Wearable Flexible Electronics Based Cardiac Electrode for Researcher Mental Stress Detection System Using Machine Learning Models on Single Lead Electrocardiogram Signal

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Abstract: In the modern world, wearable smart devices are continuously used to monitor people's health. This study aims to develop an automatic mental stress detection system for researchers based on Electrocardiogram (ECG) signals from smart T-shirts using machine learning classifiers. We used 20 subjects, including 10 from mental stress (after twelve hours of continuous work in the laboratory) and 10 from normal (after completing the sleep or without any work). We also applied three scoring techniques: Chalder Fatigue Scale (CFS), Specific Fatigue Scale (SFS), Depression, Anxiety, and Stress Scale (DASS), to confirm the mental stress. The total duration of ECG recording was 1800 min, including 1200 min during mental stress and 600 min during normal. We calculated two types of features, such as demographic and extracted by ECG signal. In addition, we used Decision Tree (DT), Naive Bayes (NB), Random Forest (RF), and Logistic Regression (LR) to classify the intra-subject (mental stress and normal) and inter-subject classification. The DT leave-one-out model has better performance in terms of recall (93.30%), specificity (96.70%), precision (94.40%), accuracy (93.30%), and F1 (93.50%) in the intra-subject classification. Additionally, The classification accuracy of the system in classifying inter-subjects is 94.10% when using a DT classifier. However, our findings suggest that the wearable smart T-shirt based on the DT classifier may be used in big data applications and health monitoring. Mental stress can lead to mitochondrial dysfunction, oxidative stress, blood pressure, cardiovascular disease, and various health problems. Therefore, real-time ECG signals help assess cardiovascular and related risk factors in the initial stage based on machine learning techniques.

Keywords: diagnosis; decision tree; electrode; flexible electronics; machine learning; mitochondria; oxidative stress; overwork; stress; smart device

1. Introduction

Long working times are an essential issue in the world [1,2]. It leads to many disorders such as mental disorders, cerebrovascular/cardiovascular diseases, diabetes, and cancer. According to China Daily (http://www.chinadaily.com.cn/china/2016-12/11/content_27635578.htm accessed on 20 November 2021) (http://www.chinadaily.com.cn/opinion/2012-10/31/content_15859379.htm accessed on 20 November 2021) approximately six hundred thousand Chinese people die due to overwork. The International Labor Organization (http://www.ilo.org/global/topics/safety-and-health-at-work/lang--de/index.htm accessed on 20 November 2021) reported that about 2.78 million employees die yearly because of overwork. China Radio International stated that approximately 1600 people die every day because of the long-time spans in the workplace (https://www.beaconjournal.com/article/20140629/news/306299492 accessed on 20 November 2021). In Japan, 368 people have committed suicide in 5 years due to overwork. According to the Japanese government, more than 200 people died due to long working times (https://www.nupoliticalreview.com/2020/07/15/japans-vicious-death-by-overwork-cycle/ accessed on 20 November 2021) [3,4]. It is tough to calculate overwork based on the number of working hours. So, mental stress is an excellent way to detect overwork. It is a type of mental tiredness due to overwork or continuous work. Overwork is a significant source of shortening human life.

Stress is a kind of symptom of underlying sicknesses. The leading causes of stress are anemia, antihistamines, congestive heart failure, depression, hypothyroidism, insomnia, muscle exertion, narcolepsy, obesity, and tuberculosis. The main symptoms of stress are brittle hair, dry skin, polydipsia, polyuria, shortness of breath, and tiredness. It is divided into two parts such as physical stress and mental stress. Physical stress is exertion due to physical work such as lifting, playing, and running continuously for a long time.

Mental stress is prevalent at this time, related to deteriorating performance on cognitive tasks [5,6]. Mental stress also affects accidents and injuries associated with human life, such as reducing work output, making decisions, and sleeping problems. It is speculated that acute mental stress could lead to atrial and ventricular arrhythmias. Electrical signal processing techniques such as the Electrocardiogram (ECG) explain stress-induced arrhythmias through electrophysiological mechanisms. In general, stress affects the significant components of the averaged ECG signals, and the changes that are repeated long-term by stressors could lead to arrhythmias [7]. The long-term stress response of the human body releases a high level of cortisol hormone, which can increase blood pressure, blood glucose levels, cholesterol levels, and triglycerides, which are the significant risk factors for heart problems. In addition, the increased level of cortisol causes stimulation of the Sympathetic Nervous System (SNS), which organizes the activities of body functions during a rapid stress response to severe circumstances; similarly, the Parasympathetic Nervous System (PNS) has been activated during the non-stress time and normalizes body functions, including cardiac function [8,9]. The heart is the most important organ with high oxygen consumption, which is very sensitive to oxidative reactions and prone to oxidative stress [10]. There are many reasons for the increase in the production of Reactive Oxygen Species (ROS). Besides, the aging factor, mental stress, and other related factors could affect the functions of mitochondria.

On the other hand, specific molecules resembling bacterial molecules may be released by mitochondria due to disruption or damage. Based on this, our immune system may treat them as foreign bodies and trigger a harmful inflammatory response against our own cells. Stress-induced mitochondrial dysfunction may alter the dynamics of cardiac function due to changes in the electrophysiological substrate and increase susceptibility to arrhythmias [11]. Mitochondrial dysfunction or damage also increases ROS production, which reduces the ability of Adenosine Triphosphate (ATP) production due to the disruption of mitochondrial membrane potentials and altered cellular redox potential. So, these kinds of excessive ROS production can lead to cardiac arrhythmias, myocardial remodeling, and cell hypertrophy [12,13]. ECG data and diagnosis can detect most cardiac arrhythmias and cardiovascular and related diseases in the early stages. Moreover, many studies have

shown that ECG abnormalities are the sovereign interpreter for coronary artery disease and related problems [14,15].

Various researchers have detected mental stress using physiological signals such as Electroencephalogram (EEG) [16–18], Electrooculogram (EOG), ECG [19,20], and Electromyogram (EMG). Zhang et al. [21] designed convolutional and brain function-based mental stress detection using a partially directed coherence graph as a neural network classifier. Wu et al. [22] represented the pilots' stress detection using a deep learning classifier on the EEG signal. Ahmadi et al. [23] designed a wavelet-based automatic system for mental stress detection in drivers using a Support Vector Machine (SVM) based machine learning classifier. They used eye-tracking technology to record the signals. Chen et al. [24] developed the stress model of watching television using EEG signals. Monteiro et al. [25] designed a sensor fusion-based system to recognize mental stress using physiological signals, including EEG, ECG, and EMG. Zhen et al. [26] used 15 subjects between the ages of 22 to 33 to develop a detection system of mental stress on functional near-infrared spectroscopy data. Pang et al. [27] recorded the EEG signal for 25 h and concluded that the auditory vigilance task could easily recognize mental stress. Chang et al. [28] used the wireless EMG, a thermometer, and a hand dynamometer to analyze the data and detect the mental stress of security guards. Li et al. [29] used 21 features of the single-channel EEG signal to detect mental stress. Laurent et al. [30] studied that multimodal information improved the detection of mental stress using physiological signals such as EEG, ECG, and EOG. Xiao et al. [31] suggested that using brain signals, Principal Component Analysis (PCA) and SVM classifiers easily detect mental stress in manufacturing industry workers.

In addition, Le et al. [32] designed a Machine Learning (ML) framework to detect lung cancer. Ahamed et al. [33] reported an ecological etiquette for preparing Ag/RGO NCs using orange peel extract to treat cancer. Moreover, he also introduced the role of Zn-doping in the anticancer activity of Bi2O3 NPs [34]. Previously, some researchers suggested that ML is suitable for the automatic classification, prediction, and detection of psycho-neurological human behaviors [35–39]. The groups of Lai [40–46] and Siddiqui [47–50] have also used machine learning models to automatically detect sleep disorders such as bruxism and insomnia based on physiological signals.

Wearable smart devices are mainly used by humans in today's modern world. The wearable smart devices record the physiological signals, heartbeat, temperature, and time of sleeping and waking [51,52]. In the proposed study, we used a smart T-shirt to detect researchers' mental stress based on demographic and extracted features from ECG signals. We extracted nine features from the ECG signal. As per our knowledge, it is the first time to detect the researcher's mental stress. In addition, we used four machine learning classifiers: Decision Tree (DT), Naive Bayes (NB), Random Forest (RF), and Logistic Regression (LR), with four models as leave one out and three cross-validation folds, such as 10, 3, and 2. Additionally, we also used a DT classifier for inter-subject classification. We have developed an automatic real-time mental stress detection system using a single lead ECG signal of the wearable smart T-shirt. The main contributions of this study are:

(a) Introducing flexible dry electrodes based on wearable smart T-shirts to monitor researchers' health.
(b) An automatic system based on extracted features from ECG signals and demographic features for the detection of researchers' mental stress.
(c) Relationship between demographic and extracted features based on clustering technique.
(d) Comparison between different machine learning classifiers to find a suitable classification method for the automatic mental stress detection system.
(e) To achieve the average accuracy for the inter-subject (subject-wise) classification using the best performer classifier of the intra-subject (mental stress and normal) classification.

The proposed paper is organized in the standard format, such as the introduction, details of the wearable smart-shirt, materials and methods, results and discussion, and conclusion of the study.

