performed better compared to all the recent research work. We are comparing on the basis of their model's performance on ECG dataset for stress classification. Following table 4.2 summarizes the comparative analysis with most recent work.

Table 4.2: Comparative Analysis of the proposed work

Reference	**Accuracy**	**Model**	**Type of Signals**	**Window Size**	**Stress Classification**
[20]	90.19	CNN	ECG	10 s	2
[21]	89.8	CNN	ECG	60 s	2
[22]	87.39	CNN-RNN	ECG	10 s	2
[23]	83.9	CNN	ECG and RSP	50 s	2
[24]	82.7	CNN	ECG	10 s	2
[25]	92.8	CNN	ECG	25 s	3
[26]	86.5	CNN-BiLSTM	ECG	10 s	3
[27]	85.45	CNN	ECG	30 s	3
[28]	80.00	SVC	ECG	60s	2
[29]	98.5	KNN	ECG	60s	2
Proposed Work	96.73	Random Forest	ECG	30s	3

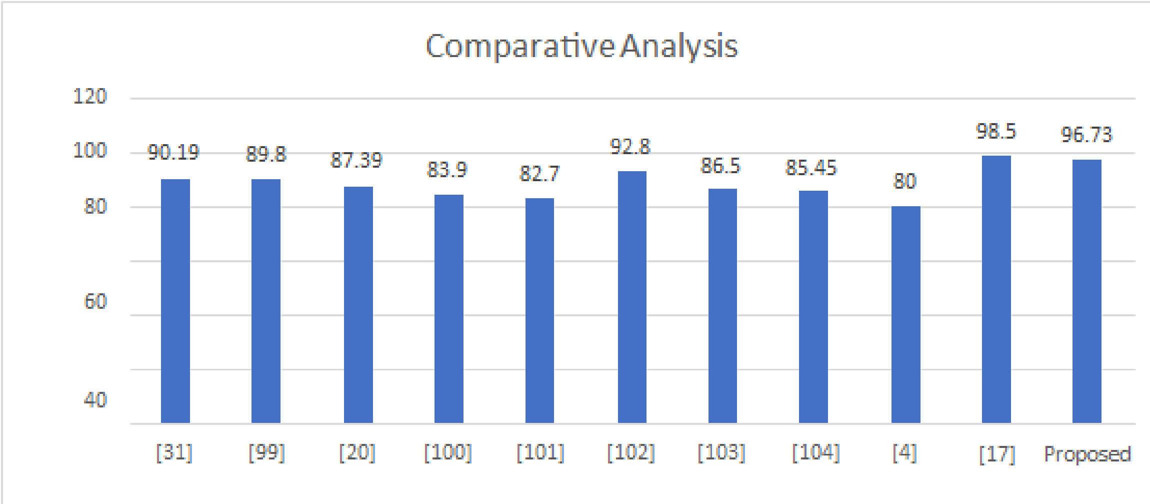

Figure 4.2 Comparative Analysis

V. CONCLUSION & FUTURE SCOPE

In our study, we leveraged the Random Forest (RF) algorithm, identified as the top-performing model during our training phase with the MIT-BIH database, to classify stress levels in real-time ECG data sourced from a cardiologist in Mumbai. The RF model achieved an impressive accuracy of 96.73% in this real-world application.

Upon testing the RF model with ECG signals from 11 patients, our findings revealed a breakdown of stress classifications as follows: one patient was categorized under normal stress levels, seven patients under moderate stress, and three patients under high stress.

This study stands out as pioneering in its application of the Random Forest algorithm for stress classification, achieving high accuracy with an average prediction time of just 0.17 seconds. These results highlight the efficacy of our approach in early stress prediction using ECG signals, contributing significantly to the field's efforts in developing robust real-time stress monitoring systems.

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