2. Wearable Smart T-Shirt

People's health monitoring is a measurement challenge in the current world because people's health is influenced due to stressful life. We used a smart T-shirt to monitor researchers' cardiac activity. We recorded the ECG signals to develop the detection of mental stress. This device was developed by Hexin Medical Co. Ltd., Shenzhen, China. Silver-coated flexible dry electrodes with screen printing technology were used to develop this smart T-shirt. This device is capable of processing ECG signals in real-time. The processing time is less than 0.1 s for each 10 s segment with the embedded Microcontroller (MCU). It consists of a Bluetooth 4.0 model with a 2.4 GHz frequency, a 0.259-watt battery for up to 24 h of data acquisition, a smartphone, and an effective distance for data transmission of 10 m. According to the International Standards, the data packet loss rate of Bluetooth is less than 1% [53]. The sampling frequency of the ECG signal is 250 Hz. The wearable smart T-shirt works based on flexible dry electrodes and low-power ECG signals. The main function of this device is to record ECG and transfer the signal to the smartphone or other display devices. Smart clothes or textiles for the wearable system were first introduced in 1990 [54,55]. Our smart T-shirt is stationary and wearable; it has built-in textile silver-coated dry Nano electrodes. These silver-coated dry Nano electrodes are pasted on the right side, left side, and right side on the back of the chest. All electrodes are connected to the recorder base. The ECG recorder is connected to the base during the recording of the ECG signal. The recorder has a Pre-amplifier, an Analog to Digital Converter (ADC), a Nordic MCU model nRF528xx, and Bluetooth for recording, amplification, conversion, data acquisition, and transmission of the recorded ECG signal to display devices such as smartphones, laptops, and so on. All operations are performed by line-by-line command and saving the time for data acquisition. The system for ECG data acquisition by a wearable smart T-shirt is shown in Figure 1 [56,57] and the circuit module diagram of the device are mentioned in Figure 2.
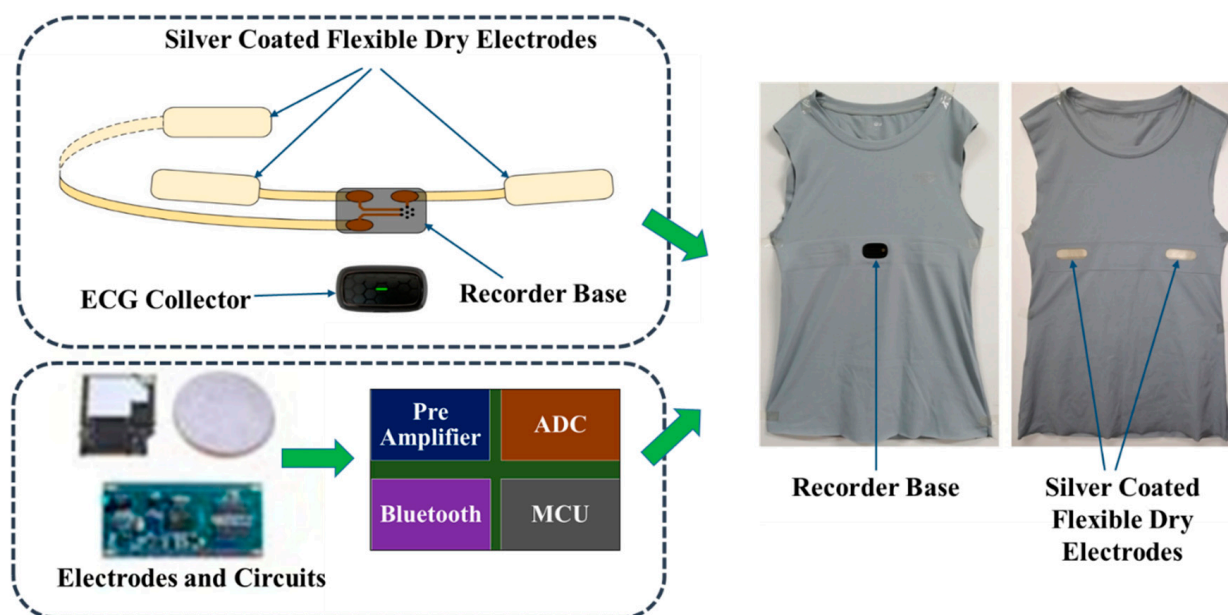
Figure 1. ECG acquisition system of the wearable smart T-shirt used in this study. A wearable smart T-shirt has three silver-coated dry electrodes, one smart textile, one recorder base, and one ECG collector [56,57]. The ECG signal is transferred through Bluetooth in display devices, such as smartphones, computers, laptops, and tablets.
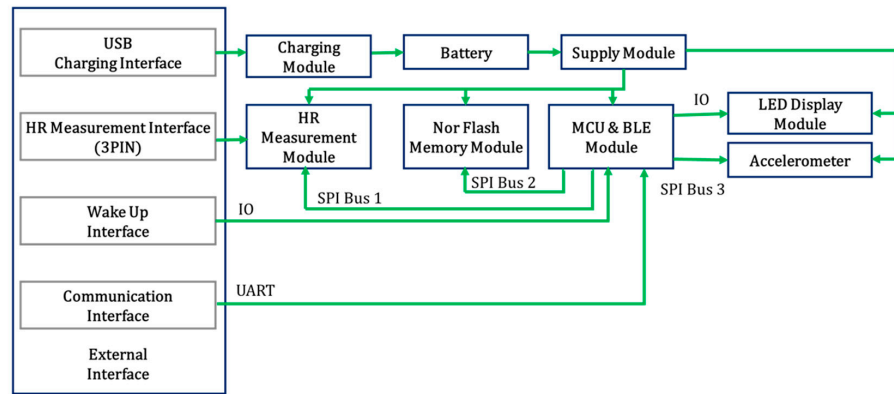
Figure 2. Circuit module diagram of the wearable smart T-shirt.

3. Materials and Methods

The proposed study was completed in some steps, such as the selection of the researchers as a subject, recording the ECG signals of the researchers in real-time from 20 subjects (mental stress and normal) using a wearable smart T-shirt, collecting the demographic features, analysis of the ECG signal, extraction of the ECG features, and classification of the intra-subject (mental stress and normal) using DT, NB, RF, and LR machine learning classifiers (Figure 3). In addition, we also used inter-subject classification using the DT machine learning classifier. This study was implemented in MATLAB 2016a and Anaconda3 (64-bit) on Windows 10.

Figure 3. Block diagram of the proposed study.

3.1. Experimental Design and Data Collection

For this proposed study, a total of twenty male researchers without mental and heart diseases were recruited from the University of Electronic Science and Technology of China, Chengdu, Sichuan, China (Table 1). Their ages ranged from 23 to 35 years, height from 162 to 187 cm, weight from 48 to 88 Kg, and Body Mass Index (BMI) from 18.289 to 29.068 Kg/m^2 with no history of medication and sleep disorders. All subjects were asked not to drink alcohol, c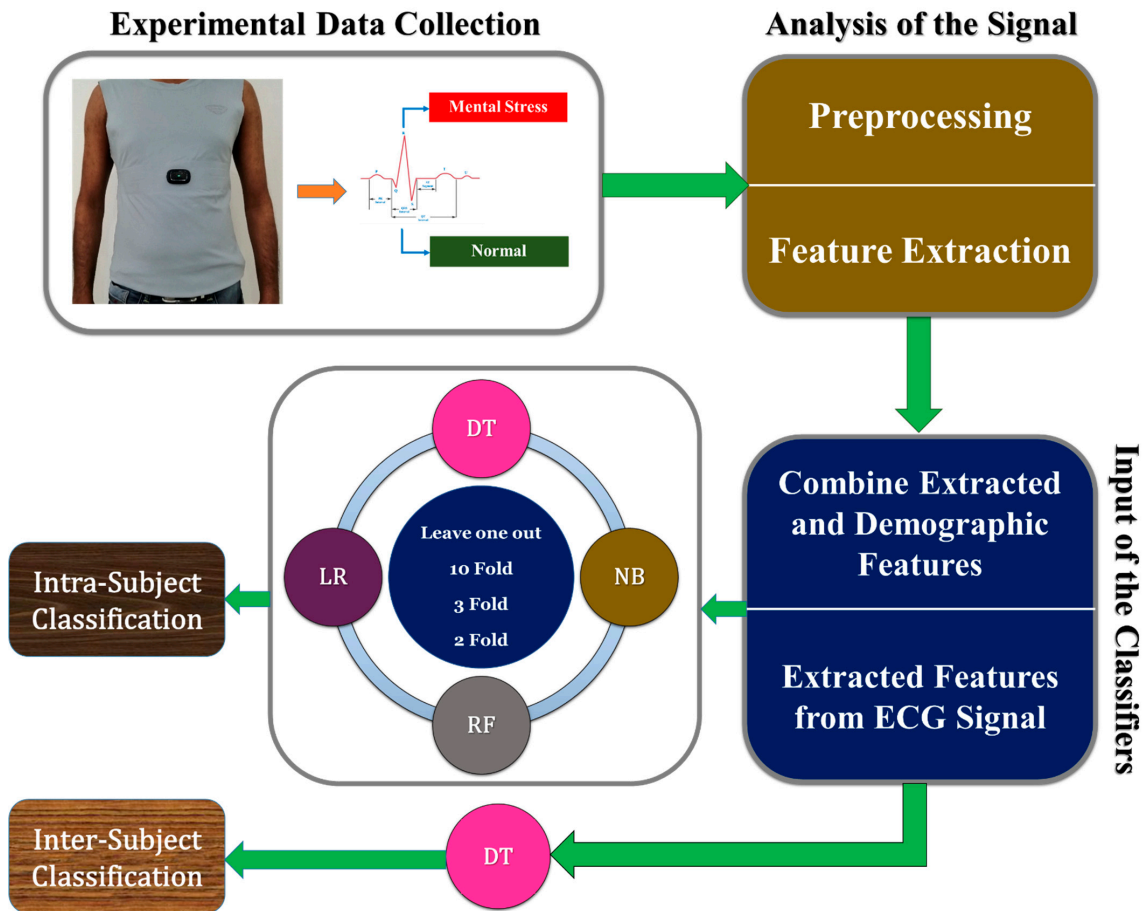offee, or tea for twelve hours before ECG recording. All subjects gave informed consent to the proposed study procedures, and the University Ethical Committee (No: 1061420210210829008) approved the proposed study. Before the experiment, each subject filled the Chalder Fatigue Scale (CFS) [58], Specific Fatigue Scale (SFS) [59], and Depression, Anxiety, and Stress Scale (DASS) [60,61] to measure the mental stress and other mental problems. Previously, the Cold Pressor Stress (CPS) test [62–66], stress determination test, Montreal imaging stress task [67,68], and DASS [60,61] have been used to detect the mental stress.

Table 1. Description of the experimental dataset.

Total No. of the Subjects (N)	20
Occupation of the Subjects	Research (Ph.D. and Research Associate)
Conditions of the Subjects	Mental Stress and Normal
Gender of the Subjects	All are Male
The total duration of the recordings (T)	1800 min
The total duration of the mental stress recordings (T$_{MF}$)	1200 min
The total duration of the normal recordings (T$_N$)	600 min

In the experiment, we used a smart T-shirt to record ECG signals. We choose the 2:1 ratio between mental stress and normal condition. We recorded the mental stress conditions after 12 h of continuous work in the laboratory. We also recorded the normal conditions after waking up in the morning when not working in the laboratory. We recorded the mental stress of the researchers at one-day intervals. This reduces the likelihood of errors in data acquisition.

3.2. Preprocessing and Features Calculation

We preprocess the ECG signal using a Fast Fourier Transform (FFT) with a low pass Finite Impulse Response (FIR) filter to remove signal noise. The demographic characteristics are computed during the experiment. Additionally, the other features are calculated during the analysis of the signal. For the demographic features, we calculated age (year), height (cm), weight (Kg), and BMI (Kg/m^2).

Heart Rate Variability (HRV) is a set of methodical evaluation indicators obtained from cardiac signals [69]. It reveals information about the variant of RR intervals of the heart [70]. It is measured to reproduce the body's capacity to adapt or modify the exogenous and endogenous impact on blood supply requirements [71]. We also calculated some features like Average Heart Rate (AHR), Mean of the RR interval (MRR), and HRV features such as Root Mean Square (RMS), Turning Point Rating (TPR), the Standard Deviation of the Heart Rate (SDHR), Root Mean Square Distance of Successive RR interval (RMSSD), several R peaks in ECG that differs more than 50 milliseconds (NN50), Percentage of the Number of R peaks in ECG that differs more than 50 milliseconds (PNN50), and Standard Deviation of the RR interval (SDRR) from ECG signal.

3.3. Classification Techniques

For this study, we used five machine learning classifiers such as DT, NB, RF, and LR, with four models such as leave one out, 10-fold, 3-fold, and 2-fold. These classifiers are well

defined: DT is a directed learning method used for regression and classification processes. Each outcome of the DT is represented in a separate leaf [72–74]. DT has two nodes in its structure: (i) the Decision node, which has multiple branches and is used to make any decision; (ii) the Leaf node, which is the output of the decision nodes without any further branches. DT is easy to understand because it mimics human thinking ability for decision making. The output of the DT algorithm can be easily represented in a tree-like structure. The main challenge of the DT is the identification of the characteristic for the root node at every level, which is called attribute determination. We used a minimum induce binary tree with two number of instances in leaves in our DT classifier.

NB classifier is based on the Bayes theorem with free expectations between predictors. It is easy to build without difficult iterative parameter estimation, making it individually useful for massive datasets [38]. Bayes theorem provides the calculation of posterior probability from the prior probability of target, the prior probability of predictor, and the probability of predictor given target. NB classifier accepts the effect of the value of a prior probability of predictor on a given target.

RF is an ensemble learning technique for regression, classification, and other works. It constructs a multitude of trees in training and output based on a single tree [75,76]. We used ten number of trees and five number of attributes considered at each split.

LR is a linear method to make the relationship between the dependent and independent variables. The independent variable event is called simple linear regression. The LR models frequently fit using the least square method. LR was the first type of regression analysis to be used rigorously in real-time applications [77].

3.4. Performance Evaluation of the Proposed System

We used DT, NB, RF, and LR classifiers with leave one out, 10-fold, 3-fold, and 2-fold models for the intra-subject (mental stress and normal) classification. We also used two inputs, such as nine features including AHR, MRR, and seven HRV, and thirteen features including AHR, MRR, seven HRV, and four demographic features, of the classifiers. In addition, we also classify the inter-subject classification using the DT classifier based on the leave one out model. We obtained some performance measures such as recall, specificity, precision, accuracy, F1, and Area Under the Curve (AUC) [42,43,78,79]. The standard performance measures are described in Equations (1)–(5).

$$recall = \left(\frac{TP}{TP + FN} \right) \tag{1}$$

$$specificity = \left(\frac{TN}{FP + TN} \right) \tag{2}$$

$$precision = \left(\frac{TP}{TP + FP} \right) \tag{3}$$

$$accuracy = \left(\frac{TP + TN}{TP + FP + TN + FN} \right) \tag{4}$$

$$F1 = \left(\frac{2 \times recall \times precision}{recall + precision} \right) \tag{5}$$

where *TP* is the true positive, *TN* is the true negative, *FP* is the false positive, and *FN* is the false negative.

3.5. Normalization Method

The common normalization aspects used for HRV comprise the variance of the R-R interval and the length of the data segment evaluated. The variance is statistically equal to the total power of the RR interval in the time series [44,80]. It is the standard method used before classification to normalize the value of the feature.

3.6. Statistical Analysis

Statistical analysis is very important for the significant difference. We applied the *t*-test to check the significant difference between the model performances [81–85]. We set the value of $p < 0.05$. If the probability is less than 0.05, the difference is significant; otherwise, it is not significant.

4. Results and Discussion

Progressively, most studies indicate that heart problems and related diseases are predicted based on abnormalities in the ECG [86,87]. In general, the corrected QT interval (QTc) is the most important pathological finding in the ECG. Whether a person has a heart problem or not, QTc calculation is used to predict cardiovascular mortality because the QT interval reflects ventricular repolarization and depolarization based on the heartbeat [88,89]. Furthermore, most diseases in which there is an association between QTc prolongation and cardiovascular mortality are due to the fatal ventricular arrhythmias caused by QTc prolongation because of the early development of ventricular depolarization. Some recent studies confirm the association between cardiovascular mortality and QTc prolongation in patients with type 2 diabetes mellitus [90,91].

Mitochondrial dysfunction leads to oxidative stress, which is associated with various pathological processes in many metabolic diseases such as diabetes mellitus, age-related disorders associated with cardiovascular mortality and morbidity, and death [92,93]. Also, in mental stress and mental trauma, mitochondrial dysfunction affects many physiological functions of the endocrine system, nervous system, and immune system, which plays a significant role in allostatic and stress pathophysiology, leading to various types of health problems [94–96].

Psychological stress generally influences cardiovascular diseases such as coronary heart disease. In 1910, *Obraztsov* and *Strazhesko* first time described that coronary thrombosis and negative emotions could trigger the development of acute myocardial infarction. Schwartz et al. [97] described that terrorist attacks, wars, natural disasters, and financial crises are among the stressful, life-threatening events and positive emotions, such as sports competitions, Christmas and New Year, etc., that have been diagnosed as crucial triggers of cardiovascular risks and related problems in susceptible persons. According to the interheart case-control study, negative psychosocial factors also represent variable risk factors associated with adverse cardiovascular prognosis and mortality [98]. De Vente et al. [99] also mentioned that most metabolic syndromes are caused by work-related stress. Significantly, male workers suffering from fatigue and psychological stress have shortened parasympathetic activity, increased sympathetic activity, and decreased Hypothalamic Pituitary Adrenal (HPA) axis response. This work-related stress can also lead to dysregulation of mitochondria and sympathetic-vagal balance. In addition, this type of mental stress stimulates the activity of the sympathetic nervous system and leads to changes in cardiac arrhythmias and a reduction in the occurrence of atrial and ventricular arrhythmias; these variations lead to changes in ECG signals based on the cardiac repolarization phase [100]. So, if a person has cardiovascular problems or has no symptoms, it is recommended to examine his heart functions by ECG and echocardiography to identify and treat the problems and other metabolic disorders as soon as possible [35,101]. Therefore, this study was designed to assess the mental stress of scientific researchers in real-time using ECG signals to evaluate cardiovascular risk factors and associated problems based on machine learning techniques.

4.1. Analysis of the Signal

We used real-time researchers' ECG signals in both mental stress and normal conditions (Figure 4). We used 20 subjects of the ECG signal for a total of 1800 min with one-minute data segmentation in this study. Besides, the sampling rate of the ECG signals is 250 Hz. In the preprocessing of the ECG signal, we removed the lower frequencies of the ECG signal using FFT and eliminated the noise of the ECG signal using a low pass FIR

filter (Figure 5). The FIR filters are designed by finite-length approximation to an ideal impulse response of infinite-length in the mean square sense obtained by truncation. The number of tabs used is 143. Therefore, the order of the filter is 142. A rectangular window function is used and the cut-off frequency is 50 Hz.
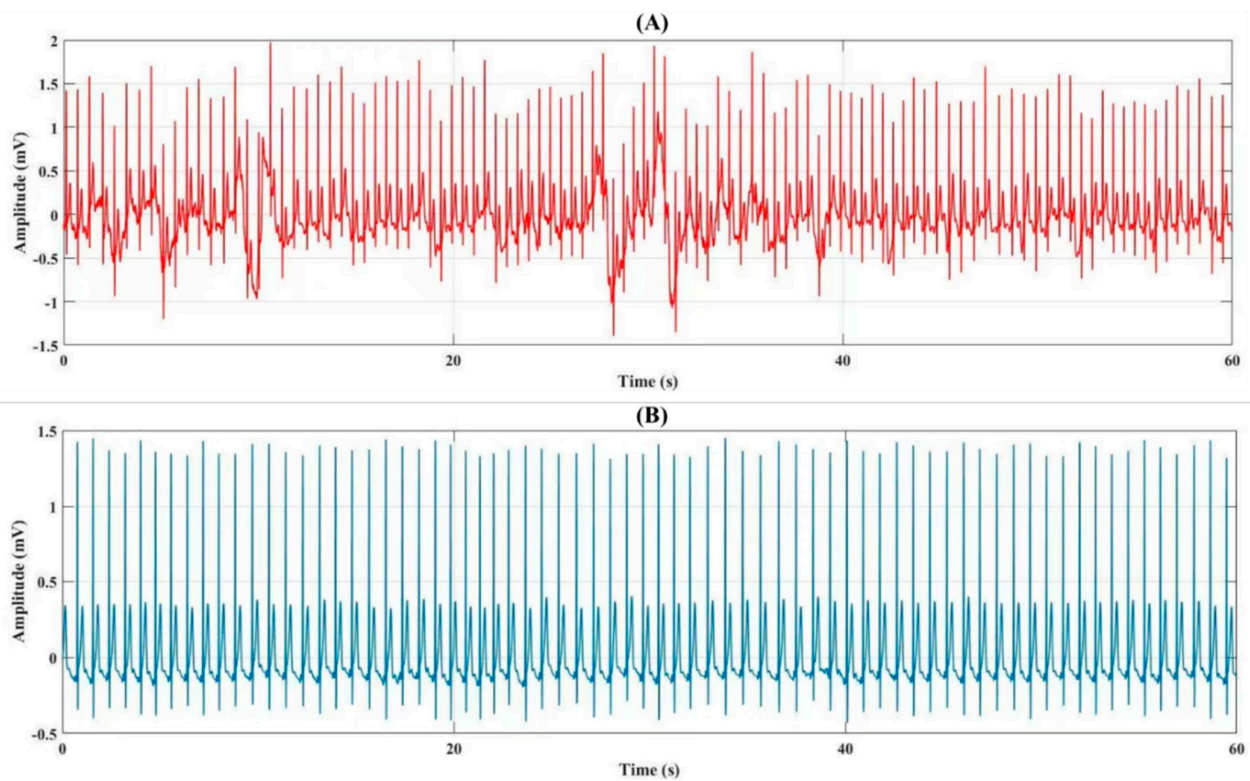
Figure 4. One minute signal representation of the single-lead raw ECG signal from (**A**) mental stress and (**B**) normal subjects.
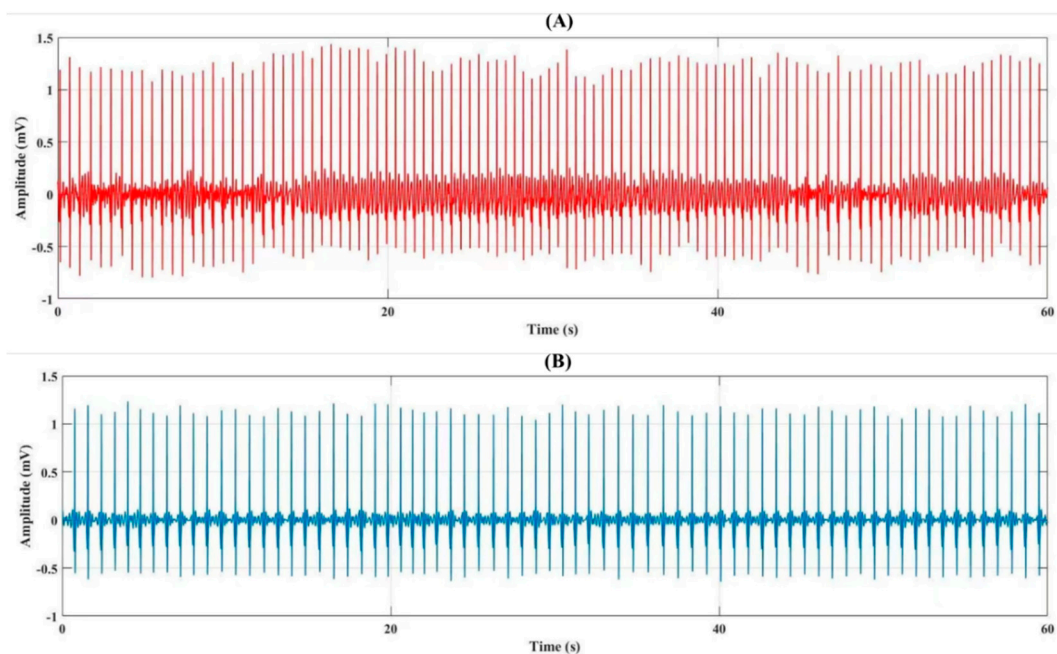
Figure 5. One minute signal representation of the single-lead filtered ECG signal from (**A**) mental stress and (**B**) normal subjects.

The advantages of FIR are: (i) they allow maintaining the exact linear phase between input and output signals, and (ii) the filter transfer function always remains stable with quantized coefficients. However, FIR filters suffer from higher computational complexity than their Infinite Impulse Response (IIR) counterparts. Nevertheless, the use of FIR filters should not be a problem unless the designer has a choice between digital signal processors and computers. We designed the relationship of the features using the heat map shown in Figure 6, which is based on clustering techniques.
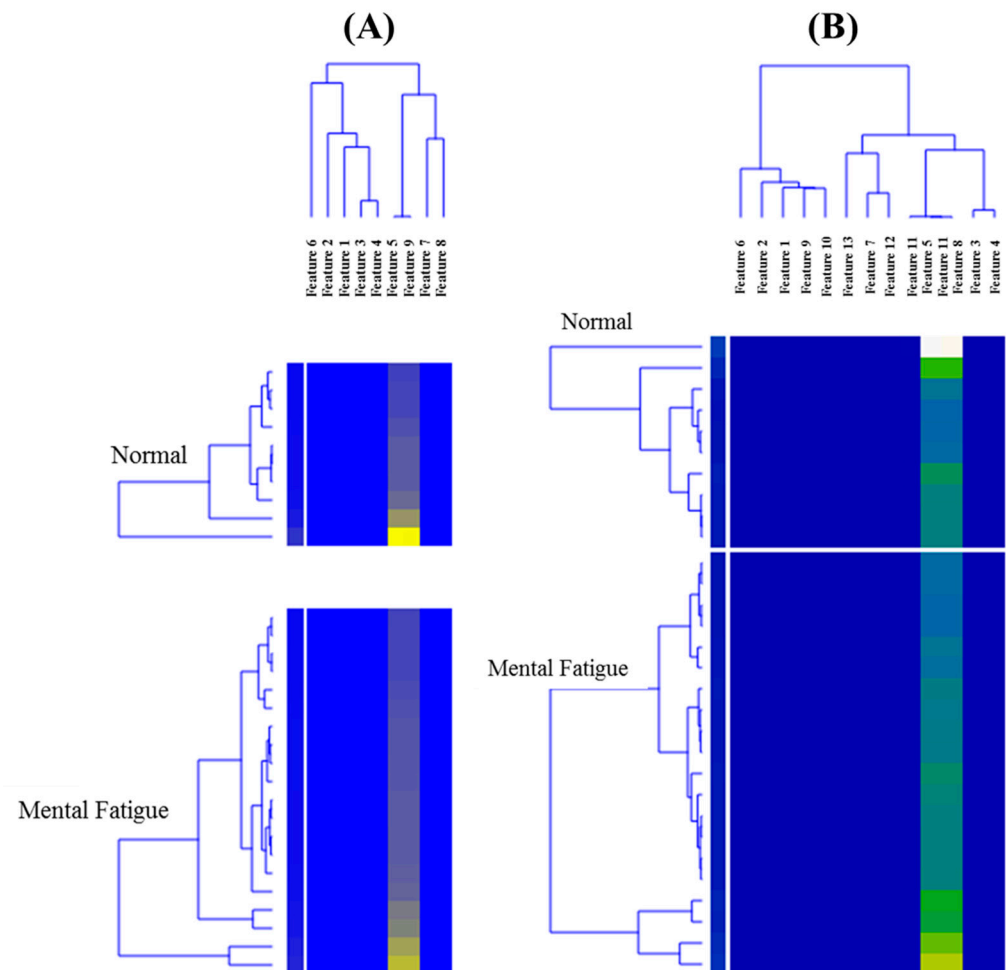
Figure 6. Heat map of the (**A**) AHR, MRR, and seven HRV features, and (**B**) AHR, MRR, seven HRV, and four demographics from mental stress and normal subjects. It showed the relationship between the two features of the subjects, including mental stress and normal.

4.2. Intra-Subject (Mental Stress and Normal) Classification Results of the Proposed System

We used four classifiers such as DT, NB, RF, and LR classifiers with four models: leave one out, 10-fold, 3-fold, and 2-fold for the classification of mental stress and normal subject. Besides, we used two types of inputs for the classifier: (i) AHR, MRR, and seven HRV features, and (ii) AHR, MRR, seven HRV, and four demographic features.

The system's performance using AHR, MRR, and seven HRV features are mentioned in Table 2. The DT leave one out model that achieved the highest performance in terms of recall, specificity, precision, accuracy, and F1, which were found to be 0.933, 0.967, 0.944, 0.933, and 0.935, respectively. The NB 3-fold model achieved the lowest performance in terms of recall, specificity, precision, accuracy, and F1, which were 0.467, 0.333, 0.467, 0.467, and 0.467, respectively. Additionally, the average performance with ±Standard Deviation (SD) in terms of recall, specificity, precision, accuracy, F1, and AUC was found to be 0.664 ± 0.136, 0.597 ± 0.165, 0.679 ± 0.132, 0.664 ± 0.136, 0.661 ± 0.134, and 0.676 ± 0.173,

respectively. However, it indicates that the LR classifier has good performances in three models such as 10-fold, 3-fold, and 2-fold. In addition, the NB classifier has poor performances in all models. The Receiver Operating Characteristics (ROC) curve of the models using AHR, MRR, and seven HRV features is mentioned in Figure 7.

Table 2. Performance of the intra-subject (mental stress and normal) classification using nine features, including AHR, MRR, and seven HRV features.

Model	Classifier	Recall	Specificity	Precision	Accuracy	F1	AUC
Leave one out	**DT**	**0.933**	**0.967**	**0.944**	**0.933**	**0.935**	0.990
	NB	0.733	0.817	0.807	0.733	0.741	0.840
	RF	0.900	0.800	0.913	0.900	0.895	1.000
	LR	0.800	0.700	0.795	0.800	0.794	0.835
10-fold	DT	0.567	0.483	0.577	0.567	0.571	0.540
	NB	0.533	0.467	0.556	0.533	0.542	0.570
	RF	0.633	0.467	0.607	0.633	0.614	0.530
	LR	0.700	0.550	0.683	**0.700**	0.684	0.630
3-fold	DT	0.467	0.483	0.533	0.467	0.481	0.530
	NB	0.467	0.333	0.467	0.467	0.467	0.410
	RF	0.633	0.467	0.607	0.633	0.614	0.435
	LR	0.767	0.683	0.762	**0.767**	0.763	0.815
2-fold	DT	0.667	0.433	0.628	0.667	0.617	0.680
	NB	0.500	0.550	0.579	0.500	0.512	0.633
	RF	0.633	0.667	0.689	0.633	0.644	0.692
	LR	0.700	0.700	0.729	**0.700**	0.707	0.700
Average		0.664	0.597	0.679	**0.664**	0.661	0.676
±Standard Deviation		0.136	0.165	0.132	**0.136**	0.134	0.173

The performance of the system using AHR, MRR, seven HRV, and four demographic features are mentioned in Table 3. The DT leave one out model achieved the highest performance in terms of recall, specificity, precision, accuracy, and F1, which were found to be 0.933, 0.967, 0.944, 0.933, and 0.935, respectively. The NB 10-fold model achieved the lowest performance in terms of recall, specificity, precision, accuracy, and F1, which were 0.400, 0.450, 0.481, 0.400, and 0.411, respectively. Additionally, the average performance with ± SD in terms of recall, specificity, precision, accuracy, F1, and AUC was found to be 0.656 ± 0.148, 0.603 ± 0.166, 0.677 ± 0.138, 0.656 ± 0.148, 0.654 ± 0.145, and 0.673 ± 0.185, respectively. However, it indicates that the LR classifier has good performances in three models such as 10-fold, 3-fold, and 2-fold. In addition, the NB classifier has poor performances in all models. The ROC curve of the models using AHR, MRR, seven HRV, and four demographic features are shown in Figure 8.
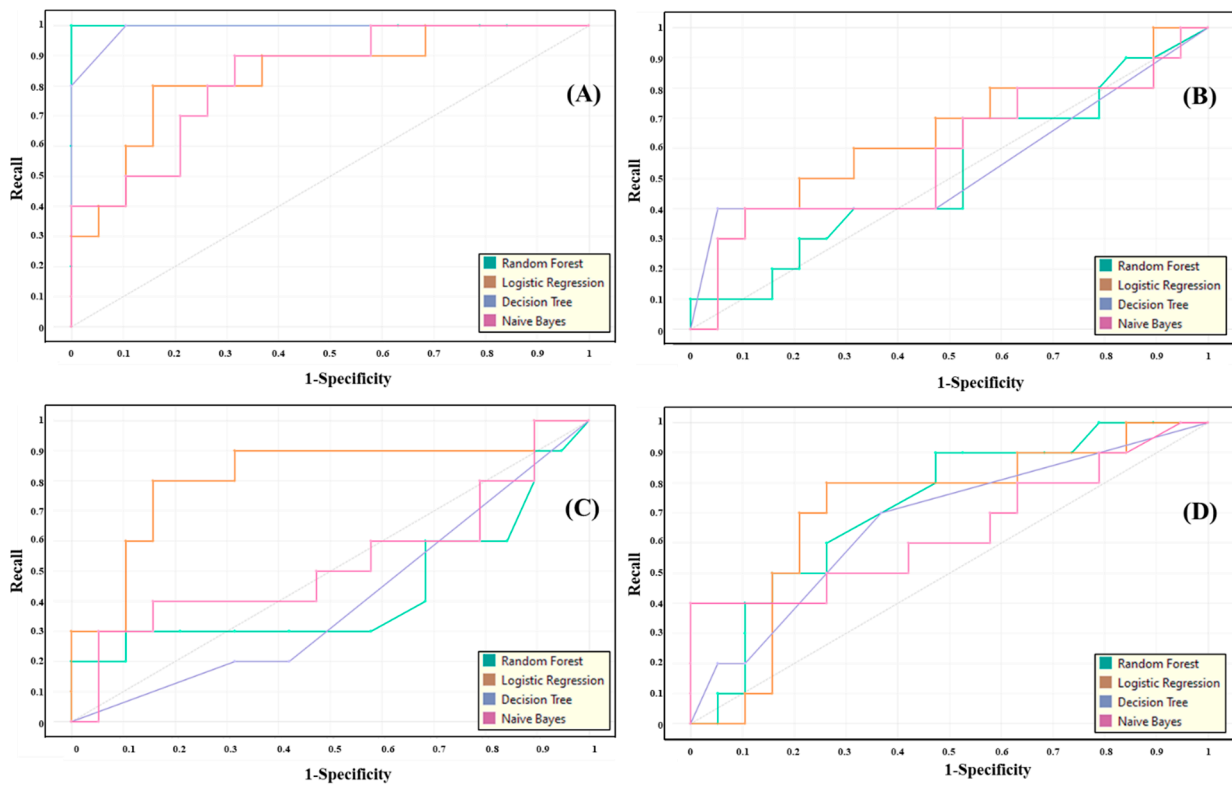
Figure 7. ROC curves of the intra-subject (mental stress and normal) classification with models such as (**A**) leave one out, (**B**) 10-fold, (**C**) 3-fold, and (**D**) 2-fold on nine features extracted by the ECG signal.

Table 3. Performance of the intra-subject (mental stress and normal) classification using thirteen features, including AHR, MRR, seven HRV, and four demographic features.

Model	Classifier	Recall	Specificity	Precision	Accuracy	F1	AUC
Leave one out	DT	**0.933**	**0.967**	**0.944**	**0.933**	**0.935**	0.990
	NB	0.733	0.817	0.807	0.733	0.741	0.840
	RF	0.867	0.733	0.889	0.867	0.856	1.000
	LR	0.867	0.833	0.867	0.867	0.867	0.880
10-fold	DT	0.567	0.483	0.577	0.567	0.571	0.550
	NB	0.467	0.433	0.512	0.467	0.481	0.495
	RF	0.633	0.467	0.607	0.633	0.614	0.573
	LR	0.733	0.617	0.723	**0.733**	0.725	0.685
3-fold	DT	0.500	0.400	0.512	0.500	0.505	0.438
	NB	0.400	0.450	0.481	0.400	0.411	0.440
	RF	0.567	0.433	0.556	0.567	0.561	0.418
	LR	0.733	0.667	0.733	**0.733**	0.733	0.790
2-fold	DT	0.667	0.433	0.628	0.667	0.617	0.680
	NB	0.500	0.600	0.608	0.500	0.505	0.537
	RF	0.633	0.617	0.664	0.633	0.642	0.737
	LR	0.700	0.700	0.729	**0.700**	0.707	0.730
Average		0.656	0.603	0.677	**0.656**	0.654	0.673
±Standard Deviation		0.148	0.166	0.138	**0.148**	0.145	0.185
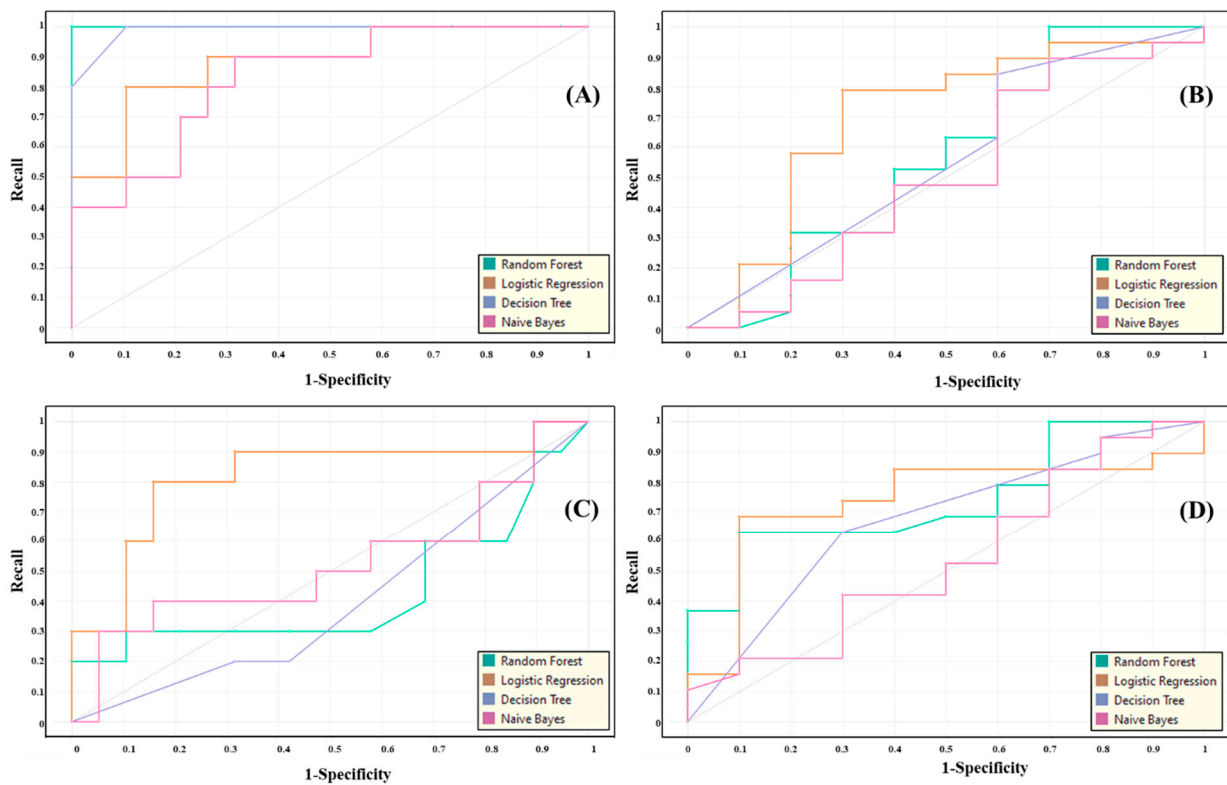
Figure 8. ROC curves of the intra-subject (mental stress and normal) classification with models such as (**A**) leave one out, (**B**) 10-fold, (**C**) 3-fold, and (**D**) 2-fold on thirteen features, including demographic and extracted through ECG signal.

4.3. Performance of the Inter-Subject Classification Using DT Classifier

We found that the DT classifier for the leave one out model based on both inputs had maximum accuracy in the system. However, we applied the DT classifier for the inter-subject classification mentioned in Table 4. The average performance (inter-subject) measures in terms of recall, specificity, precision, accuracy, F1, and AUC was found to be 0.938, 0.964, 0.947, 0.941, 0.939, and 0.990, respectively.

Table 4. Performance of the inter-subject (subject-wise) classification using DT classifier for the leave leave-one-out model.

Subject	Recall	Specificity	Precision	Accuracy	F1	AUC
Normal 1	0.966	0.984	0.969	0.966	0.966	0.997
Normal 2	0.966	0.984	0.969	0.966	0.966	0.994
Normal 3	0.931	0.969	0.944	0.931	0.933	0.989
Normal 4	0.931	0.969	0.944	0.931	0.933	0.989
Normal 5	0.931	0.969	0.944	0.931	0.933	0.989
Normal 6	0.931	0.969	0.944	0.931	0.933	0.989
Normal 7	0.931	0.969	0.944	0.931	0.933	0.989
Normal 8	0.966	0.984	0.969	0.966	0.966	0.994
Normal 9	0.931	0.969	0.944	0.931	0.933	0.989
Normal 10	0.931	0.969	0.944	0.931	0.933	0.989
Mental Stress 1	0.964	0.980	0.968	0.964	0.965	0.997
Mental Stress 2	0.929	0.960	0.940	0.989	0.930	0.989

Table 4. *Cont.*

Subject	Recall	Specificity	Precision	Accuracy	F1	AUC
Mental Stress 3	0.929	0.916	0.929	0.929	0.929	0.986
Mental Stress 4	0.929	0.960	0.940	0.929	0.930	0.989
Mental Stress 5	0.929	0.916	0.929	0.929	0.929	0.986
Mental Stress 6	0.929	0.960	0.940	0.929	0.930	0.989
Mental Stress 7	0.929	0.960	0.940	0.929	0.930	0.989
Mental Stress 8	0.929	0.960	0.940	0.929	0.930	0.986
Mental Stress 9	0.929	0.960	0.940	0.929	0.930	0.989
Mental Stress 10	0.964	0.980	0.968	0.964	0.965	0.997
Average	**0.938**	**0.964**	**0.947**	**0.941**	**0.939**	**0.990**
±Standard Deviation	0.015	0.018	0.012	0.018	0.014	0.003

4.4. Comparison between Proposed and Previously Selected Methods

Machine learning technique is the one type of application of artificial intelligence. It is used in the different areas of human research, from early prediction to treatment. In mental stress, we have used DT, NB, RF, and LR machine learning classifiers to detect the researchers' mental stress. Researchers are an essential part of modern societies. Without their help, it is impossible to obtain emerging technology. We used a wearable smart T-shirt to record the researchers' ECG signals, and this device can easily record the signals without any problem. Previously, many researchers have used different wearable smart devices to record the physiological signals to detect the mental stress of the assembly-line operators, brain-injured patients, drivers, equipment operators, pilots, security guards, and traffic controllers [28,31,102–105]. They employed various techniques to find a more accurate detection system using wearable smart devices such as SYMTOP NT9200, NI USB-6008, ST-BTA, Storm 3G Ranger X, ADS1292R, Emotiv EPOC, and HD-BTA (Table 5). Various kinds of stress may facilitate atrial and ventricular arrhythmias. Evaluation of ECG signals related to stress symptoms may provide systematic evidence for further studies to improve cardiovascular and related therapy. Our analysis achieved the maximum accuracy (intra-subject classification: 93.30% and inter-subject classification: 94.10%) compared with the previous mental stress detection system based on intra-subject (mental stress vs. normal) and inter-subject classifications (Figure 9).

Table 5. Comparison between previously selected and proposed methods.

Reference	Year	Subject	Recording Device	Signal	Accuracy
Huang et al. [105]	2018	35	ADS1292R	ECG	75.50
Xiao et al. [31]	2018	5	Emotiv EPOC	EEG	77.12
Son et al. [106]	2018	32	AgCl Electrodes	EEG, EOG, EMG	72.00
Hasan et al. [107]	2019			EEG	73.00
Proposed (Intra-subject)		20	**Smart T-Shirt**	**ECG**	**93.30**
Proposed (Inter-subject)					**94.10**
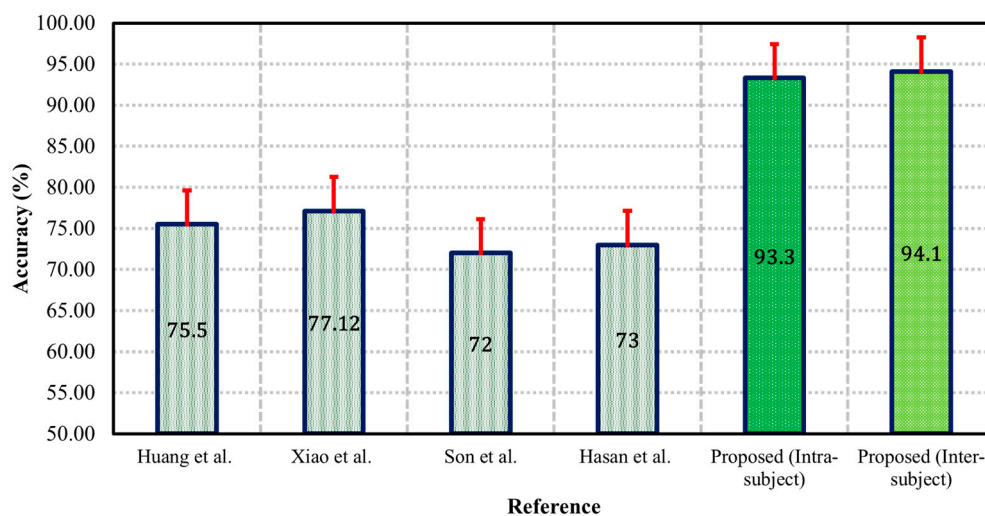
Figure 9. Comparison between previously published and proposed accuracy of the system.

4.5. Applications and Limitations of the Proposed Study

The proposed work shows the application for researchers' mental stress using a wearable smart T-shirt. The DT and LR machine learning classifiers easily classify both mental stress and normal conditions using ECG signals. The proposed system would provide a more accurate, reliable, and efficient automatic system for detecting mental stress. It is used in the assessment of sleep quality, prediction of the Sudden Cardiac Death (SCD), detection of the heartbeat, sleep disorder, premature beat, mental stress of human beings, and associated metabolic syndromes [45,108–112]. This system will help doctors save harmful diseases and increase the efficiency of their work.

The proposed work has some limitations, such as gender equality, the number of subjects, and only one psychological signal, because it is difficult to find volunteers for the study in the given time and also in the current COVID-19 epidemic policy. We also discussed mental stress and its association with mitochondrial dysfunction leading to cardiovascular diseases such as atrial and ventricular arrhythmias and associated problems to illustrate the importance of this study. In addition, there is the possibility of over-fitting all models due to the limited sample size, the fact that the subjects are relatively young and healthy, and that this is a group of scientific researchers different from a group of truck drivers, etc.

5. Conclusions

Mental stress is prevalent in the modern world and is related to reduce performance on cognitive tasks. This proposed study has developed an automatic detection system for the researchers' mental stress using an ECG signal recorded by a wearable smart T-shirt. The obtained results show that the DT classifier achieved the highest accuracy (93.30%) for intra-subject classification. In addition, the inter-subject classification of the DT classifier has a 94.10% average accuracy. This system is more efficient and easier to monitor the cardiac signal, especially for the researchers in this study. To the best of our knowledge, the proposed system is better than the previously selected systems using wearable smart devices. In the future, an automatic detection system for psycho-neurological human behaviors based on mitochondrial dysfunction and anxiety using physiological signals could be planned to save researchers from harmful diseases with a large number of subjects.

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References

1. Kim, I.; Koo, M.J.; Lee, H.E.; Won, Y.L.; Song, J. Overwork-related disorders and recent improvement of national policy in South Korea. *J. Occup. Health* **2019**, *61*, 288–296. [CrossRef] [PubMed]
2. Yamauchi, T.; Yoshikawa, T.; Takamoto, M.; Sasaki, T.; Matsumoto, S.; Kayashima, K.; Takeshima, T.; Takahashi, M. Overwork-related disorders in Japan: Recent trends and development of a national policy to promote preventive measures. *Ind. Health* **2017**, *55*, 293–302. [CrossRef] [PubMed]
3. Asgari, B. Karoshi and Karou-jisatsu in Japan: Causes, statistics and prevention mechanisms. *Asia Pacific Bus. Econ. Perspect.* **2016**, *4*, 49–72.
4. Ke, D.S. Overwork, stroke, and karoshi-death from overwork. *Acta Neurol Taiwan* **2012**, *21*, 54–59. [PubMed]
5. Chaudhuri, A.; Behan, P.O. Fatigue in neurological disorders. *Lancet* **2004**, *363*, 978–988. [CrossRef]
6. Kroemer, K.H.E.; Grandjean, E. *Fitting the Task to the Human: A Textbook of Occupational Ergonomics*; CRC Press: Boca Raton, FL, USA, 1997; ISBN 020348391X.
7. Lampert, R. ECG signatures of psychological stress. *J. Electrocardiol.* **2015**, *48*, 1000–1005. [CrossRef]
8. Von Rosenberg, W.; Chanwimalueang, T.; Adjei, T.; Jaffer, U.; Goverdovsky, V.; Mandic, D.P. Resolving Ambiguities in the LF/HF Ratio: LF-HF Scatter Plots for the Categorization of Mental and Physical Stress from HRV. *Front. Physiol.* **2017**, *8*, 360. [CrossRef]
9. Ishaque, S.; Khan, N.; Krishnan, S. Trends in Heart-Rate Variability Signal Analysis. *Front. Digit. Health* **2021**, *3*, 639444. [CrossRef]
10. Giordano, F.J. Oxygen, oxidative stress, hypoxia, and heart failure. *J. Clin. Investig.* **2005**, *115*, 500–508. [CrossRef]
11. Zhou, L.; Solhjoo, S.; Millare, B.; Plank, G.; Abraham, M.R.; Cortassa, S.; Trayanova, N.; O'Rourke, B. Effects of regional mitochondrial depolarization on electrical propagation: Implications for arrhythmogenesis. *Circ. Arrhythmia Electrophysiol.* **2014**, *7*, 143–151. [CrossRef]
12. Terman, A.; Brunk, U.T. The Aging Myocardium: Roles of Mitochondrial Damage and Lysosomal Degradation. *Heart Lung Circ.* **2005**, *14*, 107–114. [CrossRef] [PubMed]
13. Saadeh, K.; Fazmin, I.T. Mitochondrial Dysfunction Increases Arrhythmic Triggers and Substrates; Potential Anti-arrhythmic Pharmacological Targets. *Front. Cardiovasc. Med.* **2021**, *8*, 646932. [CrossRef] [PubMed]
14. Balsam, P.; Lodziński, P.; Tymińska, A.; Ozierański, K.; Januszkiewicz, Ł.; Główczyńska, R.; Wesołowska, K.; Peller, M.; Pietrzak, R.; Książczyk, T.; et al. Study design and rationale for biomedical shirt-based electrocardiography monitoring in relevant clinical situations: ECG-shirt study. *Cardiol. J.* **2018**, *25*, 52–59. [CrossRef]
15. Desai, C.S.; Ning, H.; Soliman, E.Z.; Burke, G.L.; Shea, S.; Nazarian, S.; Lloyd-Jones, D.M.; Greenland, P. Electrocardiographic abnormalities and coronary artery calcium for coronary heart disease prediction and reclassification: The Multi-Ethnic Study of Atherosclerosis (MESA). *Am. Heart J.* **2014**, *168*, 391–397. [CrossRef] [PubMed]
16. Pei, D.; Burns, M.; Chandramouli, R.; Vinjamuri, R. *Neural Decoding of Upper Limb Movements Using Electroencephalography*; Springer: Cham, Switzerland, 2020.
17. Bin Heyat, B.; Hasan, Y.M.; Siddiqui, M.M. EEG signals and wireless transfer of EEG Signals. *Int. J. Adv. Res. Comput. Commun. Eng.* **2015**, *4*, 10–12. [CrossRef]
18. Pal, R.; Bin Heyat, M.B.; You, Z.; Pardhan, B.; Akhtar, F.; Jafar Abbas, S.; Guragai, B.; Acharya, K. Effect of Maha Mrityunjaya HYMN Recitation on Human Brain for the Analysis of Single EEG Channel C4-A1 Using Machine Learning Classifiers on Yoga Practitioner. In Proceedings of the 2020 17th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), Chengdu, China, 18–21 December 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 89–92.

19. Fifer, M.S.; Milsap, G.W.; Greenwald, E.; McMullen, D.P.; Anderson, W.S.; Thakor, N.V.; Crone, N.E.; Vinjamuri, R. Design and implementation of a human ECoG simulator for testing brain-machine interfaces. In Proceedings of the 2013 6th International IEEE/EMBS Conference on Neural Engineering (NER), San Diego, CA, USA, 6–8 November 2013.

20. Lai, D.; Zhang, Y.; Zhang, X.; Su, Y.; Bin Heyat, M.B. An Automated Strategy for Early Risk Identification of Sudden Cardiac Death by Using Machine Learning Approach on Measurable Arrhythmic Risk Markers. *IEEE Access* **2019**, *7*, 94701–94716. [CrossRef]

21. Zhang, W.; Wang, F.; Wu, S.; Xu, Z.; Ping, J.; Jiang, Y. Partial directed coherence based graph convolutional neural networks for driving fatigue detection. *Rev. Sci. Instrum.* **2020**, *91*, 074713. [CrossRef]

22. Wu, E.Q.; Deng, P.Y.; Qu, X.Y.; Tang, Z.; Zhang, W.M.; Zhu, L.M.; Ren, H.; Zhou, G.R.; Sheng, R.S.F. Detecting Fatigue Status of Pilots Based on Deep Learning Network Using EEG Signals. *IEEE Trans. Cogn. Dev. Syst.* **2020**, *13*, 575–585. [CrossRef]

23. Ahmadi, A.; Bazregarzadeh, H.; Kazemi, K. Automated detection of driver fatigue from electroencephalography through wavelet-based connectivity. *Biocybern. Biomed. Eng.* **2020**, *41*, 316–332. [CrossRef]

24. Chen, C.; Li, K.; Wu, Q.; Wang, H.; Qian, Z.; Sudlow, G. EEG-based detection and evaluation of fatigue caused by watching 3DTV. *Displays* **2013**, *34*, 81–88. [CrossRef]

25. Monteiro, T.G.; Li, G.; Skourup, C.; Zhang, H. Investigating an integrated sensor fusion system for mental fatigue assessment for demanding maritime operations. *Sensors* **2020**, *20*, 2588. [CrossRef] [PubMed]

26. Zhang, Z.; Xu, F.; Yang, H.; Jiang, J.; Cao, Y.; Jiao, X. Mental fatigue detection based on the functional near infrared spectroscopy. In Proceedings of the International Conference on Optical and Photonics Engineering (icOPEN 2016), Chengdu, Sichuan, 26–30 September 2016.

27. Pang, Y.Y.; Li, X.P.; Shen, K.Q.; Zheng, H.; Zhou, W.; Wilder-Smith, E.P.V. An auditory vigilance task for mental fatigue detection. In Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference, Shanghai, China, 31 August–3 September 2005.

28. Chang, K.M.; Xu, H.C.; Ching, C.T.S.; Liu, S.H. Wireless Patrol Sign-In System with Mental Fatigue Detection. *J. Healthc. Eng.* **2018**, *2018*, 6419064. [CrossRef] [PubMed]

29. Li, P.; Jiang, W.; Su, F. Single-channel EEG-based mental fatigue detection based on deep belief network. In Proceedings of the 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, USA, 16–20 August 2016.

30. Laurent, F.; Valderrama, M.; Besserve, M.; Guillard, M.; Lachaux, J.P.; Martinerie, J.; Florence, G. Multimodal information improves the rapid detection of mental fatigue. *Biomed. Signal Process. Control* **2013**, *8*, 400–408. [CrossRef]

31. Xiao, H.; Duan, Y.; Zhang, Z.; Li, M. Detection and estimation of mental fatigue in manual assembly process of complex products. *Assem. Autom.* **2017**, *38*, 239–247. [CrossRef]

32. Le, N.Q.K.; Kha, Q.H.; Nguyen, V.H.; Chen, Y.-C.; Cheng, S.-J.; Chen, C.-Y. Machine Learning-Based Radiomics Signatures for EGFR and KRAS Mutations Prediction in Non-Small-Cell Lung Cancer. *Int. J. Mol. Sci.* **2021**, *22*, 9254. [CrossRef]

33. Ahamed, M.; Akhtar, M.J.; Khan, M.A.M.; Alhadlaq, H.A. A Novel Green Preparation of Ag/RGO Nanocomposites with Highly Effective Anticancer Performance. *Polymers* **2021**, *13*, 3350. [CrossRef]

34. Ahamed, M.; Akhtar, M.J.; Khan, M.A.M.; Alaizeri, Z.M.; Alhadlaq, H. Facile Synthesis of Zn-Doped Bi_2O_3 Nanoparticles and Their Selective Cytotoxicity toward Cancer Cells. *ACS Omega* **2021**, *6*, 17353–17361. [CrossRef]

35. Teelhawod, B.N.; Akhtar, F.; Bin Heyat, M.B.; Tripathi, P.; Mehrotra, R.; Asfaw, A.B.; Al Shorman, O.; Masadeh, M. Machine Learning in E-health: A Comprehensive Survey of Anxiety. In Proceedings of the 2021 International Conference on Data Analytics for Business and Industry (ICDABI), Sakheer, Bahrain, 25–26 October 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 167–172.

36. AlShorman, O.; Masadeh, M.; Alzyoud, A.; Bin Heyat, M.B.; Akhtar, F. The Effects of Emotional Stress on Learning and Memory Cognitive Functions: An EEG Review Study in Education. In Proceedings of the 2020 Sixth International Conference on e-Learning (econf), Sakheer, Bahrain, 6–7 December 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 177–182.

37. Akhtar, F.; Bin Heyat, M.B.; Li, J.P.; Patel, P.K.; Rishipal; Guragai, B. Role of Machine Learning in Human Stress: A Review. In Proceedings of the 2020 17th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), Chengdu, China, 17–19 December 2021; IEEE: Piscataway, NJ, USA, 2020; pp. 170–174.

38. AlShorman, O.; Masadeh, M.; Bin Heyat, M.B.; Akhtar, F.; Almahasneh, H.; Ashraf, G.M.; Alexiou, A. Frontal lobe real-time EEG analysis using machine learning techniques for mental stress detection. *J. Integr. Neurosci.* **2022**, *21*, 20. [CrossRef]

39. Guragai, B.; AlShorman, O.; Masadeh, M.; Heyat, M.B. Bin A Survey on Deep Learning Classification Algorithms for Motor Imagery. In Proceedings of the 2020 32nd International Conference on Microelectronics (ICM), Aqaba, Jordan, 14–17 December 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1–4.

40. Bin Heyat, M.B.; Lai, D.; Khan, F.I.; Zhang, Y. Sleep Bruxism Detection Using Decision Tree Method by the Combination of C4-P4 and C4-A1 Channels of Scalp EEG. *IEEE Access* **2019**, *7*, 102542–102553. [CrossRef]

41. Bin Heyat, M.B.; Lai, D.; Akhtar, F.; Ammar, M.; Hayat, B.; Azad, S.; Azad, S.; Azad, S. Bruxism Detection Using Single-Channel C4-A1 on Human Sleep S2 Stage Recording. In *Intelligent Data Analysis: From Data Gathering to Data Comprehension*; Gupta, D., Bhattacharyya, S., Khanna, A., Eds.; John Wiley & Sons: Hoboken, NJ, USA, 2020; pp. 347–367.

42. Bin Heyat, M.B.; Akhtar, F.; Khan, M.H.; Ullah, N.; Gul, I.; Khan, H.; Lai, D. Detection, Treatment Planning, and Genetic Predisposition of Bruxism: A Systematic Mapping Process and Network Visualization Technique. *CNS Neurol. Disord. Drug Targets* **2021**, *20*, 755–775. [CrossRef]

43. Bin Heyat, M.B.; Akhtar, F.; Ansari, M.A.; Khan, A.; Alkahtani, F.; Khan, H.; Lai, D. Progress in Detection of Insomnia Sleep Disorder: A Comprehensive Review. *Curr. Drug Targets* **2021**, *22*, 672–684. [CrossRef] [PubMed]

44. Lai, D.; Bin Heyat, M.B.; Khan, F.I.; Zhang, Y. Prognosis of Sleep Bruxism Using Power Spectral Density Approach Applied on EEG Signal of both EMG1-EMG2 and ECG1-ECG2 Channels. *IEEE Access* **2019**, *7*, 82553–82562. [CrossRef]

45. Bin Heyat, M.B.; Akhtar, F.; Khan, A.; Noor, A.; Benjdira, B.; Qamar, Y.; Abbas, S.J.; Lai, D. A Novel Hybrid Machine Learning Classification for the Detection of Bruxism Patients Using Physiological Signals. *Appl. Sci.* **2020**, *10*, 7410. [CrossRef]

46. Bin Heyat, M.B.; Lai, D.; Akhtar, F.; Bin Hayat, M.A.; Azad, S. Short Time Frequency Analysis of Theta Activity for the Diagnosis of Bruxism on EEG Sleep Record. In *Advanced Computational Intelligence Techniques for Virtual Reality in Healthcare. Studies in Computational Intelligence*; Gupta, D., Hassanien, A.K., Eds.; Springer: Berlin/Heidelberg, Germany, 2020; pp. 63–83.

47. Bin Heyat, B.; Akhtar, F.; Singh, S.K.; Siddiqui, M.M. Hamming Window are used in the Prognostic of Insomnia. In Proceedings of the International Seminar on Present Scenario & Future Prospectives of Research in Engineering & Sciences (ISPSFPRES-17), Lucknow, Uttar Pradesh, India, 21 January 2017; pp. 65–71.

48. Bin Heyat, M.B.; Akhtar, F.; Bin Hayat, M.A.; Azad, S. Power Spectral Density are used in the Investigation of insomnia neurological disorder. In Proceedings of the XL-Pre Congress Symposium, Lucknow, Uttar Pradesh, India, 15–18 August 2016; pp. 45–50.

49. MBB, H.; Akhtar, F.; Mehdi, A.; Azad, S.; Azad, S.; Azad, S. Normalized Power are used in the Diagnosis of Insomnia Medical Sleep Syndrome through EMG1-EMG2 Channel. *Austin J. Sleep Disord.* **2017**, *4*, 2–4.

50. Bin Heyat, M.B. *Insomnia: Medical Sleep Disorder & Diagnosis*, 1st ed.; Anchor Academic Publishing: Hamburg, Germany, 2016.

51. Mishra, T.; Wang, M.; Metwally, A.A.; Bogu, G.K.; Brooks, A.W.; Bahmani, A.; Alavi, A.; Celli, A.; Higgs, E.; Dagan-Rosenfeld, O.; et al. Pre-symptomatic detection of COVID-19 from smartwatch data. *Nat. Biomed. Eng.* **2020**, *4*, 1208–1220. [CrossRef]

52. Witt, D.R.; Kellogg, R.A.; Snyder, M.P.; Dunn, J. Windows into human health through wearables data analytics. *Curr. Opin. Biomed. Eng.* **2019**, *9*, 28–46. [CrossRef]

53. Tipparaju, V.V.; Mallires, K.R.; Wang, D.; Tsow, F.; Xian, X. Mitigation of Data Packet Loss in Bluetooth Low Energy-Based Wearable Healthcare Ecosystem. *Biosensors* **2021**, *11*, 350. [CrossRef]

54. Randell, C. *Wearable Computing: A Review*; University of Bristol: Bristol, UK, 2005. Available online: https://research-information.bris.ac.uk/en/publications/wearable-computing-a-review (accessed on 20 November 2021).

55. Chan, M.; Estève, D.; Fourniols, J.Y.; Escriba, C.; Campo, E. Smart wearable systems: Current status and future challenges. *Artif. Intell. Med.* **2012**, *56*, 137–156. [CrossRef]

56. Bu, Y.; Hassan, M.F.U.; Lai, D. The Embedding of Flexible Conductive Silver-Coated Electrodes into ECG Monitoring Garment for Minimizing Motion Artefacts. *IEEE Sens. J.* **2020**, *21*, 14454–14465. [CrossRef]

57. Ul Hassan, M.F.; Lai, D.; Bu, Y. Characterization of single lead continuous ECG recording with various dry electrodes. In Proceedings of the 2019 3rd International Conference on Computational Biology and Bioinformatics, Nagoya, Japan, 17–19 October 2019.

58. Chalder, T.; Berelowitz, G.; Pawlikowska, T.; Watts, L.; Wessely, S.; Wright, D.; Wallace, E.P. Development of a fatigue scale. *J. Psychosom. Res.* **1993**, *37*, 147–153. [CrossRef]

59. Al-Shair, K.; Kolsum, U.; Berry, P.; Smith, J.; Caress, A.; Singh, D.; Vestbo, J. Development, dimensions, reliability and validity of the novel Manchester COPD fatigue scale. *Thorax* **2009**, *64*, 950–955. [CrossRef] [PubMed]

60. McCarthy, L.; Fuller, J.; Davidson, G.; Crump, A.; Positano, S.; Alderman, C. Assessment of yoga as an adjuvant treatment for combat-related posttraumatic stress disorder. *Australas. Psychiatry* **2017**, *25*, 354–357. [CrossRef] [PubMed]

61. Chin, E.G.; Buchanan, E.M.; Ebesutani, C.; Young, J. Depression, Anxiety, and Stress: How Should Clinicians Interpret the Total and Subscale Scores of the 21-Item Depression, Anxiety, and Stress Scales? *Psychol. Rep.* **2019**, *122*, 1550–1575. [CrossRef] [PubMed]

62. Marx, P. How useful are the cold pressor test and sustained isometric handgrip exercise with radionuclide ventriculography in the evaluation of patients with coronary artery disease? *Heart* **1987**, *58*, 678–679. [CrossRef] [PubMed]

63. Wirch, J.L.; Wolfe, L.A.; Weissgerber, T.L.; Davies, G.A.L. Cold presser test protocol to evaluate cardiac autonomic function. *Appl. Physiol. Nutr. Metab.* **2006**, *31*, 235–243. [CrossRef] [PubMed]

64. Wirch, J.L.; Wolfe, L.A.; Weissgerber, T.L.; Davies, G.A.L. Development of a Cold Pressor Test Protocol to Evaluate Cardiac Autonomic Function. *Med. Sci. Sport. Exerc.* **2005**, *37*, S232. [CrossRef]

65. Silverthorn, D.U.; Michael, J. Cold stress and the cold pressor test. *Am. J. Physiol. Adv. Physiol. Educ.* **2013**, *37*, 93–96. [CrossRef]

66. Schwabe, L.; Haddad, L.; Schachinger, H. HPA axis activation by a socially evaluated cold-pressor test. *Psychoneuroendocrinology* **2008**, *33*, 890–895. [CrossRef]

67. Al-shargie, F.M.; Tang, T.B.; Badruddin, N.; Kiguchi, M. Mental Stress Quantification Using EEG Signals. In Proceedings of the International Conference for Innovation in Biomedical Engineering and Life Sciences, Putrajaya, Malaysia, 6–8 December 2015; pp. 15–19.

68. Folle, A.M.; Kitano, E.S.; Lima, A.; Gil, M.; Cucher, M.; Mourglia-Ettlin, G.; Iwai, L.K.; Rosenzvit, M.; Batthyány, C.; Ferreira, A.M. The Montreal Imaging Stress Task: Using functional imaging to investigate the effects of perceiving and processing psychosocial stress in the human brain Katarina. *PLoS Negl. Trop. Dis.* **2017**.

69. Mulder, L.J.M. Measurement and analysis methods of heart rate and respiration for use in applied environments. *Biol. Psychol.* **1992**, *34*, 205–236. [CrossRef]

70. Schwerdtfeger, A.R.; Schwarz, G.; Pfurtscheller, K.; Thayer, J.F.; Jarczok, M.N.; Pfurtscheller, G. Heart rate variability (HRV): From brain death to resonance breathing at 6 breaths per minute. *Clin. Neurophysiol.* **2019**, *131*, 676–693. [CrossRef] [PubMed]

71. Thayer, J.F.; Åhs, F.; Fredrikson, M.; Sollers, J.J.; Wager, T.D. A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. *Neurosci. Biobehav. Rev.* **2012**, *36*, 747–756. [CrossRef] [PubMed]

72. Momeny, M.; Jahanbakhshi, A.; Jafarnezhad, K.; Zhang, Y.-D. Accurate classification of cherry fruit using deep CNN based on hybrid pooling approach. *Postharvest Biol. Technol.* **2020**, *166*, 111204. [CrossRef]

73. Ahmed, F.S.; Ali, L.; Joseph, B.A.; Ikram, A.; Ul Mustafa, R.; Bukhari, S.A.C. A statistically rigorous deep neural network approach to predict mortality in trauma patients admitted to the intensive care unit. *J. Trauma Acute Care Surg.* **2020**, *89*, 736–742. [CrossRef] [PubMed]

74. Ali, L.; He, Z.; Cao, W.; Rauf, H.T.; Imrana, Y.; Bin Heyat, M.B. MMDD-Ensemble: A Multimodal Data-Driven Ensemble Approach for Parkinson's Disease Detection. *Front. Neurosci.* **2021**, *15*, 1–11. [CrossRef]

75. Ho, T.K. The random subspace method for constructing decision forests. *IEEE Trans. Pattern Anal. Mach. Intell.* **1998**, *20*, 832–844. [CrossRef]

76. Ho, T.K. A data complexity analysis of comparative advantages of decision forest constructors. *Pattern Anal. Appl.* **2002**, *5*, 102–112. [CrossRef]

77. Yan, X.; Su, X. *Linear Regression Analysis: Theory and Computing*; World Scientific: Singapore, 2009; ISBN 9789812834119.

78. Ukwuoma, C.C.; Zhiguang, Q.; Heyat, M.B.B.; Ali, L.; Almaspoor, Z.; Monday, H.N. Recent Advancements in Fruit Detection and Classification Using Deep Learning Techniques. *Math. Probl. Eng.* **2022**, *2022*, 9210947. [CrossRef]

79. Nawabi, A.K.; Jinfang, S.; Abbasi, R.; Iqbal, M.S.; Bin Heyat, M.B.; Akhtar, F.; Wu, K.; Twumasi, B.A. Segmentation of Drug-Treated Cell Image and Mitochondrial-Oxidative Stress Using Deep Convolutional Neural Network. *Oxid. Med. Cell. Longev.* **2022**, *2022*, 5641727. [CrossRef]

80. Vest, A.N.; Da Poian, G.; Li, Q.; Liu, C.; Nemati, S.; Shah, A.J.; Clifford, G.D. An open source benchmarked toolbox for cardiovascular waveform and interval analysis. *Physiol. Meas.* **2018**, *39*, 105004. [CrossRef]

81. Zulfiqar, H.; Yuan, S.S.; Huang, Q.L.; Sun, Z.J.; Dao, F.Y.; Yu, X.L.; Lin, H. Identification of cyclin protein using gradient boost decision tree algorithm. *Comput. Struct. Biotechnol. J.* **2021**, *19*, 4123–4131. [CrossRef] [PubMed]

82. Zulfiqar, H.; Sun, Z.-J.; Huang, Q.-L.; Yuan, S.-S.; Lv, H.; Dao, F.-Y.; Lin, H.; Li, Y.-W. Deep-4mCW2V: A sequence-based predictor to identify N4-methylcytosine sites in *Escherichia coli*. *Methods* **2021**, *203*, 558–563. [CrossRef] [PubMed]

83. Zulfiqar, H.; Khan, R.S.; Hassan, F.; Hippe, K.; Hunt, C.; Ding, H.; Song, X.M.; Cao, R. Computational identification of N4-methylcytosine sites in the mouse genome with machine-learning method. *Math. Biosci. Eng.* **2021**, *18*, 3348–3363. [CrossRef] [PubMed]

84. Zulfiqar, H.; Huang, Q.-L.; Lv, H.; Sun, Z.-J.; Dao, F.-Y.; Lin, H. Deep-4mCGP: A Deep Learning Approach to Predict 4mC Sites in *Geobacter pickeringii* by Using Correlation-Based Feature Selection Technique. *Int. J. Mol. Sci.* **2022**, *23*, 1251. [CrossRef] [PubMed]

85. Zulfiqar, H.; Ahmed, Z.; Ma, C.-Y.; Khan, R.S.; Grace-Mercure, B.K.; Yu, X.-L.; Zhang, Z.-Y. Comprehensive Prediction of Lipocalin Proteins Using Artificial Intelligence Strategy. *Front. Biosci.* **2022**, *27*, 84. [CrossRef]

86. Du, Y.T.; Pasupathy, S.; Neil, C.; Beltrame, J.F. A comparison of ECG scores for area at risk. *Heart* **2012**, *98*, 1257–1258. [CrossRef]

87. Bin Heyat, M.; Siddiqui, M.M. Recording of EEG, ECG, EMG Signal. *Int. J. Adv. Res. Comput. Sci. Softw. Eng.* **2015**, *5*, 813–815.

88. Lai, D.; Zhang, X.; Zhang, Y.; Bin Heyat, M.B. Convolutional Neural Network Based Detection of Atrial Fibrillation Combing R-R intervals and F-wave Frequency Spectrum. In Proceedings of the 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 23–27 July 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 4897–4900.

89. Schouten, E.G.; Dekker, J.M.; Meppelink, P.; Kok, F.J.; Vandenbroucke, J.P.; Pool, J. QT interval prolongation predicts cardiovascular mortality in an apparently healthy population. *Circulation* **1991**, *84*, 1516–1523. [CrossRef]

90. Salles, G.F.; Bloch, K.V.; Cardoso, C.R.L. Mortality and Predictors of Mortality in a Cohort of Brazilian Type 2 Diabetic Patients. *Diabetes Care* **2004**, *27*, 1299–1305. [CrossRef]

91. Okin, P.M.; Devereux, R.B.; Lee, E.T.; Galloway, J.M.; Howard, B.V. Electrocardiographic Repolarization Complexity and Abnormality Predict All-Cause and Cardiovascular Mortality in Diabetes. *Diabetes* **2004**, *53*, 434–440. [CrossRef]

92. Youdim, K.A.; Shukitt-Hale, B.; MacKinnon, S.; Kalt, W.; Joseph, J.A. Polyphenolics enhance red blood cell resistance to oxidative stress: In vitro and in vivo 1 Mention of trade name, proprietary product, or specific equipment does not constitute a guarantee by the US Department of Agriculture and does not imply its approval. *Biochim. Biophys. Acta Gen. Subj.* **2000**, *1523*, 117–122. [CrossRef]

93. Stehbens, W.E. Coronary heart disease, hypercholesterolemia, and atherosclerosis I. False premises. *Exp. Mol. Pathol.* **2001**, *70*, 103–119. [CrossRef] [PubMed]

94. Dubois-Deruy, E.; Peugnet, V.; Turkieh, A.; Pinet, F. Oxidative Stress in Cardiovascular Diseases. *Antioxidants* **2020**, *9*, 864. [CrossRef] [PubMed]

95. Puterman, E.; Epel, E. An Intricate Dance: Life Experience, Multisystem Resiliency, and Rate of Telomere Decline throughout the Lifespan. *Soc. Personal. Psychol. Compass* **2012**, *6*, 807–825. [CrossRef]

96. Tuppen, H.A.L.; Blakely, E.L.; Turnbull, D.M.; Taylor, R.W. Mitochondrial DNA mutations and human disease. *Biochim. Biophys. Acta Bioenerg.* **2010**, *1797*, 113–128. [CrossRef]

97. Schwartz, B.G.; French, W.J.; Mayeda, G.S.; Burstein, S.; Economides, C.; Bhandari, A.K.; Cannom, D.S.; Kloner, R.A. Emotional stressors trigger cardiovascular events. *Int. J. Clin. Pract.* **2012**, *66*, 631–639. [CrossRef]

98. Yusuf, S.; Hawken, S.; Ôunpuu, S.; Dans, T.; Avezum, A.; Lanas, F.; McQueen, M.; Budaj, A.; Pais, P.; Varigos, J.; et al. Effect of potentially modifiable risk factors associated with myocardial infarction in 52 countries (the INTERHEART study): Case-control study. *Lancet* **2004**, *364*, 937–952. [CrossRef]

99. De Vente, W.; Van Amsterdam, J.G.C.; Olff, M.; Kamphuis, J.H.; Emmelkamp, P.M.G. Burnout Is Associated with Reduced Parasympathetic Activity and Reduced HPA Axis Responsiveness, Predominantly in Males. *Biomed. Res. Int.* **2015**, *2015*, 431725. [CrossRef]

100. Shen, M.J.; Zipes, D.P. Role of the autonomic nervous system in modulating cardiac arrhythmias. *Circ. Res.* **2014**, *114*, 1004–1021. [CrossRef]

101. Zeviani, M.; Di Donato, S. Mitochondrial disorders. *Brain* **2004**, *127*, 2153–2172. [CrossRef]

102. Li, G.; Li, B.; Wang, G.; Zhang, J.; Wang, J. A New Method for Human Mental Fatigue Detection with Several EEG Channels. *J. Med. Biol. Eng.* **2017**, *37*, 240–247. [CrossRef]

103. Wang, F.; Wang, H.; Fu, R. Real-time ECG-based detection of fatigue driving using sample entropy. *Entropy* **2018**, *20*, 196. [CrossRef] [PubMed]

104. Lamti, H.A.; Ben Khelifa, M.M.; Hugel, V. Mental fatigue level detection based on event related and visual evoked potentials features fusion in virtual indoor environment. *Cogn. Neurodyn.* **2019**, *13*, 271–285. [CrossRef] [PubMed]

105. Huang, S.; Li, J.; Zhang, P.; Zhang, W. Detection of mental fatigue state with wearable ECG devices. *Int. J. Med. Inform.* **2018**, *119*, 39–46. [CrossRef]

106. Shon, D.; Im, K.; Park, J.H.; Lim, D.S.; Jang, B.; Kim, J.M. Emotional stress state detection using genetic algorithm-based feature selection on EEG signals. *Int. J. Environ. Res. Public Health* **2018**, *15*, 2461. [CrossRef]

107. Hasan, M.J.; Kim, J.M. A hybrid feature pool-based emotional stress state detection algorithm using EEG signals. *Brain Sci.* **2019**, *9*, 376. [CrossRef]

108. Bsoul, M.; Minn, H.; Nourani, M.; Gupta, G.; Tamil, L. Real-time sleep quality assessment using single-lead ECG and multi-stage SVM classifier. In Proceedings of the 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, Buenos Aires, Argentina, 31 August–4 September 2010.

109. Song, M.H.; Cho, S.P.; Kim, W.; Lee, K.J. New real-time heartbeat detection method using the angle of a single-lead electrocardiogram. *Comput. Biol. Med.* **2015**, *59*, 73–79. [CrossRef]

110. Lai, D.; Zhang, Y.; Zhang, X. Single Lead ECG-based Ventricular Repolarization Classification for Early Identification of Unexpected Ventricular Fibrillation. In Proceedings of the 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Montréal, QC, Canada, 20–24 July 2020.

111. Cai, Z.; Li, J.; Johnson, A.E.W.; Zhang, X.; Shen, Q.; Zhang, J.; Liu, C. Rule-based rough-refined two-step-procedure for real-time premature beat detection in single-lead ECG. *Physiol. Meas.* **2020**, *41*, 054004. [CrossRef]

112. Bozkurt, F.; Uçar, M.K.; Bozkurt, M.R.; Bilgin, C. Detection of Abnormal Respiratory Events with Single Channel ECG and Hybrid Machine Learning Model in Patients with Obstructive Sleep Apnea. *IRBM* **2020**, *41*, 241–251. [CrossRef]